# Essays on the Economics of Risky Health Behaviors

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Qihua Qiu

ABSTRACT

ESSAYS ON THE ECONOMICS OF RISKY HEALTH BEHAVIORS

By

QIHUA QIU

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Committee Chair: Dr. Charles Courtemanche

Major Department: Economics

This dissertation consists of three essays studying the economics of risky health behaviors. Essay 1 estimates the effects of Graduated Driver Licensing (GDL) restrictions on weight status among adolescents aged 14 to 17 in the U.S. The findings suggest that a night curfew significantly raises adolescents' probability of being "overweight or obese" by 1.32 percentage points, corresponding to an increase in "overweight or obesity" rate of 4.8%. A night curfew combined with a passenger restriction increases this rate by 5.8%. Overall, I estimate that nearly 16% of the rise in "overweight or obesity" rate among teenagers aged 14 to 17 in the U.S from 1999 to 2015 can be explained by the presence of the GDL restrictions. In addition, the restrictions reduce teenagers' exercise frequency while increasing their time spent watching TV, which may help to explain the adverse effects on obesity.

Essay 2 exploits the effects of the Graduated Driver Licensing (GDL) restrictions on youth smoking and drinking. It finds that being subject to minimum entry age, a learner stage, or only a night curfew has no statistically significant effect whereas, interestingly, a night curfew combined with a passenger restriction reduces youth smoking and drinking. The estimated effects become more statistically significant and larger in magnitude in the medium run, which is in line with the addictive nature of these substances.

Essay 3 investigates the underlying causes of suicide. It uses data from the U.S. at the county level and the primary methodology is a two-level Bayesian hierarchical model with spatially correlated random effects. The results show that the significant effects of observable factors on suicides found by earlier research may partially stem from excluding small area effects and time trends, without controlling for which the true contribution of unobserved propensities and time trends can be hidden within observable factors. Most importantly, a lot can be learned from unobserved yet persistent propensity toward suicide captured by the spatially correlated county specific random effects. Resources should be allocated to counties with high suicide rates, but also counties with low raw suicide rates but high unobserved propensities of suicide.

ESSAYS ON THE ECONOMICS OF RISKY HEALTH BEHAVIORS

BY

QIHUA QIU

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ACCEPTANCE

This dissertation was prepared under the direction of Qihua Qiu's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

| | |
|---|---|
| Dissertation Chair: | Dr. Charles Courtemanche |
| Committee: | Dr. H. Spencer Banzhaf<br>Dr. Roby Greenwald<br>Dr. Rusty Tchernis |

Electronic Version Approved:

Sally Wallace, Dean
Andrew Young School of Policy Studies
Georgia State University
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## General Introduction

Risky health behaviors, such as sedentary lifestyles, smoking, drinking, and suicide impose enormous social and economic costs to the society. Childhood obesity, which is mainly caused by lack of physical activity and unhealthy diet, leads to direct medical costs of $14.1 billion per year in prescription drugs, emergency visits, and outpatient costs, plus inpatient costs of $237.6 million per year (Cawley, 2010). One percentage point of additional youth smoking in U.S. could result in a forgone value of life years of $36-$73 billion (Gruber and Zinman, 2001). Excessive youth drinking is also estimated to cost $24.3 billion in 2010 (Sacks et al., 2015). The lifelong medical and work-loss costs from suicides are estimated to be $50.8 billion in the United States alone (Florence et al., 2015). This dissertation studies the economics of these risky health behaviors focusing on some causes which have barely been given attention in prior literature.

Essay 1 estimates the effects of Graduated Driver Licensing (GDL) restrictions on weight status among adolescents aged 14 to 17 in the U.S. The findings suggest that a night curfew significantly raises adolescents' probability of being "overweight or obese" by 1.32 percentage points, corresponding to an increase in "overweight or obesity" rate of 4.8%. A night curfew combined with a passenger restriction increases this rate by 5.8%. Overall, I estimate that nearly 16% of the rise in "overweight or obesity" rate among teenagers aged 14 to 17 in the U.S from 1999 to 2015 can be explained by the presence of the GDL restrictions. In addition, the restrictions reduce teenagers' exercise frequency while increasing their time spent watching TV, which may help to explain the adverse effects on teenage weight gains.

Essay 2 exploits the effects of the Graduated Driver Licensing (GDL) restrictions on youth smoking and drinking. It finds that being subject to minimum entry age, a learner stage, or only a night curfew has no statistically significant effect whereas, interestingly, a night curfew combined with a passenger restriction reduces youth smoking and drinking. The estimated effects become more statistically significant and larger in magnitude in the medium run, which is in line with the addictive nature of these substances. It also finds that girls or white teenagers are more responsive to the combined restriction in smoking but less responsive in drinking compared to boys or non-white teenagers.

Essay 3 investigates the underlying causes of suicide. In contrast to previous literature, it uses data from the United States at the county level. The primary methodology is a two-level Bayesian hierarchical model with spatially correlated random effects. The results show that the significant effects of observable factors on suicides found by earlier research may partially stem from excluding small area effects and time trends. Without controlling for these area and time effects, the true contribution of unobserved propensities and time trends can be hidden within observable factors. Most importantly, it finds that a lot can be learned from unobserved yet persistent propensity toward suicide captured by the spatially correlated county specific random effects. Resources should be allocated to counties with high suicide rates, but also counties with low raw suicide rates but high unobserved propensities of suicide.

**Essay 1: The Effects of the Graduated Driver Licensing Restrictions on Teenage Weight**

## 1. Introduction and background

The issue of rising teenage obesity has come to the fore. The prevalence of obesity among adolescents aged 12-19 years has more than quadrupled from 4.2% in the 1966-1970 period to 20.6% in the 2013-2014 period.[1] Teenage obesity has been shown to cause a number of adverse consequences. First, obese children are found to be at a higher risk of becoming obese adults than non-obese children (Serdula et al., 1993), and obesity is known to cause serious health risks such as diabetes and hypertension for adolescents as well as for adults (Pinhas-Hamiel et al., 1996; Dietz, 1998; Strum, 2002). In addition, adolescents who are overweight and obese tend to have lower life satisfaction than healthy weight youths (Forste and Moore, 2012). They often experience discrimination or even stigmatization from peers (Schwartz & Puhl, 2003; Strauss & Pollack, 2003), which may adversely impact their education, occupation choices, and wages in the future (Han et al., 2011). The social and economic costs of childhood obesity include direct medical costs of $14.1 billion per year in prescription drug, emergency room, and outpatient costs, plus $237.6 million per year in inpatient costs. There is also a future cost of teenage obesity stemming from the obesity-related illness treatments for obese adults, which is currently estimated at $147 billion per year (Cawley, 2010).

Therefore, what causes childhood obesity is at issue and prior studies have tried to determine the underlying factors. The factors in my interest contributing to weight gain for teenagers include sedentary lifestyles (inadequate calorie expenditure) and unhealthy diets

[1] Data source: National Center of Health Statistics (NCHS) and National Health and Nutrition Examination Survey (NHANES). Obesity among children and adolescents aged 2-19 is defined as Body Mass Index (BMI) greater than or equal to the 95th percentile of BMI distribution within same sex and age based on the 2000 Centers for Disease Control and Prevention (CDC) growth charts for the United States (Kuczmarski et al., 2002; Ogden et al., 2010; Fryar et al., 2016). BMI is calculated as weight in kilograms divided by squared height in meters.

(excessive calorie intake) that are closely associated with the time spent at home. Watching TV, playing video and computer games, and using the internet at home are major sedentary lifestyle patterns which have been associated with obesity among children and adolescents (Rey-Lopez et al., 2008). Results of several studies suggest that more time spent watching TV or playing video games each day is significantly associated with greater body weight among adolescents (Dietz and Gortmaker, 1985; Anderson et al., 1998; Eisenmann et al., 2008). Besides, more time spent at home may lead to more consumption of foods at home because they are at closer hand and cheaper than restaurant foods. Also, watching TV may imply more exposure to food advertising, which is found to be associated with a rise in consumption of fast-food and soft drinks among children (Andreyeva et al., 2011). Grossman et al. (2012) suggest that exposure to fast-food advertising on TV significantly increases percentage body fat (PBF) and body mass index (BMI) among adolescents.

My paper aims to estimate the effect of a plausibly exogenous driving-related policy, the Graduated Driver Licensing (GDL) program, on teenage obesity. I also investigate the underlying mechanisms of teenagers' sedentary lifestyles and diets through which the policy affects their weight status. While literature suggests that for adults, less driving is associated with more physical activities and healthier diets, thus reducing obesity prevalence (Frank et al., 2004; Wen and Rissel, 2008; Courtemanche, 2011), I present evidence that mandatory GDL driving restrictions imposed on teenage drivers may have adverse effects on adolescents' physical activities and dietary behaviors, resulting in an increase in teenage obesity.

Growing evidence has shown a positive correlation between vehicle travel and adult obesity. Bassett et al. (2011) find that countries with higher rates of car ownership and driving amount, such as the U.S., Canada, and Australia, have higher obesity rates when compared to the

European countries which are less auto-dependent. People in driving-intensive occupations, such as bus and taxi drivers, have higher obesity rates than those in occupations involving less or no driving activity (Rosengren et al., 1991; Wang and Lin, 2001). More specifically, Frank et al. (2004) find that each additional hour spent driving per day is associated with a 6% increase in the probability of obesity. Courtemanche (2011) provides indirect evidence of a link between driving and weight, as a drop in gasoline price increases the frequency of walking and reduces the frequency of eating at restaurants, thus reducing the prevalence of obesity. In their recent comprehensive review of the literature regarding the association between driving amount and adult weight status, McCormack and Virk (2014) find that most studies suggest a positive association between driving amount and obesity among adults.

To the best of my knowledge however, no one has analyzed the effect of automobile travel on teenage obesity. In practice, estimating the causal relationship between automobile driving and teenage obesity is challenging because there is a potential endogeneity issue in that obese adolescents may prefer driving to walking/cycling compared to healthy weight ones. In this paper, I take advantage of an exogenous source of policy variation from the Graduated Driver Licensing (GDL) system, a teenage driver licensing program designed to reduce car accident rates that phases in new teenage drivers to their full driving privileges by progressively exposing them to more challenging driving circumstances (Williams et al., 2016). In the U.S., the GDL system first emerged in Florida in 1996. From then to 2015, all U.S. states have adopted the GDL system, allowing full/unrestricted licensure for drivers younger than 18 years old only after a mandatory holding period of supervised driving and an intermediate period of unsupervised driving that limits driving at night, transporting multiple young passengers, or both (Masten et al., 2011).

GDL policy variation across states and time has been used to investigate the relationship between driving restrictions and at-fault accident rates. Prior literature provides empirical findings that the GDL restrictions have reduced fatal crash rates among teen drivers (Dee et al., 2005; Baker et al., 2007; Masten et al., 2011). However, some studies argue that this desirable outcome might result from the reduction in the amount of driving for teenage drivers rather than the improvement of their driving quality (Karaca-Mandic and Ridgeway, 2010; Masten et al., 2011). The reduction in driving may lead to some unintended effects, such as changes in teenagers' risky behaviors. A recent study finds that the GDL system, especially the restriction of a night curfew, keeps teenagers "off the street" and significantly contributes to the reduction of criminal participation measured by state-age-specific arrest accounts among teenagers (Deza and Litwok, 2016).

This paper contributes to the GDL literature by introducing a potential adverse unintended effect of the GDL program: adolescent obesity. Since prior literature argues the prohibition of driving under restricted circumstances due to the presence of GDL reduces amount of driving for teenage drivers and keep them "off the street" (Karaca-Mandic and Ridgeway, 2010; Deza and Litwok, 2016), teenagers may spend more time at home, where they are likely to have more sedentary lifestyle behaviors such as watching television or playing video games, during which they may also consume higher calorie snacks and soda drinks. The GDL restrictions might also reduce teenagers' opportunities to get along with their peers. Studies find that other's support or involvement is closely associated with adolescent physical activity (Vilhjalmsson and Thorlindsson, 1998; Sallis et al., 2000). An example of this is having fewer chances to play sports with friends. On the contrary, driving restrictions could lead to more walking/cycling or taking public transportation as alternatives that are related to more physical activity and, in turn, less likelihood of teenage obesity. Therefore, finding the overall effect of GDL restrictions on teenage obesity requires empirical evidence.

Using policy information for the Insurance Institute for Highway Safety (IIHS), I construct a set of state-age-specific treatment variables of the GDL restrictions for adolescents aged 14 to 17 years across states from 1999 to 2015 to match with the biannual Youth Risky Behavior Surveillance Survey (YRBS) dataset which provides data on teenage body weight outcomes, physical activity, and dietary behaviors. The novel specification of state-age-specific GDL treatment variables enables me to explore the age cut-offs and timing of each restriction in each state at the month level, which is different from the prior studies of GDL policies (Dee et al., 2005; Karaca-Mandic and Ridgeway, 2010; Deza and Litwok, 2016). My findings suggest that a night curfew significantly raises adolescents' probability of being "overweight or obese" by 1.32 percentage points, corresponding to an increase in "overweight or obesity" rate of 4.8%. A night curfew combined with a passenger restriction increases this rate by 5.8%. The effect of a single night curfew is stronger among girls, while the effect of a night curfew combined with a passenger restriction is stronger among boys or white teenagers. A cumulative effect analysis suggests that from 1999 to 2015, nearly 16% of the increase in rate of "overweight or obesity" among adolescents aged 14 to 17 can be explained by the presence of the GDL restrictions. In addition, the evidence shows that the GDL restrictions reduce teenagers' exercise frequency and increase their time spent watching TV, which may help to explain the unintended adverse effects of the GDL restrictions on teenage obesity. As an alternative approach, following prior studies, I also generate a set of GDL rating variables in each state and estimate a triple-difference model. My results suggest a good GDL system significantly contributes to weight gains among teenagers aged 16 to 17 who are the major subjects of night curfew and passenger restriction, further supporting my main findings.

The rest of the essay proceeds as follows: Section 2 provides a conceptual model and mechanisms. Section 3 introduces data. Section 4 describes the major identification strategy. Section 5 presents the main results. Section 6 discusses the alternative approach and the results. Section 7 concludes the essay.

## 2. Conceptual set-up and mechanisms

In this section, I provide a conceptual set-up to describe intuitively the underlying mechanisms through which the GDL policies influence teenagers' weight status. The presence of the GDL restrictions increases the opportunity cost of driving in prohibited ways (i.e. driving without parent's supervision, driving at night, or driving with multiple youth passengers) and tends to reduce not only time spent driving among teenage drivers, but also the chance of riding with peers among teenage non-drivers.[2] Teenagers may walk, bike, or take public transit as alternatives to driving/riding, or they might just spend more time at home.[3] The GDL policies keep adolescents "off the street" as Deza and Litwok (2016) suggest, and therefore might lead them to spend more time at home.

The equations below present a conceptual basis for my analysis. Consider a representative teenager whose BMI ($B$) is a function increasing in total caloric intake ($C$) and decreasing in total caloric expenditure ($E$), which is suggested by equations (1) and (5). She has a constant *spare* time constraint normalized to one which is partitioned into time spent "at home"

[2] GDL restrictions could also influence a teenage non-driver because friends or siblings who have driver's licenses and whose ages apply to the restrictions can otherwise give her rides.

[3] Factors affecting teenagers' preferences of staying at home include walkability of the neighborhood, accessibility to public transportation, and safety concerns of their parents.

($T_H$) and "outside" ($T_O$) in equations (2) and (3).[4] Being "at home" is defined as being exactly at home or being around her neighborhood by walking/cycling. Being "outside" means she needs to go somewhere accessible only by driving/riding or taking public transportation. For every unit of time she spends "at home" or "outside", she obtains calories $C_H$ and $C_O$ by eating, and she expends calories $E_H$ and $E_O$ through physical activity "at home" or "outside". The units of caloric intake $C_H$ and $C_O$ and caloric expenditures $E_H$ and $E_O$ are assumed to be invariant with respect to the GDL restrictions given her age, gender, race, grade, state, and year. Equation (2) implies that total caloric intake ($C$) is an average of unit caloric intakes $C_H$ and $C_O$ weighted by time spent "at home" ($T_H$) and "outside" ($T_O$). By the same token, as is in equation (3), total caloric expenditure ($E$) is an average of unit caloric expenditures $E_H$ and $E_O$ weighted by time spent "at home" ($T_H$) and "outside" ($T_O$). Equations (4) and (8) imply that time spent "at home" ($T_H$) is an increasing function of the GDL restrictions ($G$) as discussed above.

$$B = B(C, E) \tag{1}$$

$$C = C_H T_H + C_O(1 - T_H) \tag{2}$$

$$E = E_H T_H + E_O(1 - T_H) \tag{3}$$

$$T_H = f(G) \tag{4}$$

where

$$\frac{\partial B}{\partial C} > 0; \frac{\partial B}{\partial E} < 0 \tag{5}$$

$$\frac{\partial C}{\partial T_H} = C_H - C_O ? 0 \tag{6}$$

[4] Alternatively, I could divide her total time into time spent "at school", "at home", and "outside". For simplicity, I assume her time spent at school is constant given her age, gender, race, grade, state, and year that I control for in my empirical specification discussed in detail in section 4.

$$\frac{\partial E}{\partial T_H} = E_H - E_O ? 0 \qquad (7)$$

$$\frac{\partial T_H}{\partial G} > 0 \qquad (8)$$

$$\frac{dB}{dG} = \frac{\partial B}{\partial C}\frac{\boldsymbol{\partial C}}{\boldsymbol{\partial T_H}}\frac{\partial T_H}{\partial G} + \frac{\partial B}{\partial E}\frac{\boldsymbol{\partial E}}{\boldsymbol{\partial T_H}}\frac{\partial T_H}{\partial G} \qquad (9)$$

$$+ \quad ? \quad + \qquad - \quad ? \quad +$$

As the signs of equations (6) and (7) imply, the effects of changes in time spent at home on total caloric intake and caloric expenditure are unclear. Intuitively, how time spent at home affects her total calorie intake and expenditure depends on her circumstances and individual preferences over eating and physical activity "at home" and "outside".[5] Therefore, the overall effects of the GDL restrictions on the teenager's BMI described by equation (9) are also ambiguous because the sign of equation (9) depends on the signs of equations (6) and (7). Considering the various possible situations in caloric intake and expenditure which determine the signs of equations (6), (7), and (9), I propose four possible cases which could occur as follows:

Case 1: $\frac{\partial C}{\partial T_H} = C_H - C_O > 0$; $\frac{\partial E}{\partial T_H} = E_H - E_O > 0 \ \Rightarrow \ \frac{dB}{dG}$ ? 0. Intuitively, the teenager eats more but also does more exercise at home. If the increase in caloric intake substantially

[5] I suggest here all possible cases: I. $C_H - C_O > 0$ implies that caloric intake "at home" might be larger than "outside". The teenager's parents may prepare high calorie foods, or parental supervision might be relatively low, allowing the teenager to eat more snacks while at home. Also, given a small amount of spending money, she might walk/cycle to fast food restaurants nearby. The calories she obtains from such a meal usually exceed the calories she expends by walking/cycling there. She might not go "outside" to eat because healthier restaurants, which might be accessible only by driving/riding and public transportation, may be too expensive for her. II. $C_H - C_O < 0$ suggests that calorie intake "outside" could be larger if the teenager's parents usually feed her healthy food or if parental supervision is high so she is not allowed to eat many snacks at home. Alternatively, she may have adequate spending money and value the quality of food, so she usually prefers to drive or ride to full-service restaurants which are further from home. III. $E_H - E_O > 0$ implies that the teenager might expend more calories "at home" than she does "outside". This happens if she keeps active when she stays at home. She might not just sit watching TV or playing computer games. Instead, she might prefer physical activities at home (i.e. home treadmill, backyard basketball, running in the neighborhood/complex). IV. $E_H - E_O < 0$ suggests that calorie expenditure "outside" might be larger if she prefers a sedentary lifestyle at home. If she wants to exercise, she might prefer to go "outside", traveling to somewhere like a gym because she does not have adequate space or equipment at home and it may be unsafe for her to run in the neighborhood/complex. She might also enjoy participating in sports with her friends for which she needs to drive or take a ride far from home (e.g. a baseball field).

exceeds the increase in physical activity, then the GDL restrictions increase her body weight. In contrast, if the increase in physical activity is dominant, then the GDL restrictions reduce her body weight. Nevertheless, the sign of the overall effect of the GDL restrictions on her body weight remains ambiguous.

Case 2: $\frac{\partial C}{\partial T_H} = C_H - C_O < 0$; $\frac{\partial E}{\partial T_H} = E_H - E_O < 0 \;\Rightarrow\; \frac{dB}{dG} ?\, 0$. The teenager consumes fewer calories at home, but is also more sedentary. The overall effect of the GDL restrictions on the teenager's body weight depends on the relative magnitudes of her reduction in caloric intake and expenditure. Consequently, how the GDL restrictions affect her body weight is also unclear in this case.

Case 3: $\frac{\partial C}{\partial T_H} = C_H - C_O > 0$; $\frac{\partial E}{\partial T_H} = E_H - E_O < 0 \;\Rightarrow\; \frac{dB}{dG} > 0$. In this case, the teenager eats more at home, and she is also more sedentary. It is not difficult to imagine that one watches television while also eating chips at the same time. Overall, by keeping the teenager at home, the GDL restrictions increase her body weight.

Case 4: $\frac{\partial C}{\partial T_H} = C_H - C_O < 0$; $\frac{\partial E}{\partial T_H} = E_H - E_O > 0 \;\Rightarrow\; \frac{dB}{dG} < 0$. In this circumstance, the GDL restrictions reduce the teenager's body weight because she might eat healthier food and do more exercise at home. This case might be especially common among children with parents who have healthier lifestyles.

In summary, the conceptual framework cannot clearly predict how the GDL restrictions affect adolescent body weight status. I therefore next turn to empirical analysis.

**3. Data**

I construct my data by merging GDL treatment variables constructed using the information from the Insurance Institute for Highway Safety (IIHS) to individual weight status and demographic covariates from the biannual individual Youth Risky Behavior Surveillance System (YRBS).

### 3.1 YRBS dependent variables and demographic covariates

My data on individual weight outcomes, physical activities, dietary behaviors, and demographic covariates is extracted from the biannual YRBS weighted state surveys from 1999 to 2015.[6] The dataset consists of the public Combined YRBS Datasets of state surveys available online plus restricted data from the few states which are excluded from the Combined Datasets.[7] One limitation is that the data of some states are not available. First, three states (Minnesota, Oregon and Washington) do not provide any YRBS survey data.[8] Second, the District of Columbia participates in the YRBS survey as a large urban school district rather than a state-level jurisdiction, so its data cannot be simply combined with the data of other states. For the remaining 47 states, data from many states is not available for some of the 9 survey years from 1999 to 2015. Nevertheless, 21 states have data for 8 or 9 survey years, and 20 states have data for 5 to 7 survey years. Only 6 states have data for no more than 4 survey years. The availability of state-year observations within the 47 states I analyze is 74.2 percent. Therefore, I can account for information of most state-years that I need to combine with the GDL restrictions.

My main sample contains 865,652 teenagers aged 14 to 17 who are directly subject to the GDL laws. Table 1 reports the weighted summary statistics of the individual demographic covariates, including dummies for age, gender, race, and grade categories.[9] The weighting variable is provided by the YRBS. Accordingly, 58 percent of teenagers in this sample are 16

[6] The YRBS data is available from 1991 to 2015 for every odd-numbered year. My study period starts from 1999, because prior to 1999 the YRBS did not ask questions regarding the weight and height of respondents.
[7] Some states do not give the CDC permission to include their YRBS survey data in the Combined Dataset or to distribute their data without authority. These restricted data is available upon request to these states.
[8] Minnesota does not participate in the YRBS survey. Oregon and Washington only have unweighted YRBS data for a couple of years which they do not release to the public.
[9] For teenagers, the grade at school matters substantially in their lifestyle. A 16-year-old student in 9th grade might behave differently from a 16-year-old student in 12th grade.

and 17 years old, and they are the primary objects of night curfew and passenger restriction. 50 percent of the teenagers are female, and 39 percent are minorities.

**Table 1. Weighted Summary Statistics of Individual Demographic Covariates**

| Variable | Mean (St.D.) |
|---|---|
| ***Age*** | |
| 14 years old | 0.121 (0.326) |
| 15 years old | 0.300 (0.458) |
| 16 years old | 0.303 (0.459) |
| 17 years old | 0.276 (0.447) |
| ***Gender*** | |
| Female | 0.500 (0.500) |
| ***Race*** | |
| White | 0.610 (0.488) |
| Black | 0.171 (0.377) |
| Hispanic | 0.154 (0.361) |
| Other races | 0.064 (0.245) |
| ***Grade*** | |
| 9th grade | 0.332 (0.471) |
| 10th grade | 0.300 (0.458) |
| 11th grade | 0.260 (0.439) |
| 12th grade | 0.109 (0.311) |

Data source: The Youth Risky Behavior Surveillance System (YRBSS)

Table 2 displays the weighted summary statistics of the dependent variables selected from the YRBS. Note that teenager's body weight outcome needs to be expressed relative to children of the same age and gender. Specifically, teenagers' BMI Z-scores and BMI percentile by age-in-month and sex are commonly used as alternatives to BMI. BMI Z-score, along with its corresponding BMI percentile, is a measure of relative body weight of children among those of the same age and sex. The reference value is provided by the 2000 Centers for Disease Control and Prevention (CDC) growth charts, and the reference group is children surveyed by the National Center of Health Statistics (NCHS) and National Health and Nutrition Examination

Survey (NHANES) from 1960s to late 1990s in U.S. (Kuczmarski et al., 2002; Ogden et al., 2010; Fryar et al., 2016).[10] In addition, obesity and overweight status for teenagers are defined in a different way than the conventional definitions used for adults. The teenagers with a BMI percentile no lower than 95pct are categorized to be obese, and those with BMI percentile between 85pct to 95pct are classified as being overweight. I generate BMI Z-score by age-in-month and sex using the Stata package "*zanthro*", which produces "standardized anthropometric measures in children and adolescents". The calculation of BMI Z-score requires age-in-month information, but the YRBS only report age-in-year of respondents. To address this, I assume the age-in-month of each individual who reports a certain age-in-year follows a uniform distribution. As an example, if a teenager reports that she is 16 years old, then her age-in-month could be 16 years 0 month, 16 years 1 month, 16 years 2 months,…, and 16 years 11 months with a probability of $\frac{1}{12}$ each. For each individual, I calculate one BMI Z-score for each of the 12 probable age-in-months and take an average to get her final BMI Z-score.[11] According to Table 2, on average 12.4 percent of teenagers in my sample are obese and 27.5 percent of them are overweight or obese.[12] In addition, I examine several variables for potential mechanisms through which the GDL restrictions impact adolescent weight status. The summary statistics show that teenagers exercise over 60 minutes for an average of 3.85 days per week. They watch TV for 1.97 hours on an average school day, and drink soda 0.83 times per day.[13]

[10] To assess obesity on a single occasion, such as a pooled cross-sectional dataset used in this paper, BMI Z-score is an optimal measurement compared to BMI percentile (Cole et al., 2005). Therefore, I use BMI Z-score as my main outcome variables.

[11] The YRBS calculates its BMI percentile using an approximated age-in-month which is the reported age plus six months (YRBS, 2016). For instance, if a teenager's reported age is 16 years, then her approximated age-in-month is 16 years 6 months. My regression results remain robust if I instead adopt this "year-plus-6-month" assumption.

[12] Note that the obesity rate over the survey years in my YRBS dataset (among teenagers aged 14-17 from 1999 to 2015) are lower than the national obesity rate among teenagers aged 12-19 during the same time period.

[13] The YRBS does not report the hours spent on watching TV and number of times drinking soda directly. Instead, they report the hours in the form of ordinal responses. I recode these them into continuous variables.

**Table 2. Weighted Summary Statistics of Dependent Variables**

| Variable | Description | Mean (St.D.) |
|---|---|---|
| ***Obesity Status*** | | |
| BMIZ | Body Mass Index Z-score (Normalized BMI by Age and Sex) | 0.426 (1.031) |
| Overweight or Obese | = 1 if the respondent is overweight or obese | 0.275 (0.446) |
| Obese | = 1 if the respondent is obese | 0.124 (0.329) |
| ***Physical Activity & Diet*** | | |
| Exercise | # of days in past 7 days the respondent did exercise 60+minutes | 3.855 (2.539) |
| TV | # of hours per average school day the respondent watched TV | 1.965 (1.547) |
| Soda | # of times per day the respondent drank soda | 0.827 (1.079) |

Data source: The Youth Risky Behavior Surveillance System (YRBSS)
Being overweight or obese: BMI percentile ≥ 85pct. Being obese: BMI percentile ≥ 95pct.

### 3.2 GDL treatment variables

For each of the fifty states and the District of Columbia, the IIHS provides concrete details on all the GDL features including (1) minimum age to start the learner stage, (2) length of mandatory holding period during the learner stage, (3) minimum practice hours in the learner stage when teenage drivers are required to drive under supervision of an adult driver, (4) minimum age to enter the intermediate stage, (5) nighttime restriction that forbids teenagers to drive from dusk to dawn in the intermediate stage, (6) passenger restriction that prohibits them from driving while carrying more than a certain number of youth passengers in the intermediate stage, and (7) minimum age to get a full license for unrestricted driving. The IIHS also reports the effective dates when laws regarding these features were implemented or modified for each state.[14]

Table 3 presents the summary statistics of state-specific GDL restrictions weighted by total population in each state-year. Column (1) summarizes information for all fifty states plus the District of Columbia in every year from 1999 to 2015. During the period from 1999 through

[14] Insurance Institute for Highway Safety (IIHS) GDL policy information: http://www.iihs.org/iihs/topics/laws/graduatedlicenseintro?topicName=teenagers#tableData

2015, 93.4 percent of state-years require a mandatory holding period in the learner stage. In the intermediate stage, 23.8 percent of states-years have only a night curfew, 1 percent of state-years have only a passenger restriction, and 66.8 percent of state-years have a night curfew combined with a passenger restriction. In addition, the average minimum age to start the learner stage is 15.3 and the average minimum age to enter the intermediate stage is 16.1. The minimum age that the night curfew is lifted is 17.3 on average, and the average minimum age that the passenger restriction is lifted is slightly lower at 17.1. The average mandatory holding period is 6.4 months and the average number of mandatory supervised practice hours is 35. Night curfew starts around 11:20 pm, and the average night curfew duration is 5.8 hours. Maximum youth passenger number is 0.75 on average.[15]

Column (2) summarizes the above policy features for the 47 YRBS sampled states in their available odd-numbered years from 1999 to 2015. I collapse the "annual" average GDL restrictions for YRBS sampled states using only the first four months (January to April) of each survey year because YRBS state surveys are usually conducted in the spring semesters of odd-numbered years (YRBS, 2016). Column (3) displays the p-values of t-tests checking the statistical difference between the GDL restrictions of "all state-years" and the "YRBS sampled state-years". Proportions of state-years with certain restrictions, minimum age cutoffs, and most restriction details are not statistically different between the two columns. The mandatory holding period in the "YRBS sampled state-years" is about 11 days longer. Nighttime restriction begins earlier and ends later in the "YRBS sampled state-years", leading to a 10 minutes longer night

[15] To give a clearer picture of the evolution of the GDL system, Figures 1 to 3 depict the proportions of states with certain GDL restrictions, the minimum age cutoffs, and the GDL policy details in "all state-years" from 1999 through 2015. The figures clearly indicate that the GDL policies in the U.S. have become more prevalent and restrictive over the last two decades.

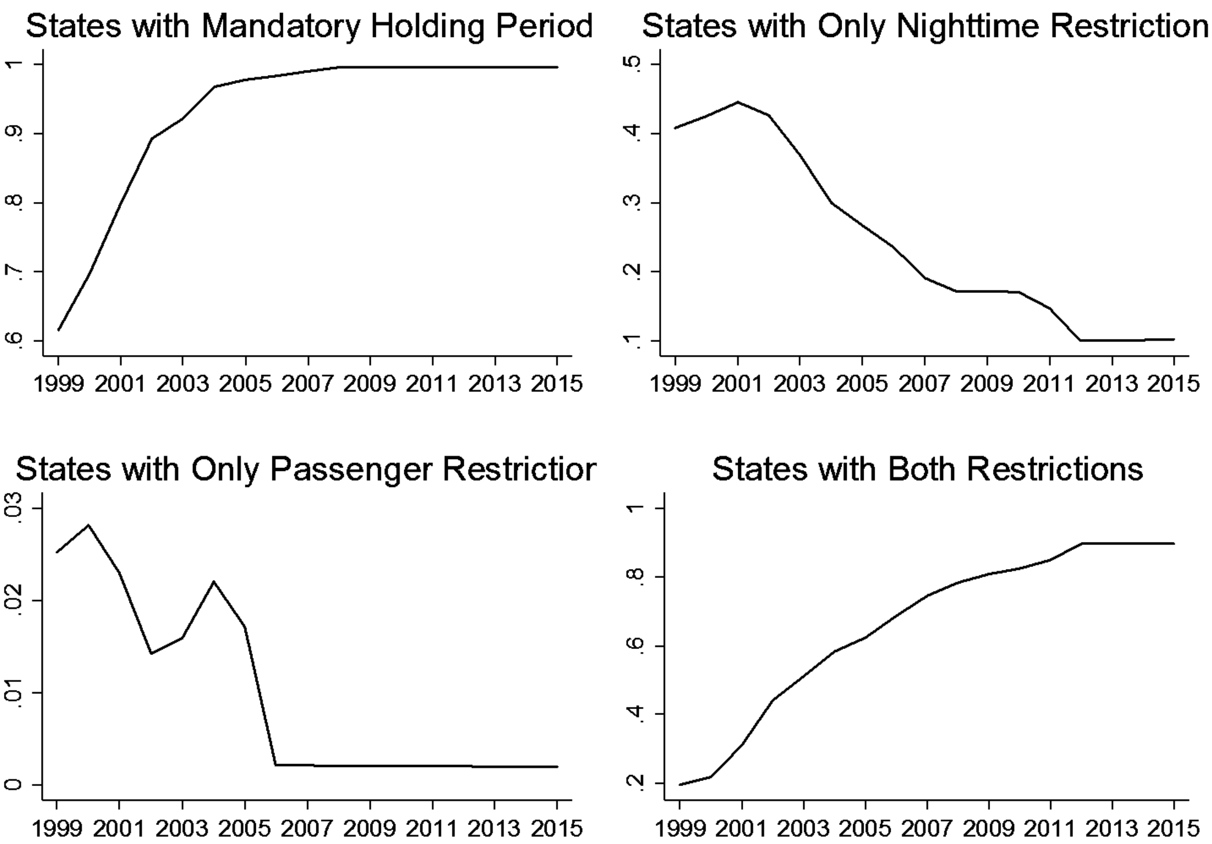
**Table 3. Summary Statistics of State-specific GDL System Information from 1999 to 2015**

| Features | (1) All State-Years[a] | (2) YRBS State-Years[b] | (3) Difference (P-value) |
|---|---|---|---|
| ***Proportion of State-Years with Restrictions*** | | | |
| With mandatory holding period | 0.934 (0.243) | 0.931 (0.254) | 0.827 |
| With only night curfew | 0.238 (0.421) | 0.253 (0.433) | 0.582 |
| With only passenger restriction | 0.009 (0.091) | 0.009 (0.095) | 0.974 |
| With both night curfew and passenger restriction | 0.668 (0.465) | 0.662 (0.471) | 0.865 |
| ***Minimum Age Cutoffs*** | | | |
| Minimum age for learner stage | 15.274 (0.477) | 15.265 (0.500) | 0.777 |
| Minimum age for intermediate stage | 16.085 (0.288) | 16.081 (0.311) | 0.818 |
| Minimum age that night curfew is lifted | 17.322 (0.583) | 17.364 (0.636) | 0.283 |
| Minimum age that passenger restriction is lifted | 17.069 (0.563) | 17.071 (0.582) | 0.943 |
| ***Restriction Details*** | | | |
| Mandatory holding period (months) | 6.364 (2.863) | 6.720 (3.148) | 0.065* |
| Minimum practice hours under supervision | 35.114 (21.203) | 33.937 (20.671) | 0.395 |
| Night curfew start time | 11.314 (1.423) | 11.186 (1.613) | 0.188 |
| Night curfew end time | 5.161 (0.478) | 5.207 (0.511) | 0.148 |
| Night curfew duration (hours) | 5.847 (1.642) | 6.021 (1.847) | 0.119 |
| Maximum youth passenger number | 0.753 (0.680) | 0.848 (0.632) | 0.031** |

Data source: The Insurance Institute for Highway Safety (IIHS).

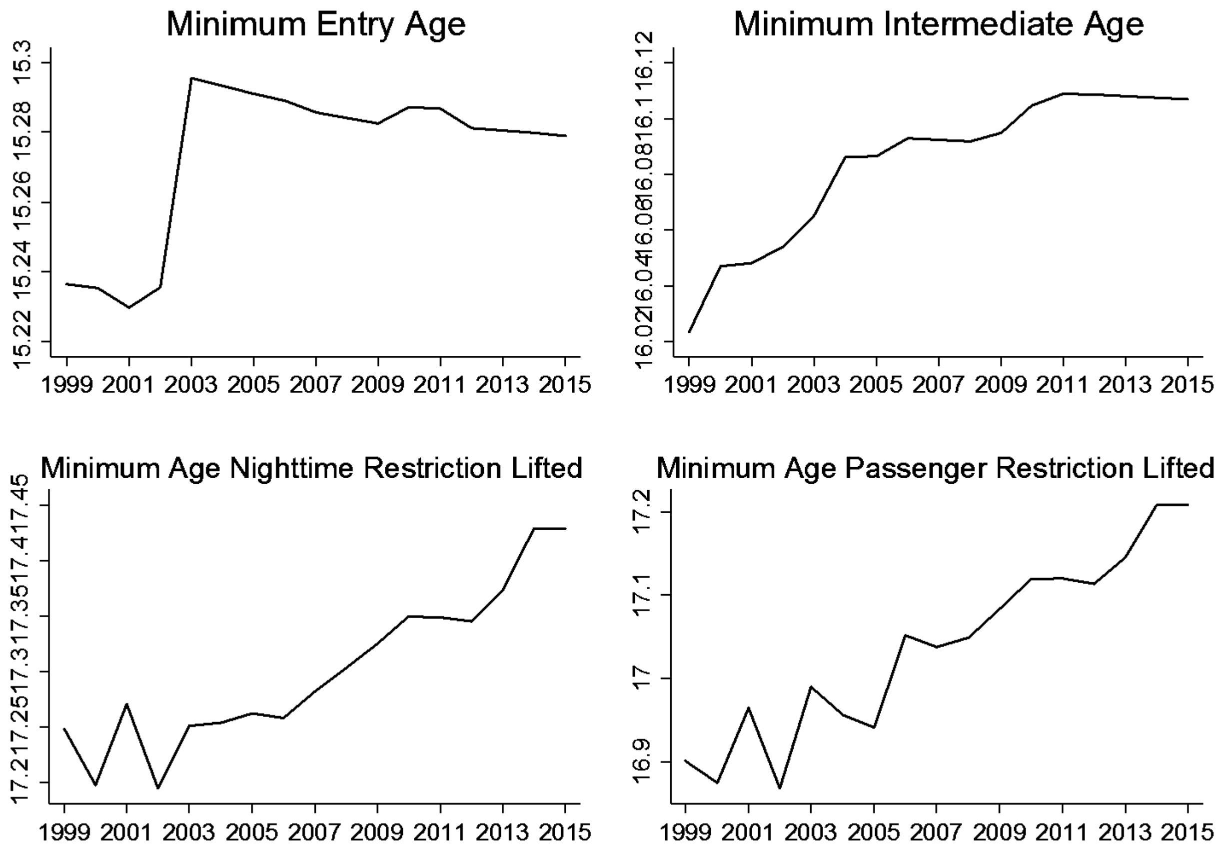
Note: a. "All States-Years" include all the 50 states and the District of Columbia in the whole year of every year from 1999 to 2015.

b. "YRBS Sampled State-Years" include the 47 sampled states in Spring (January to April) of their available odd-numbered years from 1999 to 2015.



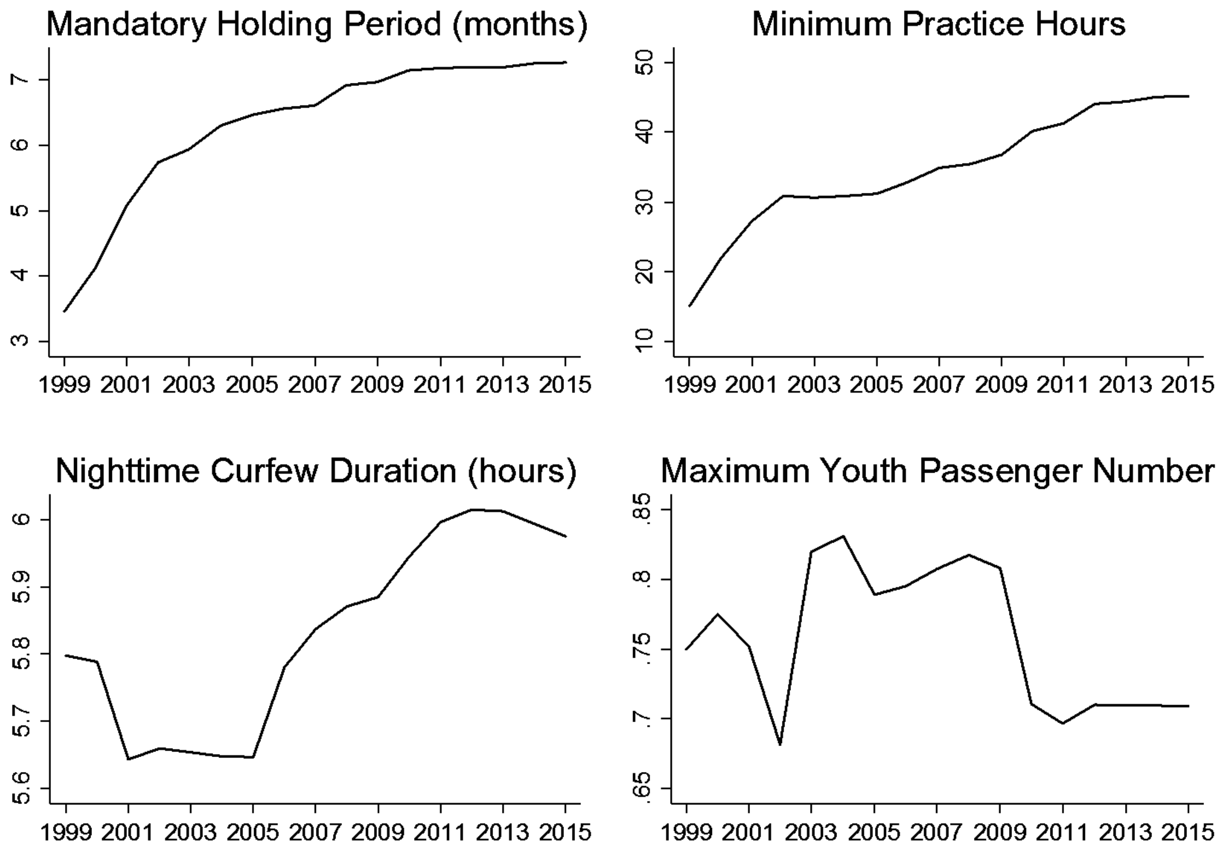

Information Source: The Insurance Institute for Highway Safety (IIHS)
Note: The figure includes policy information of all the 50 states and the District of Columbia in the whole year of every year from 1999 to 2015.

**Figure 1. Proportions of States with the GDL Restrictions from 1999 to 2015**




Information Source: The Insurance Institute for Highway Safety (IIHS)
Note: The figure includes policy information of all the 50 states and the District of Columbia in the whole year of every year from 1999 to 2015.

**Figure 2. Average Minimum Ages for Different Stages from 1999 to 2015**




Information Source: The Insurance Institute for Highway Safety (IIHS)
Note: The figure includes policy information of all the 50 states and the District of Columbia in the whole year of every year from 1999 to 2015.

**Figure 3. Average Levels of GDL Policy Features from 1999 to 2015**

curfew. The average number of maximum youth passenger is higher in the "YRBS sampled state-years", implying passenger restrictions are slightly looser on average.

I calculate a set of state-age-specific variables regarding GDL restrictions for each individual in the main sample. Specifically, I first establish a panel dataset with the details of the GDL restrictions by state-year-month-age.[16] Four initial GDL policy variables are generated: $Entry$, $Learner$, $Night$, and $Combined$, each of which indicates the probability for an individual of a certain age in a certain state-year-month being subject to a particular restriction. $Entry$ indicates the probability of individuals being below the minimum learner age. $Learner$ indicates the probability of being in the learner stage. $Night$ indicates the probability of being in the intermediate stage but restricted by only night curfew. $Combined$ indicates the probability of being restricted by a night curfew combined with a passenger restriction (hereafter I call it a combined restriction).[17] Individuals who are not restricted by any of these restrictions are in the full license stage. The probabilities are calculated by potential respondents' probable age-in-months. I assume the likelihood of each potential respondent's real age-in-month follows the aforementioned uniform distribution. As an example, assume the minimum age to enter the intermediate stage is 16.75 (16 years 9 months) in a certain state-year-month, then a 16-year-old respondent's probability of being in the learner stage is $\frac{1}{12} * 9 = 0.75$, because his/her age-in-months could be 16 years 0 month, 16 years 1 month,…, 16 years 11 months with a probability of $\frac{1}{12}$ each. Next, I collapse these state-year-month-age GDL treatment variables into state-year-

[16] I take the greatest restriction level if there are multiple restriction levels for different periods during the intermediate stage. For instance, in Colorado since July 2005, the passenger number restriction is described as: "first 6 months, no passengers; second 6 months, no more than 1 passenger". Since I am unable to identify which period (the first 6 months or the second) the individual $i$ is actually experiencing, I take as if he/she is experiencing the first 6 months and the strictest requirement: 0 passengers.

[17] Note that only 1% of state-years during my study period have a passenger restriction without a night curfew, and only 0.9% of the teenagers in my initial sample are subject to only a passenger restriction. Therefore, I exclude this 0.9% of sample from my regressions.

age-level. The YRBS state survey is conducted in the spring semester of odd-numbered years, so each teenager could be surveyed in January, February, March, or April. Thus, one might be subject to the GDL restriction in any month from January to April of the survey year with a probability of $\frac{1}{4}$ each. Now, I have four state-age-specific GDL treatment variables: $Entry_{ast}$, $Learner_{ast}$, $Night_{ast}$, and $Combined_{ast}$, each of which indicates the probability for individuals of age $a$ in state $s$ and survey year $t$ being subject to the particular restriction.

Table 4 describes the weighted summary statistics of the GDL treatment variables. Accordingly, 20.7 percent of teenagers aged 14 to 17 are not allowed to drive at all, and 22.9 percent are subject to a learner stage during which they have to drive under the supervision of an adult driver for a mandatory holding period. 15.8 percent are subject to only a night curfew, and 18.0 percent of teenagers are subject to a night curfew implemented together with a passenger restriction. 22.6 percent of adolescents aged 14 to 17 are not subject to any GDL restrictions, which means they are free to drive at any time with any passenger.

**Table 4. Summary Statistics of GDL Treatment Variables**

| Variables | Description | Mean (St.D.) |
|---|---|---|
| Entry | Probability of being younger than the minimum learner age | 0.207 (0.384) |
| Learner | Probability of being in the learner stage | 0.229 (0.380) |
| Night | Probability of being restricted by a single night curfew | 0.158 (0.350) |
| Combined | Probability of being restricted by a night curfew with a passenger restriction | 0.180 (0.340) |

Data source: The Insurance Institute for Highway Safety (IIHS); The Youth Risky Behavior Surveillance System (YRBSS)

### 3.3 Other state controls

One limitation of the YRBS dataset is that it does not provide information on family economic conditions which are likely to affect teenagers' physical activities, diets, and weight status. Therefore, I additionally control for state median household income and unemployment rate to approximate the teenagers' economic conditions. Data on annual state median household income is extracted from the U.S. Census Small Area Income and Poverty Estimates (SAIPE).[18] Since the estimates for 2015 are not available yet, I impute them by adding an average biannual change that is calculated from the estimates of 1989 through 2013 to the 2013 estimates.[19] Data on annual state unemployment rates are collected from the Bureau of Labor Statistics Local Area Unemployment Statistics.[20] Finally, I adjust median household income for inflation using the 2009 Personal Consumption Expenditures Price Index extracted from the Bureau of Economic Analysis (BEA).[21]

## 4. Empirical strategy

I estimate the regressions for BMI Z-score, number of days doing exercise, hours watching TV, and times drinking soda per day using Ordinary Least Square (OLS) models, and I use linear probability models for overweight and obesity.[22] My baseline model is described in equation (10):

$$Y_{iast} = \alpha_0 + \boldsymbol{G_{ast}\delta} + X_{ist}\beta + Z_{st}\gamma + \tau_t + \lambda_{as} + \varepsilon_{ist} \tag{10}$$

where $Y$ is the dependent variables. $G$ are the state-age-specific GDL treatment variables $Entry$, $Learner$, $Night$, and $Combined$. $X$ are dummy variables for individual covariates characterizing gender, grade at school and race. $Z$ indicates the state covariates. In the baseline

[18] SAIPE: http://www.census.gov/did/www/saipe/data/statecounty/data/index.html
[19] I will update this imputed value with the estimates of 2015 which are to be released in December 2016.
[20] BLS Local Area Unemployment Statistics: http://data.bls.gov/map/MapToolServlet?survey=la&map=state&seasonal=u
[21] Bureau of Economic Analysis Personal Consumption Expenditures Price Index: http://www.bea.gov/iTable/
[22] My main results remain robust if I instead use a negative binomial model for the number of days doing exercise and an ordered Probit model for overweight and obesity. Also, to fit an LPM model, I use the probability of being overweight or obese (BMI percentile ≥ 85) as one dependent variable.

model, I control for the year fixed effects $\tau_t$ and the state-age fixed effects $\lambda_{as}$. In a second specification, I add controls for state-specific linear time trends to capture the potential impact of state-level time-varying factors associated with the GDL policies on teenage weight outcomes. For instance, laws over snack foods and drinks at school vary widely from state to state and change over time. These laws affect adolescents' diet choices and body weight, while also being potentially associated with the GDL policies since they are issued and implemented by the same state governments. In a third specification, I additionally control for state-age-specific linear time trends to consider the potential existence of time-varying factors at the state-age level which could influence teenagers' behaviors related to body weight. All standard errors are clustered at the state-age level, since that is the level of treatment.[23]

## 5. Results

### 5.1 Weight status

Table 5 reports the effects of the GDL restrictions on teenagers' BMI Z-scores. A comparison of Column (1) and (2) indicates that the coefficient estimates remain robust to the inclusion of the state covariates. In Column (2), I do not find a significant effect of the minimum learner age or the learner stage on BMI Z-score. Both the single night curfew and the combined restriction are found to be positive and statistically significant. In Column (3), by controlling for state-specific linear trends, only the combined restriction is found to significantly increase BMI Z-score. In Column (4), after controlling for state-age-specific linear trend, no significant effect is found. A Hausman test implies that the model in Column (3) is preferable to Column (2), implying that controlling for state-specific time trends is necessary in order to address state time-varying unobserved confounders. However, a Hausman test shows the estimates in Column (4) is not statistically different from that in Column (3). Moreover, the variance inflation factors of the

[23] The estimates are robust if I cluster standard errors at state-level.

GDL treatment variables in Column (4) increase by over 100%, a decidedly non-trivial amount, compared to those in Column (3). Therefore, controlling for state-age-specific time trends may introduce additional noise into the model while making no discernable difference for bias. This gives me justification for conservatively preferring the Column (3) in my interpretations. Accordingly, being subject to a night curfew combined with a passenger restriction increases teenagers' BMI Z-score by 2.3% of a standard deviation. [24]

**Table 5. Effect of the GDL Restrictions on BMI Z-score**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Entry** | 0.0056 | 0.0071 | -0.0259 | -0.0466 |
| | (0.0309) | (0.0327) | (0.0497) | (0.0408) |
| **Learner** | 0.0211* | 0.0207 | 0.0070 | 0.0145 |
| | (0.0126) | (0.0132) | (0.0154) | (0.0222) |
| **Night** | 0.0356** | 0.0356** | -0.0006 | 0.0119 |
| | (0.0154) | (0.0145) | (0.0147) | (0.0181) |
| **Combined** | 0.0527*** | 0.0495*** | 0.0243* | 0.0342 |
| | (0.0150) | (0.0149) | (0.0138) | (0.0246) |
| Individual Covariates | Y | Y | Y | Y |
| State Covariates | | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| State-Age FE | Y | Y | Y | Y |
| State Time Trends | | | Y | - |
| State-Age Time Trends | | | | Y |

Regressions are weighted by sampling weight provided in the YRBS and clustered at state level. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. There are 788,774 observations.

[24] As is reported in Table 2, one standard deviation of BMI Z-score in this study is 1.030. Thus, the effect of combined restriction on BMI Z-score is $\frac{0.024}{1.031} * 100\% = 2.3\%$.

**Table 6. Effect of the GDL Restrictions on Teenage Overweight and Obesity**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | ***Panel A - Pr(Overweight + Obese)*** | | | |
| **Entry** | 0.0029 | 0.0036 | -0.0075 | -0.0140 |
| | (0.0179) | (0.0192) | (0.0219) | (0.0151) |
| **Learner** | 0.0100 | 0.0101 | 0.0110+ | 0.0228*** |
| | (0.0089) | (0.0093) | (0.0067) | (0.0067) |
| **Night** | 0.0195*** | 0.0194*** | 0.0132** | 0.0184** |
| | (0.0053) | (0.0048) | (0.0053) | (0.0075) |
| **Combined** | 0.0213*** | 0.0202*** | 0.0160*** | 0.0151* |
| | (0.0055) | (0.0055) | (0.0053) | (0.0082) |
| | ***Panel B - Pr(Obese)*** | | | |
| **Entry** | -0.0140 | -0.0144 | -0.0337** | -0.0716*** |
| | (0.0145) | (0.0147) | (0.0133) | (0.0199) |
| **Learner** | 0.0000 | -0.0006 | -0.0044 | -0.0010 |
| | (0.0047) | (0.0050) | (0.0048) | (0.0043) |
| **Night** | 0.0036 | 0.0037 | -0.0004 | 0.0084 |
| | (0.0032) | (0.0032) | (0.0036) | (0.0055) |
| **Combined** | 0.0092** | 0.0090** | 0.0047 | 0.0078 |
| | (0.0037) | (0.0036) | (0.0037) | (0.0083) |
| Individual Covariates | Y | Y | Y | Y |
| State Covariates | | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| State-Age FE | Y | Y | Y | Y |
| State Time Trends | | | Y | - |
| State-Age Time Trends | | | | Y |

Regressions are weighted by sampling weight provided in the YRBS and clustered at state level. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1, + p<0.11. Models control for year fixed effects, state-age fixed effects, state linear trends, and age linear trends. There are 788,774 observations.

Table 6 presents the effects of the GDL restrictions on teenagers' probability of "being overweight or obese" (Panel A) and probability of "being obese" (Panel B). Results remain robust to the inclusion state covariate, state linear trends, and state-age linear trends. Similarly, the results in Column (4) show amplified coefficients and standard errors in the effects of the night curfew and the combined restriction. For conservativeness, I again interpret the marginal effects reported in Column (3). Being subject to the learner stage increases the probability of "being overweight or obese" by 1.10 percentage points, an increase of 4.0%.[25] Being restricted by a single night curfew increases the likelihood of "being overweight or obese" by 1.32 percentage points (4.8%). Being restricted by the passenger restriction increases the probability of "being overweight or obese" by 1.60 percentage points (5.8%). No significant effect of these three restrictions is found on probability of being obese. Interestingly, being subject to the minimum entry age significantly reduces the likelihood of being obese by 3.37 percentage points (27.2%). The negative sign of the estimated coefficient could be reasonable because, compared to those who are fully licensed, teenagers too young to drive might rely more on walking or biking. The magnitude of this effect might be a bit big in light of the overall pattern of results. It could be occurring at random because of the collinearity between being subject to the minimum entry age and the respondent's own age ($\rho = -0.72$).[26]

### 5.2 Cumulative effects

Body weight is a stock variable resulting from net calorie intakes accumulated over time. In this section, I estimate the accumulative effects of GDL restrictions in past years on current weight status. Since a teenager can be subject to a particular restriction for a maximum of two years,[27] I control for the two year lagged terms of state-age-specific GDL treatment variables. As a falsification test, I also control for one year lead term which is not supposed to significantly affect current weight status. For example, a 16-year-old respondent in survey year 2005 has her

[25] For simplicity, hereafter I express the percentage change in the parenthesis directly. i.e.: 1.11 percentage points (4.0%). The probability of being overweight or obese has a mean value of 0.275 as is reported in Table 2. Therefore, $\frac{0.011}{0.275} * 100\% = 4.0\%$.

26 In addition, I conduct falsification tests by re-matching the YRBS teenagers to the GDL policies in random states or in random years. As is shown in the Table 20 in the Appendix A, I do not find an effect of the fake GDL restrictions on teenagers' BMI Z-scores and probability of being overweight or obese.

[27] The maximum gap between the minimum age to enter learner stage and minimum age to enter intermediate stage and between the minimum age to enter intermediate stage and the minimum age when night curfew or combined restriction is lifted are 2 years.

first year lagged terms calculated based on the GDL restrictions in 2004 when she was 15, her second year lagged terms based on the 2003 restrictions when she was 14, and her first year lead terms variables based on the 2006 policies when she 17.[28]

Table 7 reports the accumulative effects of the GDL restrictions on the probability of "being overweight or obese" controlling for state linear trends. The lead terms do not significantly affect body weight as expected. As Column (5) reports, over the three-year period of $t-2$, $t-1$, and $t$, the combined restriction significantly increases the probability of "being overweight or obesity" by 5.25 percentage points.

**Table 7. Cumulative Effects of the GDL Restrictions on Pr (Overweight or Obese)**

| | (1)<br>$t-2$ | (2)<br>$t-1$ | (3)<br>$t$ | (4)<br>$t+1$ | (5)<br>Sum of $t-2$, $t-1$, and $t$ |
|---|---|---|---|---|---|
| **Entry** | -0.0426** | 0.0182 | -0.0142 | -0.0241 | -0.0385 |
| | (0.0186) | (0.0210) | (0.0223) | (0.0640) | (0.0459) |
| **Learner** | -0.0157 | 0.0061 | 0.0081 | -0.0030 | -0.0015 |
| | (0.0122) | (0.0143) | (0.0075) | (0.0218) | (0.0254) |
| **Night** | -0.0031 | 0.0075 | 0.0085 | 0.0036 | 0.0128 |
| | (0.0176) | (0.0099) | (0.0060) | (0.0105) | (0.0194) |
| **Combined** | 0.0184 | 0.0214** | 0.0126 | 0.0098 | 0.0525*** |
| | (0.0124) | (0.0104) | (0.0079) | (0.0106) | (0.0174) |

Regressions are weighted by sampling weight provided in the YRBS and clustered at state-age level. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Models control for year fixed effects, state-age fixed effects, and state-specific time trend. There are 805,156 observations.

Next, I analyze the accumulative economic significance of these GDL restrictions. I calculate the percentage of the rise in rate of "being overweight or obesity" from 1999 to 2015 that can be explained by these GDL restrictions during the sample period. I assume the full

[28] Since the IIHS has not updated the GDL policy changes for 2016, I assume that all the GDL policies in 2016 match those of December 2015.

effects of the GDL restrictions on teenage obesity are reached over this three-year period. First, I denote $\hat{\beta}_1$, $\hat{\beta}_2$, $\hat{\beta}_3$ and $\hat{\beta}_4$ as the accumulative estimated effects of the four GDL treatment variables reported in Column (5) of Table 7. The percentage point change in likelihood of being overweight or obese that can be explained by the GDL restrictions from 1999 to 2015 can therefore be expressed as:

$$\widehat{Overwt} - \widehat{Overwt}_{1999} = (\overline{Entry}_{2015} - \overline{Entry}_{1999}) * \hat{\beta}_1 + (\overline{Learner}_{2015} - \overline{Learner}_{1999}) * \hat{\beta}_2 + (\overline{Night}_{2015} - \overline{Night}_{1999}) * \hat{\beta}_3 + (\overline{Combined}_{2015} - \overline{Combined}_{1999}) * \hat{\beta}_4 \quad (12)$$

where $\overline{Entry}_t$, $\overline{Learner}_t$, $\overline{Night}_t$, and $\overline{Combined}_t$ represent the proportions of teenagers aged 14 to 17 subject to each restriction in 1999 or 2015 as displayed in Table 8. [29]

**Table 8. Proportions of Teenagers Subject to Restrictions in 1999 and 2015**

| | Proportions in 1999 | Proportions in 2015 |
|---|---|---|
| **Entry** | 23.8% | 25.6% |
| **Learner** | 10.7% | 21.3% |
| **Night** | 23.9% | 11.0% |
| **Combined** | 1.0% | 24.6% |

Data source: The Insurance Institute for Highway Safety (IIHS); The Youth Risky Behavior Surveillance System (YRBSS)

Based on equation (12), the GDL restrictions explain 0.98 percentage points of the rise in likelihood of being obese from 1999 to 2015. The proportion of teenagers aged 14 to 17 who are overweight or obese rose from 23.2% in 1999 to 29.1% in 2015. Therefore, nearly 16% of the rise in prevalence of overweight or obese among teenagers aged 14 to 17 from 1999 to 2015 can

[29] In a stricter way I could calculate $\overline{Entry}_t$, $\overline{Learner}_t$, $\overline{Night}_t$ and $\overline{Combined}_t$ for the years of 1997, 1998, 2013, and 2014 as well. However, due to the fact that the YRBS only provides data in odd-numbered years, for simplicity I approximate $\overline{Entry}_t$, $\overline{Learner}_t$, $\overline{Night}_t$ and $\overline{Combined}_t$ of these years to equal those of 1999 and 2015.

be explained by the presence of these GDL restrictions.[30] The estimated economic significance of is comparable to some other factors contributing to childhood obesity. For instance, Anderson et al., (2003) estimate that from 1975 to 1994 nearly 11.8 to 34.6 percent of the rise in obesity among children in high-socioeconomic-status families can be explained by the increase in a mother's work intensity.

### 5.3 Heterogeneous effect

In this section, I partition my data into several pairs of subsamples in order to look at the potential heterogeneous effects of the GDL restrictions on teenage weight status. First, I conduct a subsample analysis by gender, because the literature finds gender differences in the patterns of risky behaviors related to obesity and effects of policies on it (e.g. Cawley et al., 2013). Second, I divide each subsample into white and non-white. The race subsample analysis not only study the heterogeneity of the GDL effects influenced by the specific genetic factors and lifestyles of different races, but also serves as an approximated income subsample analysis due to the magnitude of evidence regarding the significant disparity in economic conditions between white and non-white individuals (Trejo, 1997; Goldsmith et al., 2007; Ritter and Taylor, 2011).

Table 9 reports the effects of the GDL restrictions on the likelihood of being overweight or obese by gender and race. Models control for the year fixed effects, the state-age fixed effects, and the state-specific time trend.[31] First, the minimum age for the learner stage increases the probability of being overweight or obese among girls but reduces it among boys. It may be due to the fact that boys walk or bike more than girls when they are too young to drive.[32] It may also

[30] Considering standard errors in the estimates, I use Stata syntax of "*lincom*" to calculate it. The overall estimate has a p-value of 0.006.

[31] The estimate effects by subsamples, especially by gender, are robust to different specifications (i.e. controlling for state-age-specific linear time trends instead). The results are available upon request.

[32] I use data from the National Household Travel Survey (NHTS) in 2001 and 2009 waves to calculate the average number of walk or bike trips per week for girls and boys under 15 years old. Girls have 4.7 walk trips and 0.4 bike trips per week, while boys have 5.2 walk trips and 1.4 bike trips per week.

reflect the existence of heterogeneous effects through distribution of teenagers' body weight.[33] The learner stage or a single night curfew significantly increase girls' probability of being overweight or obese but do not significantly affect boys'. The combined restriction significantly raises boys' likelihood of overweight or obesity but do not significantly affect girls'. As for the race subsample estimation, only the combined restriction significantly increases white teenagers' probability of being overweight or obese. I do not find the GDL restrictions significantly affect obesity among non-white teenagers. I do not find significant effects of GDL restrictions on non-white teenagers' weight status.[34]

**Table 9. Heterogeneous Effects of the GDL Restrictions on Pr (Overweight or Obese)**

| | **Gender** | | **Race** | |
|---|---|---|---|---|
| | **(1) Female** | **(2) Male** | **(3) White** | **(4) Non-white** |
| **Entry** | 0.0668*** | -0.0780** | 0.0089 | -0.0465 |
| | (0.0219) | (0.0384) | (0.0298) | (0.0307) |
| **Learner** | 0.0213* | 0.0024 | 0.0131 | 0.0019 |
| | (0.0119) | (0.0196) | (0.0119) | (0.0127) |
| **Night** | 0.0165** | 0.0102 | 0.0126 | 0.0137 |
| | (0.0072) | (0.0098) | (0.0081) | (0.0155) |
| **Combined** | 0.0122 | 0.0190** | 0.0182* | 0.0126 |
| | (0.0076) | (0.0092) | (0.0101) | (0.0122) |
| # of observation | 407,917 | 380,857 | 471,037 | 317,737 |

Regressions are weighted by sampling weight provided in the YRBS and clustered at state-age level. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Models control for year fixed effects, state-age fixed effects, and state-specific time trend.

[33] Boys are overall more overweight than girls. 31.3% of boys are overweight or obese, while 23.6% of girls are. Average BMI Z-score is 0.51 among boys and 0.35 among girls.

[34] The minimum age to enter learner stage significantly reduces probability of obesity among white teenagers while has no significant impact among non-white teenagers (these results are not reported in this manuscript). The calculation using NHTS data indicates white teenagers under 15 years old have 4.9 walk trips and 1.1 bike trips per week, while non-white teenagers have 5.0 walk trips and 0.6 bike trips per week.

### 5.4 Mechanisms: exercise, TV watching, and soda consumption

Table 10 presents the effects of the GDL restrictions on exercise, TV watching, and soda consumption. Models control for the year fixed effects, the state-age fixed effects, and the state-specific time trend. The single night curfew and the combined restriction both reduce average exercise days in one week by 0.21 days (5.5%). The combined restriction increases the number of hours spent watching TV per average school day by 0.07 days (3.5%). Note that the YRBS only reports the hours watching television on an average school day, so I do not know how the GDL restrictions affect TV watching during weekends. I do not find significant effects of GDL restrictions on number of times drinking soda per day.

**Table 10. Effect of the GDL Restrictions on Exercise, TV and Soda**

| | (1)<br>Exercise | (2)<br>TV | (3)<br>Soda |
|---|---|---|---|
| **Entry** | 0.2787 | 0.1015 | -0.0347 |
| | (0.3502) | (0.0998) | (0.2083) |
| **Learner** | 0.1929 | 0.0236 | -0.0017 |
| | (0.1678) | (0.0380) | (0.1353) |
| **Night** | -0.2132*** | 0.0242 | 0.0179 |
| | (0.0675) | (0.0502) | (0.0344) |
| **Combined** | -0.2092** | 0.0707* | -0.0109 |
| | (0.1045) | (0.0423) | (0.0404) |
| # of observation | 573,988 | 767,519 | 552,270 |

Regressions are weighted by sampling weight provided in the YRBS and clustered at state-age level. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Models control for year fixed effects, state-age fixed effects, and state-specific time trend.

Unfortunately, I do not have data on high-caloric food such as snacks and fast food consumption. Nevertheless, since the combined restriction, as a night curfew combined with a passenger restriction, may reduce teenagers' time spent with friends but increase their time spent watching TV at home, it may imply more exposure to food advertising and a rise in fast food consumption (Andreyava et al., 2011). Grossman et al. (2012) suggest that exposure to fast-food advertising on TV significantly increases percentage body fat (PBF) and body mass index (BMI) among adolescents. Moreover, evidence suggests that small net change in calorie consumption can lead to considerable changes in obesity prevalence (Cutler et al., 2003; Hill et al., 2003). Given the outcome of increasing obesity prevalence, teens seem likely to be increasing consumption of food across-the-board.

## 6. An alternative approach: state GDL ratings

My alternative method characterizes the GDL system as a whole instead of analyzing each restriction at state-age level. Following Dee et al. (2005), I rate the GDL system in each state-year to be “good”, “fair”, “marginal”, or “poor” according to a score calculated based on the IIHS standard described in Table 21 in the Appendix A.[35] One merit of the scoring scheme is that it summarizes all the details of GDL restrictions (i.e., length of mandatory holding period, start time of night curfew, number of youth passengers allowed, etc.) into a whole rating system. By the IIHS standard, good systems are the most restrictive ones and score 6 or more points; fair systems score 4 to 5; marginal systems score 2 to 3; and poor systems are the least restrictive which score less than 2 points (IIHS, 2007). Four variables $Good$, $Fair$, $Marginal$, and $Poor$ for each state-year are therefore generated indicating the probability of the GDL system being a good, fair, marginal, or poor one.[36] Table 11 displays the summary statistics of the four rating variables among the YRBS sampled state-years weighted by population. Since the proportion of

[35] Another common method characterizing the GDL policy in prior studies is to create a binary variable equal to 1 if the state has implemented the GDL law and 0 if not (Dee et al., 2005; Karaca-Mandic and Ridgeway, 2010). I do not use this method because my study period is from 1999 to 2015 during which over 90% of state-years have GDL laws in effect. Therefore, it is more appropriate to characterize GDL treatments by different restrictions or system ratings.

[36] These four variables are not binary because some states change their GDL levels during some years due to modifications of their GDL policies. Nevertheless, my results remain robust if I let the variable of the GDL rating dominating the year be 1 and others 0.

state-years with a poor system is only 4.9% during my study period of 1999 to 2015, I combine $Marginal$ and $Poor$ into one variable indicating the probability of being a marginal or poor GDL system.

I estimate using the state GDL rating variables along with a standard triple-difference model as an alternative approach. I introduce an additional YRBS sample of 109,780 young adults aged 18 and above into my main sample. The regression model is shown in equation (11):

$$Y_{iast} = \alpha_0 + T_a\delta_1 + G_{st}\delta_2 + \boldsymbol{T_a * G_{st}\delta_3} + X_{ist}\beta + Z_{st}\gamma + \tau_t + \lambda_{as} + t * \lambda_s + t * \lambda_a + \varepsilon_{ist} \quad (11)$$

where $G$ are the state GDL rating variables $Good$ and $Fair$, and state-years with a marginal or poor system are the reference group in rating. $T$ is a binary variable indicating treatment status equal to 1 for teenagers aged 14 to 17 and 0 for the added sample of young adults aged 18 and above. I control for state linear trends $t * \lambda_s$ and age linear trends $t * \lambda_a$ to reflect the time-varying unobserved factors in each state and age affecting teenage weight status. Standard errors are clustered at the state level.

**Table 11. Summary Statistics of GDL Rating Variables**

| Variables | Description | Mean (St.D.) |
|---|---|---|
| Good | Probability of being a good GDL system (GDL score: 6-10) | 0.592 (0.480) |
| Fair | Probability of being a fair GDL system (GDL score: 4-5) | 0.247 (0.420) |
| Marginal | Probability of being a marginal GDL system (GDL score: 2-3) | 0.112 (0.305) |
| Poor | Probability of being a poor GDL system (GDL score: 0-1) | 0.049 (0.213) |

Data source: The Insurance Institute for Highway Safety (IIHS).

Table 12 Panel A presents the homogeneous effects of GDL system ratings on teenage weight status. Compared to a marginal or poor system, a good system significantly raises teenagers' BMI Z-scores by 5.4% of a standard deviation and probability of being overweight or obese by 1.66 percentage points (6.1%). I do not find significant effects of a fair system on teenage weight status. Panel B displays the heterogeneous effects on teenage weight status by age group. I further divide the treated group into two subgroups aged 14 to 15 and 16 to 17 respectively. It appears that the effects of a good system are stronger and statistically more significant for teenagers aged 16 to 17. This finding is consistent with my main results that night curfew and passenger restriction which are mostly imposed on elder teenagers are the restrictions leading to weight gain.

**Table 12. Effect of the GDL Ratings on Teenage Weight Status - DDD Model**

| | (1)<br>BMI Z-Scores | (2)<br>Pr (Overweight or Obese) | (3)<br>Pr (Obese) |
|---|---|---|---|
| | ***Panel A: Homogeneous Effects*** | | |
| **Treat*Good** | 0.0544* | 0.0166* | 0.0027 |
| | (0.0283) | (0.0096) | (0.0098) |
| **Treat*Fair** | -0.0320 | -0.0144 | -0.0072 |
| | (0.0429) | (0.0125) | (0.0086) |
| | ***Panel B: Heterogeneous Effects by Age Group*** | | |
| **Age1617*Good** | 0.0621** | 0.0180* | 0.0034 |
| | (0.0268) | (0.0098) | (0.0094) |
| **Age1415*Good** | 0.0437 | 0.0146 | 0.0017 |
| | (0.0328) | (0.0103) | (0.0107) |
| **Age1617*Fair** | -0.0282 | -0.0163 | -0.0084 |
| | (0.0377) | (0.0107) | (0.0078) |
| **Age1415*Fair** | -0.0373 | -0.0118 | -0.0055 |
| | (0.0510) | (0.0155) | (0.0106) |

Regressions are weighted by sampling weight provided in the YRBS and clustered at state level. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Models control for year fixed effects, state-age fixed effects, state linear trends, and age linear trends. There are 907,062 observations.

## 7. Conclusion

The Graduated Driver Licensing (GDL) laws are potential reason for reduced driving among teenagers (Karaca-Mandic and Ridgeway, 2010). In this paper, I estimate the effects of four major GDL restrictions – minimum learner age, learner stage, the single night curfew, and the combined restriction of a night curfew along with a passenger restriction – on weight gains among adolescents aged 14 to 17 in the U.S. The results show that the night curfew and the combined restriction significantly increase teenagers' probability of being overweight or obese. Overall, nearly 16% of the rise in the rate of being overweight or obese among teenagers aged 14 to 17 in the U.S. from 1999 to 2015 can be explained by the presence of the GDL restrictions. In a mechanism analysis, I find that the GDL restrictions reduce exercise frequency and increase time spent watching TV. As a robustness check, I prove that overall a good GDL system, compared to a marginal or poor system, leads to weight gain among teenagers aged 16 to 17 who are the main subject of night curfew and combined restriction.

This paper contributes to the literature by providing novel evidence of the connection between driving and weight status among adolescents. While less driving is associated with a lower likelihood of being obese for adults, youths tend to gain weight if they are not allowed to drive due to night curfew or passenger restriction. The minimum age for learner stage appears to cause weight loss, which is reasonable because walking/cycling are necessary substitutes for driving if a teenager is not allowed to drive at all. In contrast, being subject to other restrictions does not prohibit them from driving in non-restricted circumstances (e.g. during daytime, with no youth passengers). My paper also contributes to the cost-benefit analyses of GDL policies. Prior literature has established that the benefit of the GDL resulting from a reduction in traffic accident mortality and injury exceeds the administrative cost of implementing the system (Dee et al., 2005). According to my findings, however, we may wish to reexamine the cost of the GDL system.

My analysis does present several concerns. First, the YRBS does not provide any information on the number of cars and the number of siblings for an individual, each of which are likely to influence how the GDL restrictions affect a teenager's driving tendency. Better data, if available, is needed to control for these factors. Second, the state-age-specific GDL treatment variables I use do not contain information regarding the restrictiveness of the GDL system. Literature suggests that the life-saving benefits of the GDL system are found to be related to its restrictiveness (Dee et al., 2005). Evidence also finds that the effect of a night curfew (on crime participation) is larger in states with a longer length of curfew (Deza and Litwok, 2016). Therefore, future studies should look into the heterogeneous effects of the GDL restrictions by different levels of restrictiveness. Third, it is unknown whether the teenagers who became obese as a result of the GDL system lost the weight once they aged out of the system, or if they would have become obese anyway later in life even without the system. Future study is needed to investigate the long-run effects of teenage exposure to the GDL system.

## Essay 2: Do Graduated Driver Licensing Restrictions Influence Youth Smoking and Drinking?

### 1. Introduction

About 11 percent of U.S. teenagers in 9th through 12th grade smoke, 33 percent drink, and 18 percent binge drink (YRBS, 2015).[37] Youth smoking and drinking lead to substantial social and economic costs. Gruber and Zinman (2001) suggest that youth smoking is likely to persist into adulthood, and therefore each percentage point of additional youth smoking in U.S. could result in a forgone value of life years of $36-$73 billion. Excessive youth drinking is also estimated to cost $24.3 billion in 2010 (Sacks et al., 2015).

Consequently, considerable literature has focused on the determinants of youth smoking and drinking, such as peer effects, cigarette and alcohol taxes, and government regulations (Powell et al., 2005; Lundborg, 2006; Clark & Loheac, 2007; Fletcher, 2010; Nonnemaker & Farrelly, 2011; Eisenberg et al., 2014). In this paper, we exploit a plausibly exogenous source of policy variation in the Graduated Driver Licensing (GDL) program regulating teenage driving. Particularly, we estimate the effect of the GDL restrictions on youth smoking and drinking. We expect youth smoking and drinking to occur at a place beyond the surveillance of home and school, and therefore, the restrictions on teenage driving, such minimum driving age, night-time driving, or the number of peer passengers allowed in the car may reduce the likelihood of youth exposures to smoking and drinking.

In an effort to improve teen driving and reduce traffic fatalities among teenagers, GDL policies were first implemented in Florida in 1996, and have since been adopted by every state.

[37] Data is obtained from the Centers of Disease Control and Prevention (CDC) Youth Risky Behavior Surveillance System (YRBS) Factsheets at: http://www.cdc.gov/healthyyouth/data/yrbs/results.htm

The major policy components are: (1) minimum entry age-in-month to acquire a learner's permit and required hours of supervised driving during the learner stage, (2) minimum age-in-month to acquire an intermediate license stage that allows driving without supervision but constrained by a night curfew or a passenger restriction or, and (3) minimum age-in-month to acquire a full license for unrestricted driving.

Although most of prior studies regarding GDL policies have focused on their effect on youth traffic accidents, some literature explores unintended effects of GDL policies. Deza and Litwok (2016) find that the GDL night curfew reduces criminal participation among teenagers aged 16 and 17, suggesting a potential influence of GDL restrictions on other youth risky behaviors. Qiu (2017) finds statistically significant effects of GDL night curfew and passenger restriction on teenage weight along with physical activity. The presence of GDL law, defined by the effectiveness of both a learner stage and an intermediate stage, is also used as a control variable in some empirical analyses of youth smoking and drinking (Liang and Huang, 2011; Bellow and Bhatt, 2013). However, to our best knowledge, this study is the first that examines the impact of detailed GDL restrictions on youth substance use.

**2. Data and methods**

We obtain data for individual substance use and demographic characteristics of 1,017,170 teenagers aged 14 to 17 from the 1991 to 2015 waves of the biannual YRBS state survey.[38] The Insurance Institute for Highway Safety (IIHS) provides GDL policy features across both states and time, such as minimum age-in-month for each stage and effective dates of each restriction.[39]

[38] The YRBS dataset in this study is from the CDC at: https://www.cdc.gov/healthyyouth/data/yrbs/data.htm and it is combined with the restricted datasets obtained from eight states at my request.
[39] IIHS GDL policies at: http://www.iihs.org/iihs/topics/laws/graduatedlicenseintro?topicName=teenagers#tableData

We estimate Ordinary Least Square models described by equation (1):

$$Y_{iast} = \alpha_0 + E_{ast}\delta_1 + L_{ast}\delta_2 + N_{ast}\delta_3 + \boldsymbol{C_{ast}\delta_4} + X_{ist}\beta + Z_{st}\gamma + \tau_t + \lambda_{as} + t * \lambda_s + \varepsilon_{ist} \quad (1)$$

where $Y$ are four dependent variables: number of smoking days per month, number of cigarettes per smoking day among smokers, number of drinking days per month, and number of binge drinking (5 or more drinks a day) days per month for individual $i$ living in state $s$ interviewed in year $t$.[40]

$E$, $L$, $N$, and $C$ are four mutually exclusive state-age-specific GDL variables indicating the probabilities of a teenager being subject to a specific restriction with: $E$, being younger than the minimum entry age; $L$, being in the learner stage; $N$, being in the intermediate stage and subject to only a night curfew; and $C$, being in the intermediate stage and subject to a night curfew along with a passenger restriction (hereafter we call it a combined restriction).[41] The YRBS does not provide information on respondents' exact interview month and age-in-month, both of which are necessary for identification of the actual GDL treatments imposed on individuals. To address this issue, we calculate the probabilities of GDL restrictions based on respondents' probable age-in-months and probable survey months.[42] Different from prior studies of GDL policies (Dee et al., 2005; Karaca-Mandic and Ridgeway, 2010; Deza and Litwok, 2016),

[40] The YRBS provides these data in intervals. We transform them into continuous variables by taking the midpoints of each interval. For example, we let number of days be 1.5 and 4 for "1 to 2 days" and "3 to 5 days", respectively.
[41] Note that, in most states, the passenger restriction is imposed along with the night curfew, but the night curfew is often implemented alone. Only 0.06 percent of teenagers in our initial sample are subject to only a passenger restriction. Thus, we simply exclude these teenagers from our regressions, and it the estimated results of the four GDL treatment variables are robust to this exclusion.
[42] During each wave, a respondent reporting an age of 17 could be 17 years 0 month, 17 years 1 month, …, or 17 years 11 months old with a probability of $\frac{1}{12}$ respectively. This respondent could have been surveyed in January, February, March, or April with a probability of $\frac{1}{4}$ respectively because the YRBS state survey is conducted in the spring semester. Therefore, for example, a teenager who is reported as 17 years old and interviewed in 2007 could have been 17 years 0 month old and interviewed in January. In this case she is subject to the GDL treatments in January 2007 for 17 years 0 months (i.e. $E$=0, $L$=0, $N$=0, $C$=1 if the restriction $C$ was in effect in her state during January 2007) with a probability of $\frac{1}{48}$. In the same manner, we calculate each of the other 47 possible cases given that those GDL variables are mutually exclusive. We then take the expected GDL treatments of the 48 cases for the teenager as her probabilities of being subject to the restrictions in each survey year.

our novel specification enables us to capture the age cut-off and timing of policy implementation at the month level.[43] In addition, our specification allows us to isolate and identify the effects of the combined restriction ($C$) after controlling for other restrictions including the night curfew only ($N$).

$X$ is a vector of individual covariates such as gender, grade at school, and race, while $Z$ contains a vector of state covariates including median household income, unemployment rate, cigarette excise tax rates, beer excise tax rates, Zero Tolerance underage drunken driving law, and Tobacco-free Campus law.[44] We control for year fixed effects, $\tau_t$, state-age fixed effects, $\lambda_{as}$, and state-specific linear time trends, $t * \lambda_s$, to capture the potential impact of unobserved factors associated with the GDL policies on teenage risky behaviors.[45] All standard errors are clustered at the state-age level.

**3. Results**

The estimated contemporaneous effects of the GDL restrictions on youth smoking and drinking are displayed in Table 13. We find that being subject to minimum entry age or a learner stage does not significantly affect youth smoking and drinking. Interestingly, while only a night curfew has no statistically significant effects, being subject to a combined restriction reduces the number of smoking days per month by 0.56 days; corresponding to a decrease of 19.4%.[46] The restriction also lowers the number of cigarettes per smoking day among smokers by 0.23 (4.8%), though the estimated effect is statistically insignificant at the 10 percent level. The combined

[43] Same methodology is applied to a study by Qiu (2017).
[44] See Table 22 for summary statistics and data sources.
[45] Table 23 in the Appendix B reports the regression results across different specifications. Hausman tests suggest the specification in column (3) is statistically preferred to that in column (2). While the estimates in column (4) are not statistically different from that in column (3), the variance inflator factor of $P$ in column (4) is increased by 170%. Therefore, we select the most efficient and unbiased estimates in column (3) as our main results.
[46] The weighted average number of smoking days per month is 2.88 days. Thus, the percent change is calculated by: $\frac{0.56}{2.88} \times 100\% = 19.4\%$. Hereafter we calculate the percent changes for other dependent variables in the same manner.

restriction leads to a reduction in the number of drinking days per month by 0.08 days (4.1%), and decreases the number of binge drinking days per month by 0.12 days (7.8%). These findings suggest that teenagers are likely tempted and encouraged to participate in smoking and drinking by peer passengers or a driver during the night time.[47]

**Table 13. The Contemporary Effects of GDL Restrictions on Smoking and Drinking**

| | **(1) Smoking Days** | **(2) Cigarettes per Smoking Day** | **(3) Drinking Days** | **(4) Binge Drinking Days** |
|---|---|---|---|---|
| Entry (*E*) | -0.2335 | 0.6301 | 0.2484 | 0.3090 |
| | (0.3228) | (0.4410) | (0.1734) | (0.2217) |
| Learner (*L*) | 0.0033 | 0.2864 | 0.0109 | 0.0772 |
| | (0.1246) | (0.2240) | (0.0496) | (0.0615) |
| Night (*N*) | -0.0379 | -0.0599 | 0.0222 | -0.0341 |
| | (0.1627) | (0.2943) | (0.0849) | (0.0926) |
| **Combined ($C$)** | **-0.5568*** ** | **-0.2294** | **-0.0789*** | **-0.1246*** ** |
| | **(0.1918)** | **(0.1488)** | **(0.0453)** | **(0.0559)** |
| # Obs. | 952,807 | 159,959 | 969,364 | 957,774 |

Regressions are weighted using the sampling weights provided by the YRBS. Robust standard errors in parentheses are clustered at the state-age level. *** p<0.01, ** p<0.05, * p<0.1, + p=0.11. The model controls for year fixed effects, state-age fixed effects, and state-specific time trends.

Next, we explore the dynamic effects by controlling for the probabilities of a respondent being subject to GDL restrictions one year prior to the survey year (expressed by a lag term of $t-1$).[48] We report the coefficient estimates of the combined restriction in table 2, since it is the only one significantly affecting outcomes in the contemporaneous effects regression. We find

[47] Our study focuses on intensive margins of teenage substance use. We also estimate a binary choice model to examine extensive margins measured by smoking and drinking participation. We do not find the combined restriction significantly affects youth smoking and drinking participation, whereas we do find a statistically significant effect on binge drink participation which is in fact another measure of drinking intensity.

[48] A teenager can be subject to a combined restriction for a maximum of two years, but we control for only one year lag term because the respondents in this study were aged 12 to 15 two years prior to the survey year when only 0.4% of them were subject to a combined restriction.

that the estimated effects of the restriction become more statistically significant and larger in magnitude in the medium run, which is in line with our reasoning given the addictive nature of these substances. In other words, the impact of being subject to a combined restriction last year persists to this year by possibly reducing addiction to smoking and drinking. As a falsification test, we estimate along with a lead term to examine whether there was a reduction in substance use even before the teenager is subject to the restriction. The estimates of the lead term are statistically insignificant, which supports the causal effect of the combined restriction.[49]

**Table 14. The Dynamic Effects of Combined Restriction on Smoking and Drinking**

| | **(1) Smoking Days** | **(2) Cigarettes per Smoking Day** | **(3) Drinking Days** | **(4) Binge Drinking Days** |
|---|---|---|---|---|
| t-1 | -0.7870*** | -0.7737*** | -0.0853 | -0.3140*** |
| | (0.1939) | (0.2392) | (0.0588) | (0.0595) |
| t | -0.3833* | -0.3049* | -0.0656 | -0.0770 |
| | (0.1962) | (0.1814) | (0.0609) | (0.0612) |
| t+1 | -0.0895 | -0.0016 | -0.0967 | -0.0459 |
| | (0.1509) | (0.1864) | (0.0613) | (0.0603) |
| **Sum of t and t-1** | **-1.1702*** ** | **-1.0786*** ** | **-0.1510*** | **-0.3910*** ** |
| | **(0.3104)** | **(0.3163)** | **(0.0807)** | **(0.0764)** |
| # Obs. | 952,807 | 159,959 | 969,364 | 957,774 |

Regressions are weighted using the sampling weights provided by the YRBS. Robust standard errors in parentheses are clustered at the state-age level. *** p<0.01, ** p<0.05, * p<0.1. The model controls for year fixed effects, state-age fixed effects, and state-specific time trends. Coefficient estimates of combined restriction are reported.

Finally, we estimate the heterogeneous effects of the combined restriction across subgroups of sample, and present the results in table 3. First, the interaction between combined

[49] Table 24 in the Appendix B reports the dynamic effects including the other three GDL restrictions. We find that being subject to one year lag of minimum entry age significantly reduces smoking intensity and drinking frequency. We also find being subject to one year lag of night curfew reduces number of drinking days and binge drinking days. One concern is that the variable of night curfew does not pass the falsification test of controlling for a lead term. It might be due to the fact that we are testing four treatment variables at once.

restriction and gender is significantly negative for number of smoking days and positive for drinking and binge drinking days. Our results support prior studies finding that girls are more influenced by peers in smoking but less affected in binge drinking than boys (Lundborg, 2006). In addition, we find that white teenagers are more influenced by the combined restriction in smoking but less influenced in drinking than non-white teenagers.

**Table 15. The Heterogeneous Effects of Combined Restriction on Smoking and Drinking**

| | (1) Smoking Days | (2) Cigarettes per Smoking Day | (3) Drinking Days | (4) Binge Drinking Days |
|---|---|---|---|---|
| Combined × Female | -0.2545** | -0.0777 | 0.1074* | 0.1251* |
| | (0.1028) | (0.1448) | (0.0636) | (0.0636) |
| Combined × White | -0.1664 | -0.6440*** | 0.1639* | 0.1674 |
| | (0.1936) | (0.2423) | (0.0957) | (0.1057) |
| # Obs. | 952,807 | 159,959 | 969,364 | 957,774 |

Regressions are weighted using the sampling weights provided by the YRBS. Robust standard errors in parentheses are clustered at the state-age level. *** p<0.01, ** p<0.05, * p<0.1. The model controls for year fixed effects, state-age fixed effects, and state-specific time trends. Coefficient estimates of interaction terms of combined restriction and gender/race are reported.

## 4. Conclusion

This paper contributes to the literature examining the impact of GDL restrictions on youth smoking and drinking. We find that the night curfew only has no statistically significant effect on youth smoking and drinking while it has effects when combined with the passenger restriction. The combined restriction reduces frequency and intensity of smoking and drinking, with girls or white teenagers more responsive in smoking but less responsive in drinking. The estimated effects of the combined restriction become more statistically significant and larger in magnitude in medium run, reflecting the addictiveness of cigarettes and alcohol. Our findings also provide an intuition regarding peer effects on youth substance use, suggesting that teenagers are likely tempted and encouraged to participate in risky behaviors by their peers during the night time.

We further analyze the economic significance of the effects by estimating the percentage of reduction in youth smoking and drinking frequency and intensity that can be explained by the presence of the combined restriction. From 1991 to 2015, the proportion of teenagers aged 14 to 17 which are subject to the combined restriction has increased from 0% to 24.5%. According to table 2 column (1), being subject to the combined restriction through a two-year period, which is the maximum duration of the restriction, reduces smoking days per month by 1.165 days. Therefore, we calculate the presence of a combined restriction lowers smoking days by 0.286 days. The average number of smoking days declined from 4.1 days to 1.0 day during the period, so the presence of a combined restriction accounts for 9.2% of the reduction in youth smoking days per month. In the same manner, we calculate that from 1991 to 2015, the combined restriction explains 11.7 % of the reduction in number of cigarette per smoking day among smokers, 2.6% of the reduction in number of drinking days, and 7.2% of the reduction in number of binge drinking days among teenagers.[50]

Since the YRBS only contains a small sample of high school students aged 18 and above, we are unsure whether, or how, the estimated effects will persist or weaken at some point in adulthood. For future study, we will explore new data sources to examine the long-run effects of GDL restrictions on smoking and drinking among young adults (i.e. early 20s).

[50] See Table 25 in the Appendix B for the calculation procedure.

## Essay 3: Understanding Unobserved Propensities of Suicide in the United States: A Hierarchical Model with Spatially Correlated Random Effects

### 1. Introduction

Suicides in the United States have been steadily increasing in recent years, ranking as the tenth highest cause of mortality among all age groups in 2013. The U.S. suicide rate increased from 10.95 per 100,000 individuals in 2006, to 12.6 in 2013 (Centers for Disease Control and Prevention, 2009, 2015). Additionally, the lifelong medical and work-loss costs from suicides are estimated to be $50.8 billion in the United States alone (Florence et al., 2015). In an attempt to understand this major public health concern, a substantial number of studies examine the principle causes of suicide.

Some of the potential factors driving suicide mortality which prior literature has studied include: economic conditions, social and cultural factors, environmental variables, and geographic location; with most authors utilizing aggregate data from large geographic areas. For example, several studies have used national-level aggregate data to conclude that high unemployment is closely associated with increases in suicide rates (Stuckler et al., 2011, 2009; Yang and Lester, 1995). However, as Breuer (2015), Maag (2008), Andrés (2005), and Kunce and Anderson (2002) illustrate, larger geographic areas correspond to greater levels of heterogeneity across different social and economic groups within an area. Analysis across large regions is therefore unlikely to capture the sub-region-specific heterogeneity affecting suicides. Some examples of confounders leading to sub-regional heterogeneity are local labor market conditions, religion, geography, weather, race, the level of integration, and the accessibility to firearms, alcohol, and drugs. If any omitted small area propensity is correlated with the observable variables, empirical results will be biased. Consequently, several studies have applied sub-national level analysis using both U.S. states (Ruhm, 2000, 2015; Phillips and Nugent, 2014) and the Nomenclature of Units for Territorial Statistics (NUTS-2) in Europe (Breuer, 2015).[51] While these authors also find a strong causal relationship between unemployment and suicide, as Hoynes (2000) emphasizes, states in the U.S. are still too large an area to accurately capture sub-region specific labor market conditions. In this paper, we analyze county-level data for both Florida and Georgia. The use of county data allows us to capture the effects of various suicide characteristics across counties within a state.

The inclusion of regional fixed effects and time fixed effects can also have a considerable effect on empirical results. Leigh and Jencks (2007) show that without controlling for country and year fixed effects, an increase in the income share held by the top ten percent is significantly associated with reduced life expectancy and increased infant mortality. However, when using fixed effects, these associations disappear in their analyses. Time fixed effects account for both global and national trends as well as smaller area shocks which may affect suicides. Examples of such trends include across-time variation in economic conditions, weather patterns, veteran population level, and governmental regulations concerning firearms, alcohol, and drugs. With this issue in mind, it is a potential concern that most studies of suicide employing Bayesian hierarchical models exclude time trends in their analyses. Our Bayesian hierarchical model incorporates spatially correlated county random effects and time dummy variables. By including both features, we capture not only unobserved county-specific characteristics, but also the time trends that influence suicide rates.

A considerable portion of the existing literature focuses on observable determinants of suicide by including as many explanatory variables as possible. If, however, there are unobservable determinants driving suicide risk, any public health policy based solely on

[51] The NUTS-2 in the EU (European Union) correspond to states in the U.S. as similar local administrative units.

observable factors may prove misleading. The causes of suicide are complicated and influenced by a multitude of factors. Family members, friends, coworkers, and classmates who may influence an individual's suicide decision tend to live in closer proximity. In addition, suicide is a malady which not only affects individuals and entire families, but their communities. Individuals living in closer proximity to one another are more likely to share economic and social characteristics along with their living space. These characteristics could be employment status, income level, race, religion, weather, and the availability of firearms, alcohol, and drugs. Therefore, these characteristics are likely to be reflected in local area specific propensities toward suicide. Our Bayesian specification enables us to summarize the posterior distributions of unobserved suicide propensity rankings at the county level. These rank distributions provide useful information for the design and implementation of anti-suicide policy. Furthermore, our paper presents empirical evidence for the existence of spatial correlation between counties in unobserved propensity toward suicide. Allowing for spatial correlation provides additional information regarding counties which are not only at an elevated risk of suicide internally, but also more prone to transmit their risk to neighboring counties. After identifying such counties, selecting them for special treatments could be an efficient policy. Government efforts to provide proper educational facilities, public advertisement, medical treatment programs for depression, and stricter monitoring of the illegal possession of firearms and underage drinking should be concentrated in these at-risk counties.

In summary, our study provides a significant contribution to the literature for a number reasons. First, we capture the heterogeneous characteristics of suicide within a state across counties by using county-level data from Florida and Georgia. Second, by including time dummy variables, our hierarchical model captures unobserved trends and shocks which may influence suicide. Third, we produce supporting evidence for the existence of unobserved characteristics influencing suicide which vary between counties, suggesting that the true effect of unobserved propensities may be hidden within observable factors. Therefore, any public health policy implemented to prevent suicides is misguided if policymakers identify high-risk counties based solely on their observable factors. Finally, we also find that unexplained county-specific propensities toward suicide are spatially correlated. Our empirical strategy allows us to identify the counties with both high internal suicide risk and a greater likelihood of transferring their risk across county borders. To single these counties out for special treatment would be an efficient policy consideration.

The rest of the paper is structured as follows. Section 2 gives an overview of the related literature. Section 3 describes the data in our analysis. In Section 4, we present the methods utilized in the paper. Section 5 discusses our empirical results, and Section 6 concludes and discusses the policy implications of our results.

## 2. Literature review

It has long been acknowledged that economic downturns lead to unfortunate increases in suicide rates. Chang et al. (2013) analyze the 2008 global financial crisis' effect on suicide trends using data from 54 countries, for which they find a resulting suicide rate increase in 2009. Furthermore, panel analyses of European countries by Stuckler et al. (2011, 2009) demonstrate significant increases in suicides associated with higher levels of unemployment in the portion of the population younger than 65. Time series regressions for twelve countries by Yang and Lester (1995) reveal a strong relationship between unemployment and suicides in four countries including the United States. Recent studies conducted by Breuer (2015) and Phillips and Nugent (2014) examine the relationship between unemployment rates and suicide mortality at the sub-national level. Using panel data from 275 regions of 29 European countries from 1999 to 2010, Breuer (2015) finds a significant positive association between unemployment and suicides. Phillips and Nugent (2014) pool U.S. state-level data over the period of 1997 to 2010, and conduct panel analysis of the one-way fixed effects. The authors show a strong and positive causal relationship between the unemployment rate and suicide rate. Ruhm (2000, 2015) conducts a panel analysis of U.S. state-level data. Ruhm (2000) finds a significant increase in suicide mortality associated with increased unemployment rates during 1976-1995, whereas Ruhm (2015) finds no significant relationship over the 1991-2010 period.

Inequality is another important factor in the study of suicide mortality. Leigh and Jencks (2007) argue that variation in the income share held by the top ten percent of earners is unlikely to influence the suicide rates of richer countries. Using both two-way fixed effects and country-specific time trends, Andrés (2005) shows that the Gini index has little effect on suicides in fifteen European countries.

Ease of access to firearms, alcohol, and drugs has also been the subject of a considerable quantity of suicide research. Hemenway and Miller (2002), Webster et al. (2004), and Miller et al. (2013) show that higher rates of firearm ownership and the presence of less restrictive regulations over the access to firearms are likely to increase suicide rates. Rosengart et al. (2005) find no statistically significant relationship between state laws regulating firearm access and suicide rates when using state and census division-level data from the United States. Alcohol consumption and drug use are also considered to increase the risk of suicide. Andrés (2005), Kaplan et al. (2014), and Phillips and Nugent (2014) estimate a positive relationship between alcohol consumption and suicide mortality. Sullivan et al. (2013) report that death by drug overdose (poisoning) is the most common method people choose to commit suicide. The crime rate is often accepted as a natural proxy for disintegration and the accessibility to firearms, alcohol, and drugs within a region (Brainerd, 2001). Using data from the former Soviet Union in the 1990's, Brainerd (2001) finds that the crime rate is in fact not correlated with the suicide rate.

Ajdacic-Gross et al. (2010) summarize prior literature concerning the effect of seasonal changes on suicide. The authors find that the seasonal pattern of suicide in Western countries has decreased or even disappeared over time. Regarding the relationship between weather changes and suicide rates, Neumayer (2003) finds that daily sunshine hours are inversely associated with suicide rates. On the other hand, Marion et al. (1999) suggest that an increase in elderly suicides is related to warmer temperatures whereas younger suicides are related to season.[52]

Gearing and Lizardi (2009) argue that religiosity leads to a decrease in suicide risk. Becker and Woessmann (2011) show that Catholics are less likely to commit suicide than Protestants, while Neumayer (2003) finds no significant effect of religion on suicide in a panel analysis of 68 countries between 1980 and 1990.

During the Iraq and Afghanistan wars, U.S. soldiers were deployed both more often and for longer periods than in previous armed conflicts. This change has led to an increased number of studies seeking to evaluate the risk of suicide among the veteran population. Empirical findings from Kang et al. (2015), McCarten et al. (2015), and Kaplan et al. (2012) suggest that veterans are at higher risk of suicide than the general U.S. population.

There have also been several recent studies of geographical suicide patterns using Bayesian methods. Utilizing U.S. county data pooled over the five-year period from 2002 to 2006, Congdon (2011) estimates three latent variables of deprivation, social fragmentation, and rurality based on thirteen manifest variables. Congdon (2011) also allows for spatial correlation

[52] Regarding seasonality of youth suicide, Hansen and Lang (2011) suggest that youth suicide increases when school is in session.

in the latent variable estimations. Cheung et al. (2012) and Hsu et al. (2015) adopt similar Bayesian hierarchical models in the spatial analysis of suicide mortality in Australia and Hong Kong respectively. Both studies capture the spatial correlation of suicide by incorporating a conditional autoregressive (CAR) structure in the error term. Hsu et al. (2015) show weak spatial impact from neighboring areas and a strong correlation between suicide risk and observable socioeconomic variables in Hong Kong. Our paper's hierarchical specification differs from prior literature in that the variance of a county random effects stems from both county specific unobserved propensities of its own and spatial dependence among neighboring counties. Most importantly, different from prior studies, our Bayesian hierarchical random-effects model allows us to summarize the posterior distributions of county-level unobserved suicide propensity rankings.

In contrast to previous studies, we find that the significant effects of observable factors on suicides found by earlier research may partially result from the exclusion of small area effects and time trends. Without controlling for these area and time effects, the true contribution of unobserved propensities and time trends can be hidden within observable factors. We also show that unobserved county-level suicide propensity is spatially correlated.

## 3. Data

Our analysis uses county-level data from both Florida and Georgia. Prospective data from each of the 67 counties in Florida are available for 14 years (2000-2013), while data from each of the 159 counties in Georgia are available for 17 years (1997-2013).[53] For our specification, average suicide rate (per 1,000 residents) is used as the dependent variable. Our explanatory variables include: years of potential life loss (YPLL) excluding cause of suicide (per resident <75

[53] We exclude data from the 1997-1999 period for Florida because information regarding Hispanic rate is not available over that period.

years of age); mean household income; Gini index and squared Gini index; unemployment rate; veteran population rate (per resident); distance to military base; crime rate (per resident); and population rates (per resident) of county demographic characteristics such as age, race, and gender. These variables are selected based on the findings of prior literature previously discussed in Section 2.

Data on suicide mortality, years of potential life loss (YPLL), and demographic characteristics are collected from the Florida Department of Health's Community Health Assessment Resource Tool Set (CHARTS), and the Georgia Department of Community Health's Online Analytical Statistical Information System (OASIS).[54] The U.S. Department of Veteran Affairs provides data on the veteran population by county in each year. Distance to military base is calculated using the crow-fly distance from a county's centroid to the nearest military base. Military base locations are collected using Google Map's Geographic Coordination System, and county coordinates are obtained from the US Census' 1990, 2000, and 2010 Gazetteer Files. Crime statistics are collected from the Florida Department of Law Enforcement and the Georgia Bureau of Investigation. Suicide rate, veteran population rate, crime rate, and county-level demographic rates of age, race, and gender are calculated for each year by dividing total counts of each variable by the county's population. Data regarding county unemployment rate are collected from the US Bureau of Labor Statistics.

Based on Brush (2007), we approximate mean household income by multiplying income per capita by average household size. Data for inflation-unadjusted income per capita and the GDP deflator (in 2009 dollars), which we use to calculate the inflation-adjusted income per

[54] Access to mortality data is usually limited. For example, beginning in 1989, the National Center for Health Statistics (NCHS) restricts all sub-national data providing less than ten deaths. As chance would have it, both the Florida CHARTS (http://www.floridacharts.com/charts/default.aspx) and the Georgia OASIS (https://oasis.state.ga.us/) databases provide county mortality data to the public.

capita, are collected from the US Bureau of Economic Analysis. Meanwhile, starting in 2005 the American Community Survey (ACS) provides five-year estimates for average household size.[55] To approximate average household size over the periods of 1997-1999 and 2001-2004, we employ a linear interpolation method which assumes constant growth over the periods of 1990-2000 and 2000-2005. More specifically, estimates of household size in 1997, 1998, and 1999 come from linear interpolation between the U.S. Decennial Census for the years 1990 and 2000. By the same logic, we estimate household size in 2001, 2002, 2003, and 2004 using linear interpolation between the 2000 Decennial Census and the 2005-2009 ACS five-year estimates. Table 16 summarizes the sources of data used for the average household size calculations in each year.

**Table 16. Data Source of Average Household Size**

| Year | 97 | 98 | 99 | 00 | 01 | 02 | 03 | 04 | 05 | 06 | 07 | 08 | 09 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Household Size | Interpolation estimates between the 1990 Decennial Census and the 2000 Decennial Census | | | 2000 US Decennial Census | Interpolation estimates between the 2000 Decennial Census and the 2005-2009 ACS 5 years estimates | | | | 05-09 ACS 5 years estimates | | | | | 06-10 ACS 5 years estimates | 07-11 ACS 5 years estimates | 08-12 ACS 5 years estimates | 09-13 ACS 5 years estimates |

To calculate the Gini index, we use median household income as well as the previously created mean household income.[56] Data on median household income is gathered from the U.S. Census Small Area Income and Poverty Estimate (SAIPE). By assuming that household income follows a log-normal distribution, mean household income is given by $e^{\mu+\frac{\sigma^2}{2}}$, and median household income is equal to $e^{\mu}$. Solving for $\sigma = \sqrt{2\ln\frac{mean\ HH\ income}{median\ HH\ income}}$ allows us to then

[55] The U.S. Census explains that the 5-year estimates are typically more accurate than the 1-year or 3-year estimates.
[56] As an inequality measure, the Gini index ranges from 0 (perfect equality) to 1 (perfect inequality).

calculate the Gini index, such that Gini = $2\,\Phi\left(\frac{\sigma}{\sqrt{2}}\right) - 1$, where $\Phi(.)$ is the cumulative density function of the standard normal distribution (Brush, 2007; Kelly, 2000).[57]

Descriptive statistics of our data are presented in Table 17. For the most part, Florida counties have higher crude suicide rates relative to Georgia. Figure 4 displays the time trend of average suicide rates in Florida, Georgia, and the entire United States from 1997 to 2013, making the higher propensity toward suicide in Florida relative to Georgia more clear.[58] Figure 5 maps the time-average suicide rates across counties in the two states over our research period. A larger proportion of counties in Florida have suicide rates above 0.2 per 1,000 residents relative to Georgia.

The last column of Table 17 reports the significance of differences in means. The t-tests indicate that nearly all variables in both states are significantly different from one another even though they share a common border. The Hispanic population rate in Florida is 2.5 times that of Georgia, while the black population rate in Georgia is almost double that in Florida. Florida has a higher veteran population rate, but a further distance to military base from county centroid on average. In Florida, the average crime rate is higher, and the elderly comprise a larger portion of the population. In Georgia, years of potential life loss is slightly higher, mean household income is lower, and the population contains a higher relative amount of the young and female.

[57] For more explanations about this method of inequality data construction, see Sung et al. (2017).
[58] Suicide mortality data in the United States are provided by the Centers for Disease Control and Prevention's Web-based Injury Statistics Query and Reporting System (https://www.cdc.gov/injury/wisqars/index.html).

**Table 17. Descriptive Statistics of Variables for Florida and Georgia**

| Variables | Florida (N=938) | Georgia (N=2703) | Difference |
|---|---|---|---|
| suicide rate (count per 1,000 residents) | 0.1565 | 0.1210 | *** |
| | (0.0678) | (0.0939) | |
| YPLL excluding suicide cause (year per resident age<75) | 0.0843 | 0.0895 | *** |
| | (0.0206) | (0.0241) | |
| mean household income ($10,000) | 8.1790 | 7.4277 | *** |
| | (2.1433) | (1.6494) | |
| Gini index | 0.5781 | 0.5677 | *** |
| | (0.0584) | (0.0609) | |
| unemployment rate | 0.0641 | 0.0695 | *** |
| | (0.0278) | (0.0308) | |
| veteran population rate (per resident) | 0.1123 | 0.0844 | *** |
| | (0.0293) | (0.0176) | |
| distance to military base (1000 miles) | 0.0460 | 0.0342 | *** |
| | (0.2733) | (0.1655) | |
| crime rate (per resident) | 0.0349 | 0.0280 | *** |
| | (0.0146) | (0.0179) | |
| age 15-19 population rate (per resident) | 0.0638 | 0.0735 | *** |
| | (0.0113) | (0.0110) | |
| age 20-24 population rate (per resident) | 0.0655 | 0.0680 | *** |
| | (0.0226) | (0.0247) | |
| age 25-34 population rate (per resident) | 0.1218 | 0.1300 | *** |
| | (0.0249) | (0.0222) | |
| age 35-44 population rate (per resident) | 0.1344 | 0.1428 | *** |
| | (0.0212) | (0.0189) | |
| age 45-54 population rate (per resident) | 0.1381 | 0.1381 | |
| | (0.0143) | (0.0147) | |
| age 55-64 population rate (per resident) | 0.1217 | 0.1089 | *** |
| | (0.0212) | (0.0230) | |
| age over 65 population rate (per resident) | 0.1789 | 0.1285 | *** |
| | (0.0661) | (0.0356) | |
| black population rate (per resident) | 0.1448 | 0.2802 | *** |
| | (0.0956) | (0.1744) | |
| Hispanic population rate (per resident) | 0.1114 | 0.0454 | *** |
| | (0.1143) | (0.0464) | |
| female population rate (per resident) | 0.4882 | 0.5059 | *** |
| | (0.0363) | (0.0261) | |

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

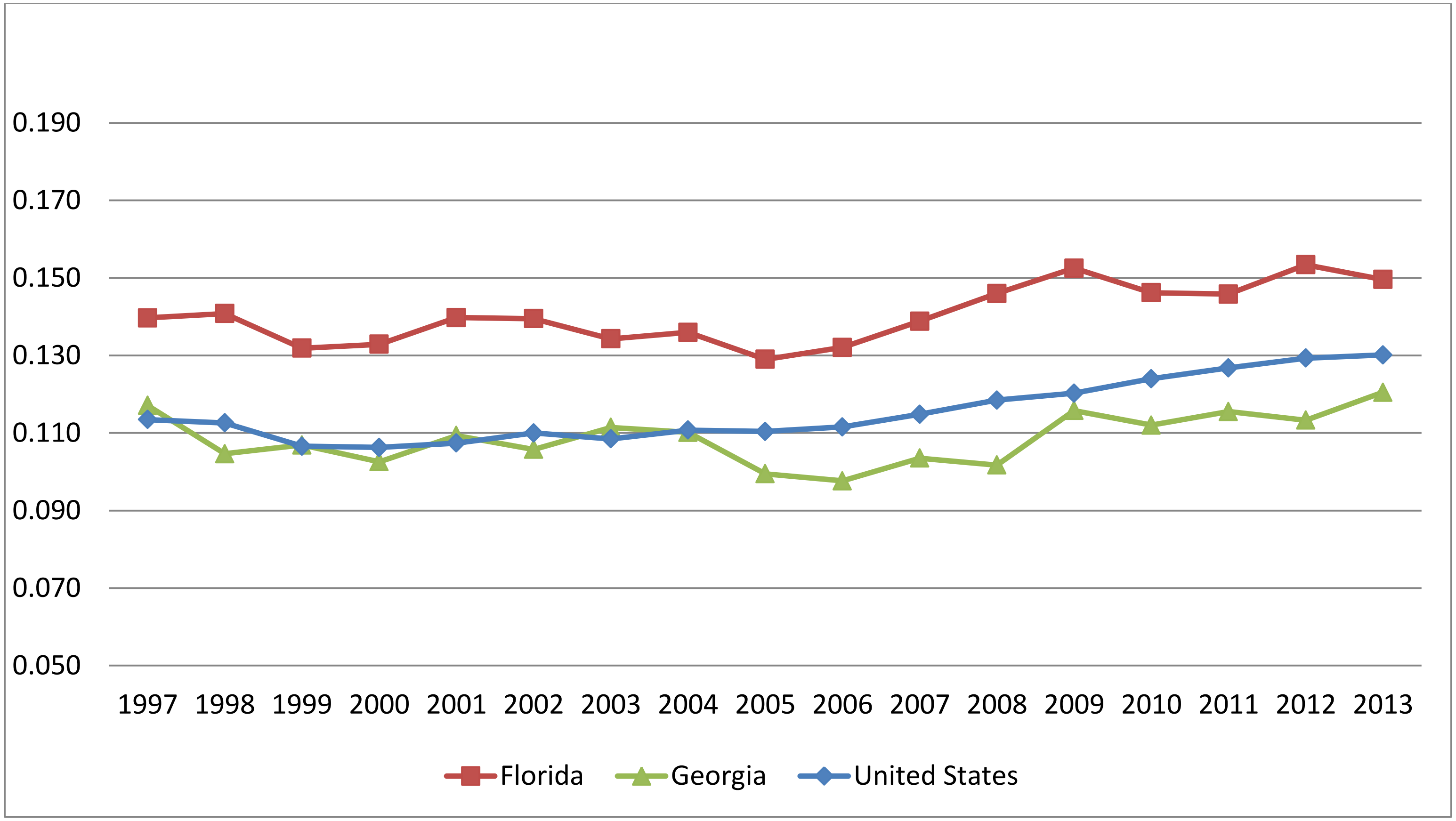
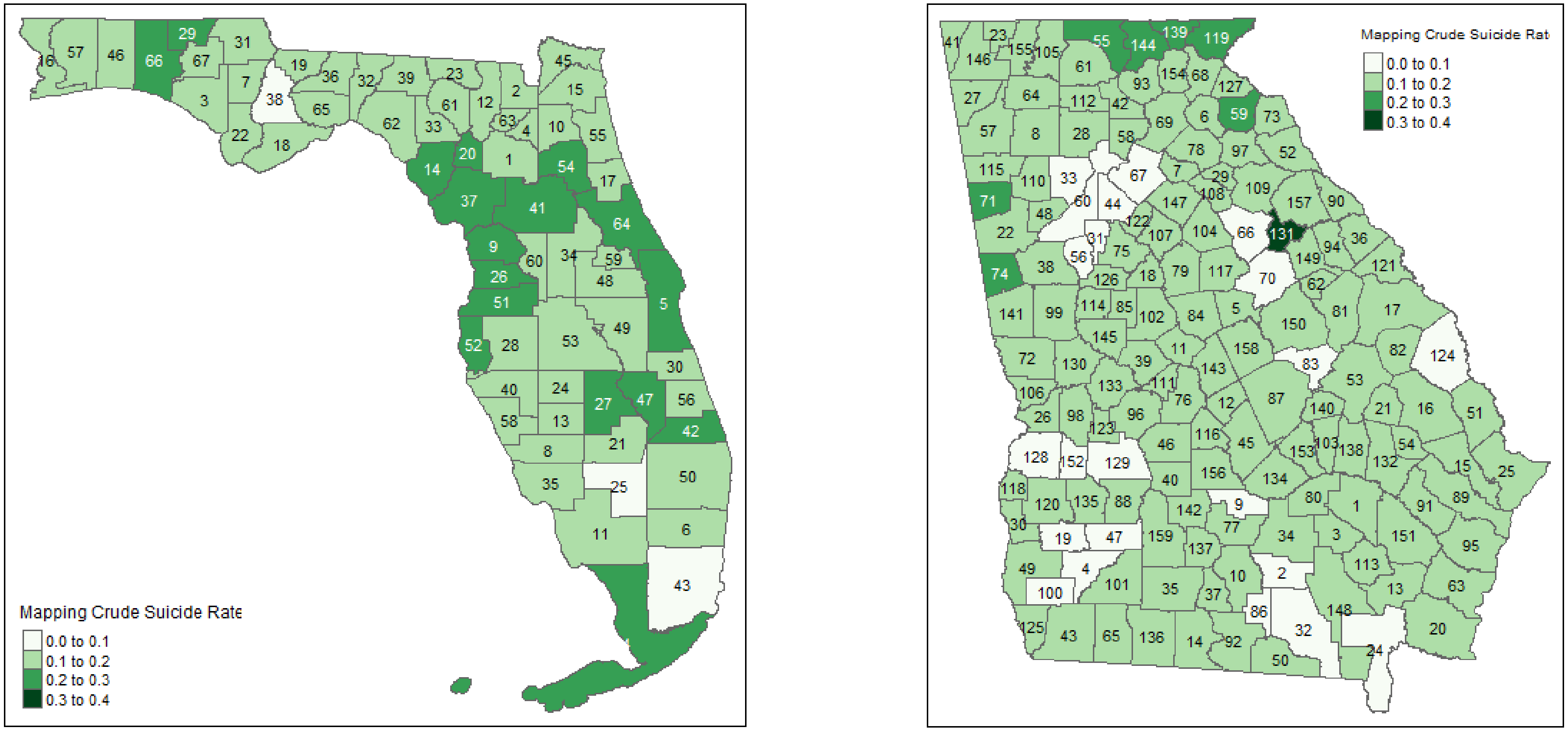



**Figure 4. Time Trends of Suicide Rate (per 1,000 population) in Florida, Georgia and U.S**




**(a) Florida** **(b) Georgia**

**Figure 5. County Maps of Suicide Rate (per 1,000 population)**

## 4. Empirical model

To analyze the relationship between suicide mortality and observable factors, we employ the following panel regression model:

$$y_{it} = x_{it}\beta + \alpha_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where the dependent variable $y_{it}$ denotes suicide rate in county $i$ for year $t$.[59] $x_{it}$ represents the explanatory variables. $\alpha_i$ indicates county-specific effects that vary across counties, but are held constant over time in the fixed-effects model. Otherwise, $\alpha_i$ represents county-specific error components of the random-effects model. $\lambda_t$ denotes year dummies that capture time trends and shocks which may affect suicides. As described in Section 3, the explanatory variables $x_{it}$ include YPLL, mean household income, Gini index and squared Gini index, unemployment rate, veteran population rate, distance to military base, crime rate, and population rates of demographic characteristics for each county $i$.[60] Breuer (2015) and Brainerd (2001) find a negative relationship between life expectancy and suicide mortality as suggested by Hamermesh and Soss (1974).[61] Since data on life expectancy at the county level for Florida and Georgia are unavailable, we use YPLL in our estimation as a proxy for life expectancy which moves in the opposite direction. Crime rate is included as a proxy for disintegration (Brainerd, 2001) and the accessibility to firearms, alcohol, and drugs. The Bayesian specification and sampling algorithm employed in our analysis is given in the Appendix C.

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[59] The percentage of county-years without a suicide case in our sample is 2.9% in Florida and 15.6% in Georgia.
[60] We include the squared Gini index because of the assumed nonlinear effect of Gini index on suicide mortality.
[61] Hamermesh and Soss (1974) are the first to provide a theoretical foundation for suicide research from an economic perspective.

## 5. Results

### 5.1 Classical regression results

Tables 18 and 19 each report the results of our classical regressions for Florida and Georgia. The regression models are built based on the specification of equation (1). Column (1) provides the results of pooled ordinary least squares (OLS) estimation excluding county effects but including time dummies, column (2) shows the outcomes of random-effects estimation including time dummies, and columns (3) and (4) present the results of one-way and two-way fixed-effects estimation respectively. Column (5) provides the result of the Bayesian two-level hierarchical model with spatial correlation based on equations (2) and (3) given in the Appendix C.

In general, the results of our pooled OLS and random-effects regressions seem consistent with the findings of prior literature which ignores unobserved county-specific propensity in that some observables do in fact influence suicides. The pooled OLS and random-effects estimation outcomes in columns (1) and (2) of Table 18 show that increases in YPLL, veteran population rate, crime rate, and population rate at ages 55-64, and reductions in mean household income and population rates of black and Hispanic individuals lead to statistically significant increases in suicide rates in Florida. Meanwhile, columns (1) and (2) of Table 19 demonstrate that increases in Gini index, unemployment rate, and population rates at ages 20-24, 35-44, above 65, and decreases in squared Gini index, distance to military base, and population rates of black and Hispanic individuals result in statistically significant increases in suicide rates in Georgia.

On the other hand, the two-way fixed-effects estimation results in column (4) of Tables 18 and 19 show both a loss of statistical significance and a considerable change in magnitude for most observable factor coefficients. Only coefficient estimates for the Hispanic rate in Florida

(Table 18) and the Gini index in Georgia (Table 19) remain statistically significant under the two-way fixed-effects estimation.[62] Consequently, between those estimations, tests of over-identifying restrictions suggest the use of fixed-effects estimators rather than the random-effects estimators for both Florida and Georgia.[63] As Neumayer (2003) suggests, this finding provides evidence for the existence of unobserved county-specific suicide propensities.[64] Moreover, the incorporation of year dummy variables changes the fixed-effects estimation results considerably for Florida. This difference can be seen by comparing columns (3) and (4) of Table 18. The incorporation of time dummies in column (4) takes away the significance of mean household income, unemployment rate, and population rate at age 35-44 in column (3) for Florida.[65]

Our empirical findings indicate that the significant effects of observable factors on suicides in prior literature may be due to the exclusion of small area effects and time trends.

[62] We assume nonlinear effect of the Gini index on suicide mortality and incorporate the quadratic term of the Gini index into our regression. Based on the estimated coefficients of the Gini index and the squared Gini index in columns (1) and (2) of Table 19 (Pooled OLS and RE), we calculate that the turning point for the Gini index is around 0.6, which is located around the 69th percentile of the Gini index distribution in Georgia counties. This suggests that 31 percent of the county-years in Georgia have Gini indices above the turning point of 0.6 and therefore experience fewer suicides as the Gini index increases. On the other hand, based on the estimated coefficients of the Gini index and the squared Gini index in column (4) of Table 19 (FE), we calculate that the turning point of the Gini index is around 0.67, which is located around the 96th percentile of the Gini index distribution in Georgia counties. This alternatively suggests that nearly all the county-years in Georgia have Gini indices lower than the turning point. Therefore, the estimated effect of the Gini index on suicide rates based on our fixed-effects estimation is generally positive, which is a more convincing result compared to the implications of the OLS and random-effects estimations.

[63] A Hausman test fails to generate valid statistics since the differences of variance matrices of FE vs. RE estimates are not positively defined. In practice, compared to the Hausman test, the test of over-identifying restrictions extends straightforwardly to heteroskedastic- and cluster-robust options, which we adopt; and is guaranteed to generate a nonnegative test statistic. With a balanced panel (under conditional homoskedasticity), the over-identification test statistic is asymptotically equivalent to the Hausman fixed-vs-random effects test. For Florida, the Sargan-Hansen test statistic is 81.01, and the $\chi^2$ test statistic is 17. For Georgia, the Sargan-Hansen test statistic is 51.26, and the $\chi^2$ test statistic is 28. All these test statistics provide evidence in favor of a FE estimation. One concern, however, is that the estimated magnitude of Hispanic rate in Florida seems to be inflated proportionally to its standard error in FE estimation relative to the OLS and RE estimates, and the estimated effects are statistically significant in all specifications of OLS, RE, and FE. We therefore conduct t-test for the coefficient, the results of which suggest statistically significant differences in the estimated coefficients between the RE (or OLS) and the FE model.

[64] Neumayer (2003) finds no difference between the fixed-effects estimation results and the random-effects estimation results. Based on this finding, he suggests that suicide analysis omitting unobserved area factors is still valid.

[65] As a robustness check, we additionally control for county-specific time trends in our FE model. A Hausman test suggests statistically insignificant differences in estimation results between the FE model and a specification that adds county-specific time trend to the FE model.

Without controlling for county and time fixed effects, the true effect of unobserved county suicide propensity may be hidden within observable factors. Therefore, suicide prevention policies focusing only on observable factors may be misguided. Instead, county-specific policies based on unobserved propensity should be used in combination with policies targeting observable factors.

Interestingly, for both states, the results of our Bayesian hierarchical model with spatially correlated random effects in column (5) are more similar to the fixed-effects estimation results in column (4) than to the random-effects estimation results in column (2).[66] Both the magnitude and statistical significance of our coefficient estimates for the fixed-effects model and the Bayesian hierarchical model are similar, supporting our hierarchical model's estimation strategy which focuses on county-specific unobserved propensity. More so, the results presented in column (5) of Tables 18 and 19 show that unobserved suicide propensity exhibits significant spatial correlation in both states. The parameter $\omega$ represents the level of spatial dependence, which we find to be both positive and within the support boundary for $\omega$ in Florida and Georgia.[67] The basic intuition behind our empirical findings is that the correlation between unobserved county-specific heterogeneity and the covariates is explained through the spatial dependence between counties, suggesting that spatial correlation should be incorporated in suicide analysis. It should also be noted that one important advantage of our hierarchical random-effects model compared to a fixed-effects model is that the Bayesian methodology allows us to summarize the posterior distributions of county-level unobserved suicide propensity rankings. We discuss this in more detail in the following section.

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[66] A more detailed explanation of our Bayesian model is given by equations (2) and (3) in the Appendix C.

[67] For notational convenience and comparability between models, we denote "being within the support boundary" using *.

## Table 18. Regression and Bayesian Model Results for Florida

| **County Effect** | (1) No | (2) Random Effects | (3) Fixed Effects | (4) | (5) Spatially Correlated Random Effects |
|---|---|---|---|---|---|
| **Year Effect** | Yes | Yes | No | Yes | Yes |
| **VARIABLES** | | | | | |
| YPLL (excluding suicide cause) | 0.357** | 0.341* | -0.120 | -0.079 | -0.094 |
| | (0.168) | (0.190) | (0.350) | (0.361) | (0.242) |
| mean household income | -0.004** | -0.003* | 0.010* | 0.008 | 0.007 |
| | (0.002) | (0.002) | (0.005) | (0.006) | (0.008) |
| Gini index | 0.131 | 0.104 | 0.095 | 0.208 | 0.229 |
| | (0.384) | (0.410) | (0.748) | (0.745) | (0.562) |
| Gini index ^2 | 0.006 | 0.020 | -0.187 | -0.303 | -0.314 |
| | (0.374) | (0.400) | (0.671) | (0.693) | (0.544) |
| unemployment rate | -0.042 | -0.047 | 0.326** | 0.134 | 0.129 |
| | (0.283) | (0.297) | (0.130) | (0.356) | (0.321) |
| veteran population rate | 0.302** | 0.301** | 0.200 | 0.324 | 0.343* |
| | (0.130) | (0.134) | (0.219) | (0.252) | (0.229) |
| distance to military base | 0.080 | 0.072 | 0.503 | 0.690 | 0.634 |
| | (0.088) | (0.092) | (0.536) | (0.641) | (0.668) |
| crime rate | 0.633** | 0.625*** | 0.157 | 0.221 | 0.167 |
| | (0.240) | (0.241) | (0.269) | (0.278) | (0.375) |
| age 15 to 19 population rate | 0.424 | 0.581 | 1.384 | 1.735* | 1.775** |
| | (0.740) | (0.759) | (0.939) | (0.957) | (1.031) |
| age 20 to 24 population rate | 0.049 | -0.014 | 0.593 | 0.500 | 0.412 |
| | (0.224) | (0.242) | (0.508) | (0.778) | (0.621) |
| age 25 to 34 population rate | 0.175 | 0.260 | 0.565 | 0.331 | 0.307 |
| | (0.480) | (0.486) | (0.657) | (0.731) | (0.547) |
| age 35 to 44 population rate | 0.019 | -0.018 | -0.981*** | -0.513 | -0.476 |
| | (0.289) | (0.277) | (0.367) | (0.378) | (0.545) |
| age 45 to 54 population rate | 0.337 | 0.231 | -0.672* | -0.845** | -0.879* |
| | (0.268) | (0.267) | (0.396) | (0.383) | (0.559) |
| age 55 to 64 population rate | 0.730** | 0.807** | 0.484 | 0.387 | 0.394 |
| | (0.343) | (0.348) | (0.393) | (0.374) | (0.517) |
| age over 65 population rate | 0.050 | 0.049 | -0.071 | -0.174 | -0.237 |
| | (0.179) | (0.177) | (0.284) | (0.278) | (0.326) |
| black population rate | -0.187*** | -0.185*** | -0.047 | -0.017 | 0.117 |
| | (0.036) | (0.037) | (0.326) | (0.340) | (0.232) |
| Hispanic population rate | -0.060** | -0.067** | -0.408*** | -0.653*** | -0.800*** |
| | (0.029) | (0.028) | (0.148) | (0.199) | (0.191) |
| female population rate | -0.042 | -0.047 | 0.040 | 0.204 | 0.290 |
| | (0.133) | (0.137) | (0.396) | (0.357) | (0.346) |
| Constant | -0.113 | -0.109 | 0.040 | -0.017 | -1.051*** |
| | (0.218) | (0.225) | (0.303) | (0.286) | (0.352) |
| ω | | | | | 0.1614*** |
| | | | | | (0.0007) |
| Observations | 938 | 938 | 938 | 938 | 938 |
| R-squared | 0.232 | | 0.063 | 0.075 | |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## Table 19. Regression and Bayesian Model Results for Georgia

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| **County Effect** | No | Random Effects | Fixed Effects | | Spatially Correlated Random Effects |
| **Year Effect** | Yes | Yes | No | Yes | Yes |
| **VARIABLES** | | | | | |
| YPLL (excluding suicide cause) | 0.047 | 0.027 | -0.070 | -0.083 | -0.084 |
| | (0.145) | (0.143) | (0.146) | (0.145) | (0.111) |
| mean household income | 0.000 | 0.000 | -0.001 | 0.002 | 0.002 |
| | (0.002) | (0.002) | (0.004) | (0.005) | (0.005) |
| Gini index | 0.835*** | 0.862*** | 0.996** | 1.062** | 1.042** |
| | (0.318) | (0.306) | (0.409) | (0.417) | (0.554) |
| Gini index ^2 | -0.707** | -0.721*** | -0.683* | -0.791* | -0.770* |
| | (0.285) | (0.274) | (0.392) | (0.404) | (0.507) |
| unemployment rate | 0.330* | 0.296* | 0.189 | 0.079 | 0.078 |
| | (0.171) | (0.174) | (0.121) | (0.229) | (0.167) |
| veteran population rate | 0.077 | 0.070 | 0.076 | 0.088 | 0.085 |
| | (0.123) | (0.123) | (0.210) | (0.225) | (0.213) |
| distance to military base | -0.241** | -0.240** | -2.230 | -2.536 | -0.702 |
| | (0.119) | (0.120) | (2.436) | (2.618) | (1.643) |
| crime rate | 0.102 | 0.108 | 0.275 | 0.237 | 0.244 |
| | (0.112) | (0.117) | (0.301) | (0.286) | (0.227) |
| age 15 to 19 population rate | 0.233 | 0.199 | -0.599 | -0.460 | -0.489 |
| | (0.345) | (0.349) | (0.564) | (0.647) | (0.551) |
| age 20 to 24 population rate | 0.252* | 0.224 | -0.884 | -0.928 | -0.922** |
| | (0.142) | (0.141) | (0.710) | (0.738) | (0.533) |
| age 25 to 34 population rate | 0.178 | 0.158 | -0.252 | -0.386 | -0.385 |
| | (0.242) | (0.247) | (0.583) | (0.766) | (0.493) |
| age 35 to 44 population rate | 0.626** | 0.589** | -0.271 | -0.125 | -0.158 |
| | (0.244) | (0.250) | (0.846) | (1.015) | (0.608) |
| age 45 to 54 population rate | -0.115 | -0.103 | -0.416 | -0.329 | -0.347 |
| | (0.276) | (0.281) | (0.644) | (0.629) | (0.465) |
| age 55 to 64 population rate | 0.327 | 0.284 | -0.521 | -0.495 | -0.537 |
| | (0.222) | (0.225) | (0.585) | (0.503) | (0.481) |
| age over 65 population rate | 0.451*** | 0.435*** | -0.128 | -0.343 | -0.346 |
| | (0.128) | (0.130) | (0.578) | (0.722) | (0.394) |
| black population rate | -0.105*** | -0.104*** | -0.031 | -0.035 | -0.023 |
| | (0.020) | (0.019) | (0.068) | (0.070) | (0.095) |
| Hispanic population rate | -0.131*** | -0.136*** | -0.145 | -0.153 | -0.164 |
| | (0.050) | (0.050) | (0.138) | (0.149) | (0.160) |
| female population rate | 0.158 | 0.148 | -0.118 | -0.116 | -0.137 |
| | (0.108) | (0.113) | (0.569) | (0.625) | (0.357) |
| Constant | -0.417*** | -0.399*** | 0.223 | 0.243 | -0.925** |
| | (0.143) | (0.148) | (0.728) | (0.794) | (0.469) |
| $\omega$ | | | | | 0.1651*** |
| | | | | | (0.0001) |
| Observations | 2,703 | 2,703 | 2,703 | 2,703 | 2,703 |
| R-squared | 0.056 | | 0.011 | 0.017 | |

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

## 5.2 Unobserved propensity toward suicide

Following the Bayesian estimation algorithm provided in the Appendix C, we rank a state's counties after each iteration based on their posterior unobserved propensity ($\delta$). The posterior distribution of unobserved county propensity ranks, which are spatially correlated, can then be estimated. Figure 6 shows a scatterplot of the relationship between the ranks of estimated unobserved propensity toward suicide and the ranks of crude suicide rate. The X-axis indicates the mean and 95% highest posterior density (HPD) of county ranks of unobserved propensity toward suicide.[68] The Y-axis represents the county ranks of time-averaged crude suicide rate.[69] The higher a county's rank, the lower their ranking number and the greater their risk of suicide. For example, a county with the rank of 1 implies that it is the highest ranked county and is therefore at the greatest risk of suicide in its respective state. As evident from Figure 6(a), there is discordance between the ranks of unobserved propensity and the ranks of crude suicide rate for Florida.[70]

Miami-Dade county (43) in Florida is to the top left of Figure 6(a). This indicates that while Miami-Dade has one of lowest crude suicide rates, it is estimated to be the county with the highest risk of suicide based on unobserved propensity.[71] Alternatively, two other Florida counties, Gilchrist (20) and Holmes (29), are toward the bottom right of Figure 6(a). This implies that relative to other counties, both Gilchrist and Holmes have higher crude suicide rates compared to their lower estimated risk of suicide based on unobserved propensity. These relationships can also be seen in the maps presented in Figure 7 (a) and (c). The darker a

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[68] The degree of uncertainty at the 95% confidential interval is represented by the length of solid line along a dot and the dot indicates the crude suicide rate rank and mean value of unobserved propensity ranks.
[69] The Y-axis ranks counties by average suicide rate over the study periods.
[70] The estimated correlation coefficient between the two ranks is 0.2696 in Florida and 0.8083 in Georgia.
[71] Refer to Tables 27 and 28 in the Appendix C for county names and numbers.

county's color on the map, the higher its rank and risk of suicide. Miami-Dade, located in the southern-most tip of Florida, shows the darkest color based on unobserved propensity but the lightest color based on crude suicide rate. Gilchrist and Holmes, located in the north and north-west of Florida respectively, show the darkest color based on crude suicide rate while showing lighter colors based on unobserved propensity. Interestingly, the rank of crude suicide rates in Figure 7(a) does not show an obvious pattern of spatial clustering. In Figure 7(c) however, southern Florida presents darker coloring in unobserved suicide propensity, whereas in northern Florida, the unobserved suicide propensity is much less severe. This presents further evidence for the existence of spatial correlation when analyzing unobserved factors of suicides.

According to Figure 6(b), Georgia is estimated to have less discordance between the ranks of unobserved suicide propensity and the ranks of crude suicide rate relative to Florida. Clarke (29) and Bulloch (16) counties in Georgia are to the top left of Figure 6(b), indicating a lower crude suicide rate, but a higher estimated unobserved suicide propensity. Alternatively, there are no noticeable counties located at the bottom-right corner of Georgia's scatterplot. Bryan (15) in Georgia is around the middle-right of Figure 6(b), implying a moderate crude suicide rate but a very low unobserved suicide propensity. These patterns are confirmed in the maps of Figure 8(a) and 8(c). Clarke and Bulloch in the north-east and east of Georgia respectively show a lighter color based on crude suicide rate, but the darkest color based on unobserved propensity. Bryan in the south-east of Georgia exhibits the lowest unobserved suicide propensity although it has a higher crude suicide rate than its neighbor, Bulloch county.[72]

[72] We also estimate unobserved propensity towards suicide by combining Florida and Georgia together in the Bayesian model. The jointly estimated map of unobserved propensity ranks produces a mostly similar pattern to the separated maps of the two states. For instance, Miami-Dade in Florida and Clarke in Georgia still show relatively higher unobserved propensity towards suicide. This jointly estimated map is available from the authors upon request.

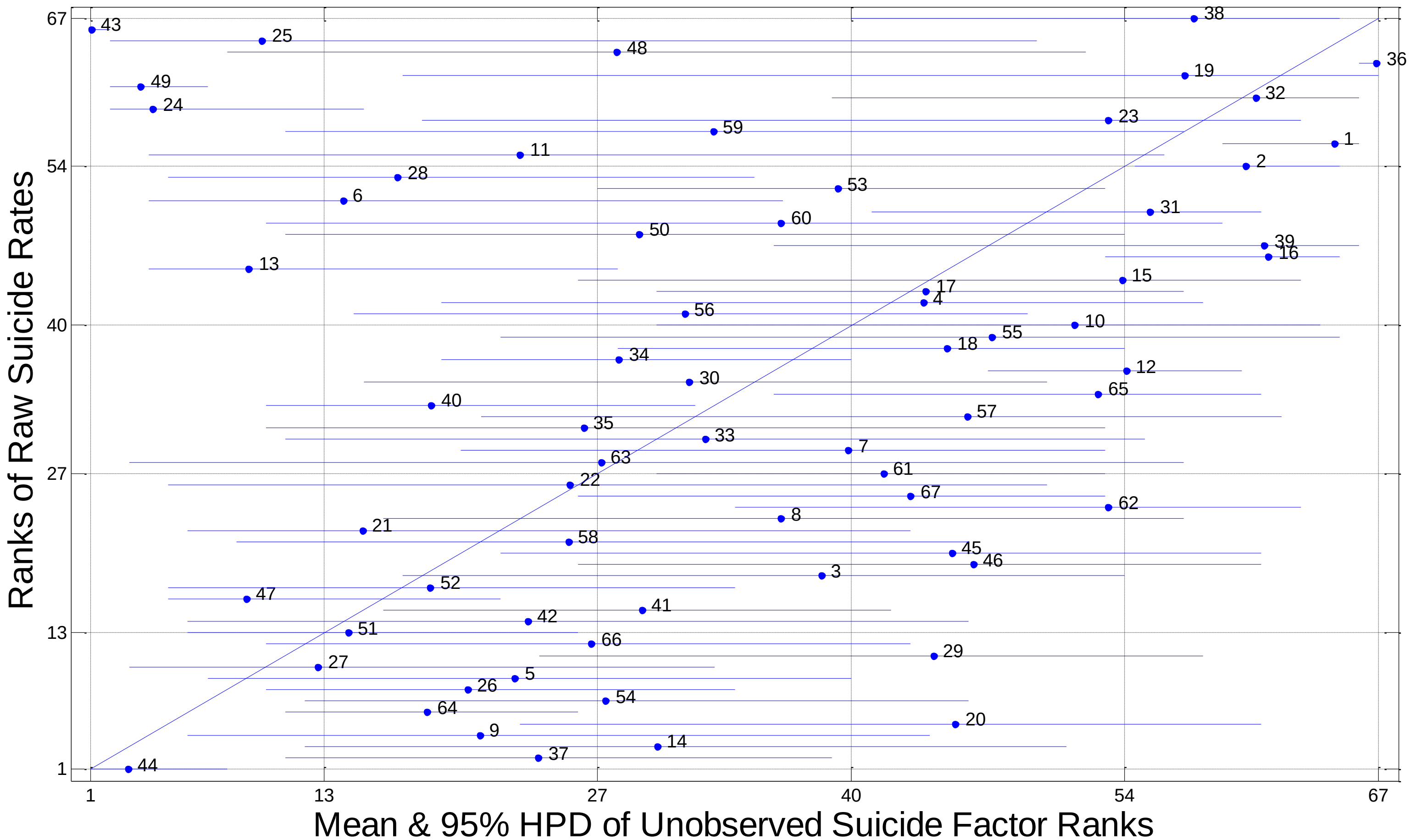



**Figure 6 (a). Florida - Ranks of Unobserved Suicide Propensity V.S. Ranks of Crude Suicide Rate**

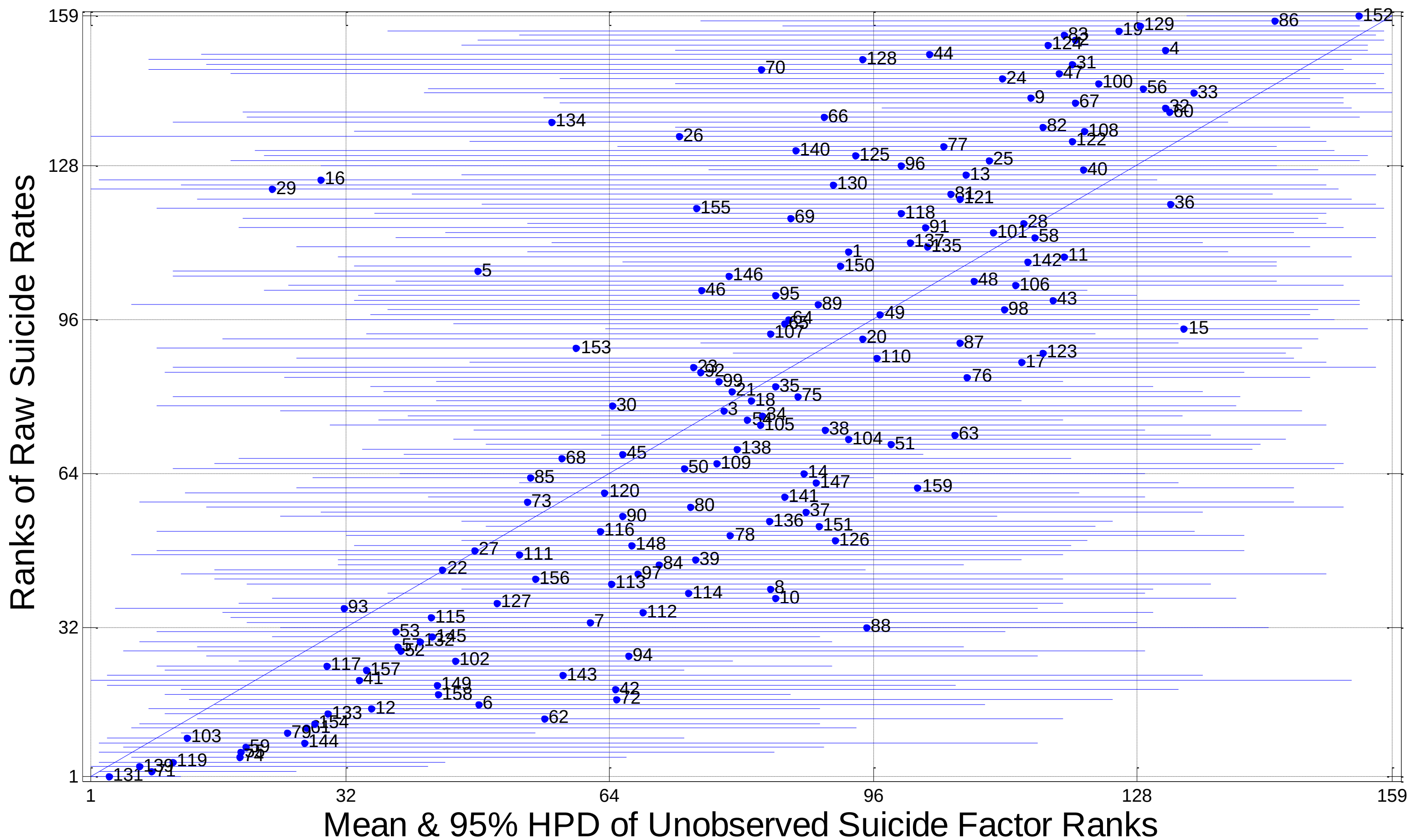
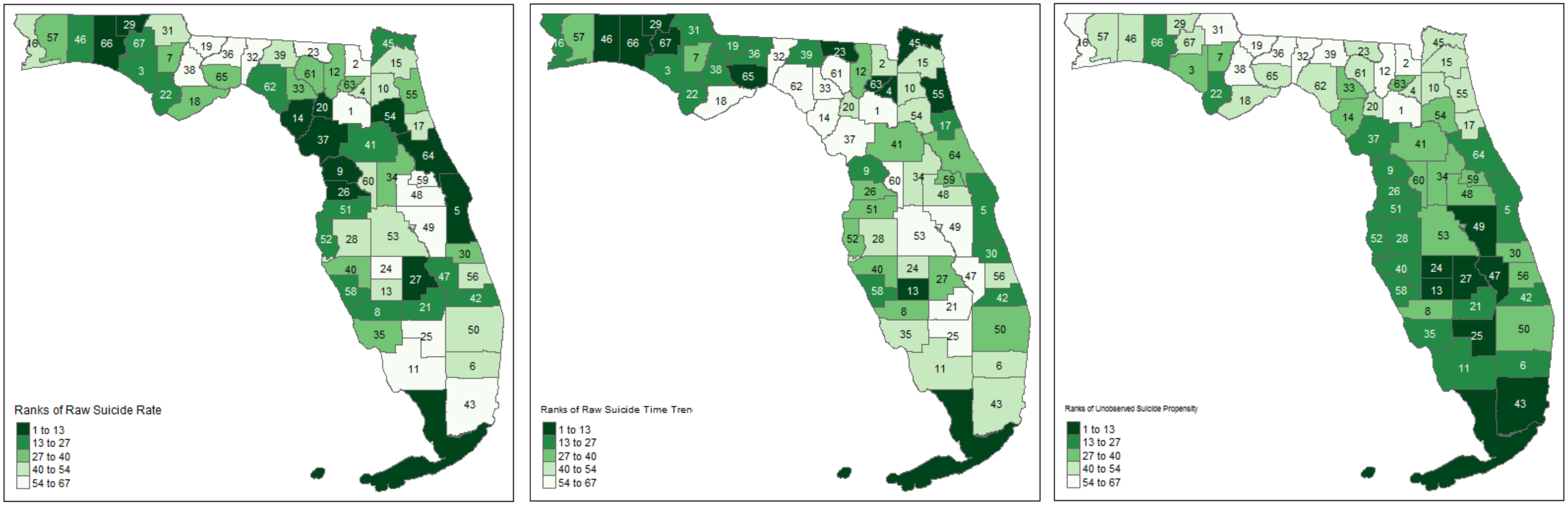
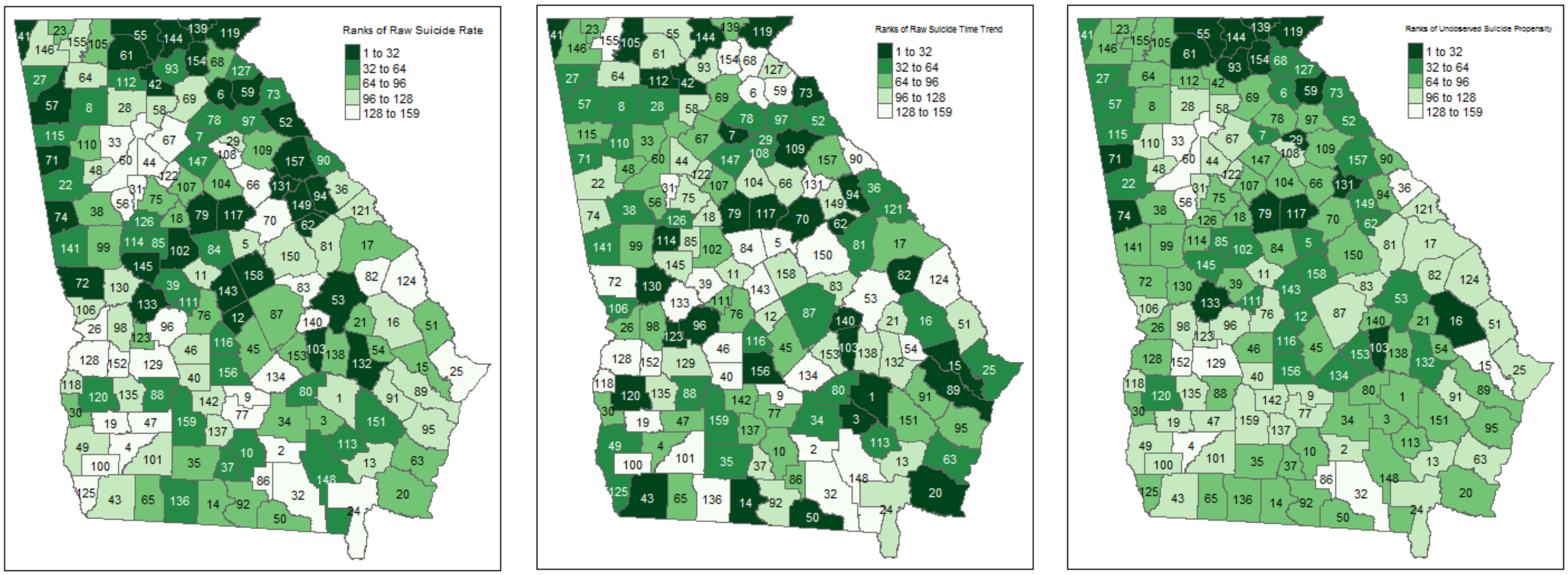



**Figure 6 (b). Georgia - Ranks of Unobserved Suicide Propensity V.S. Ranks of Crude Suicide Rate**




**(a) Rank of Time-Average Crude Suicide Rate** **(b) Rank of Crude Suicide Rate Time Trend** **(c) Average Rank of Unobserved Propensity**

**Figure 7. Maps of County Ranks in Florida**




**(a) Rank of Time-Average Crude Suicide Rate** **(b) Rank of Crude Suicide Rate Time Trend** **(c) Average Rank of Unobserved Propensity**

**Figure 8. Maps of County Ranks in Georgia**

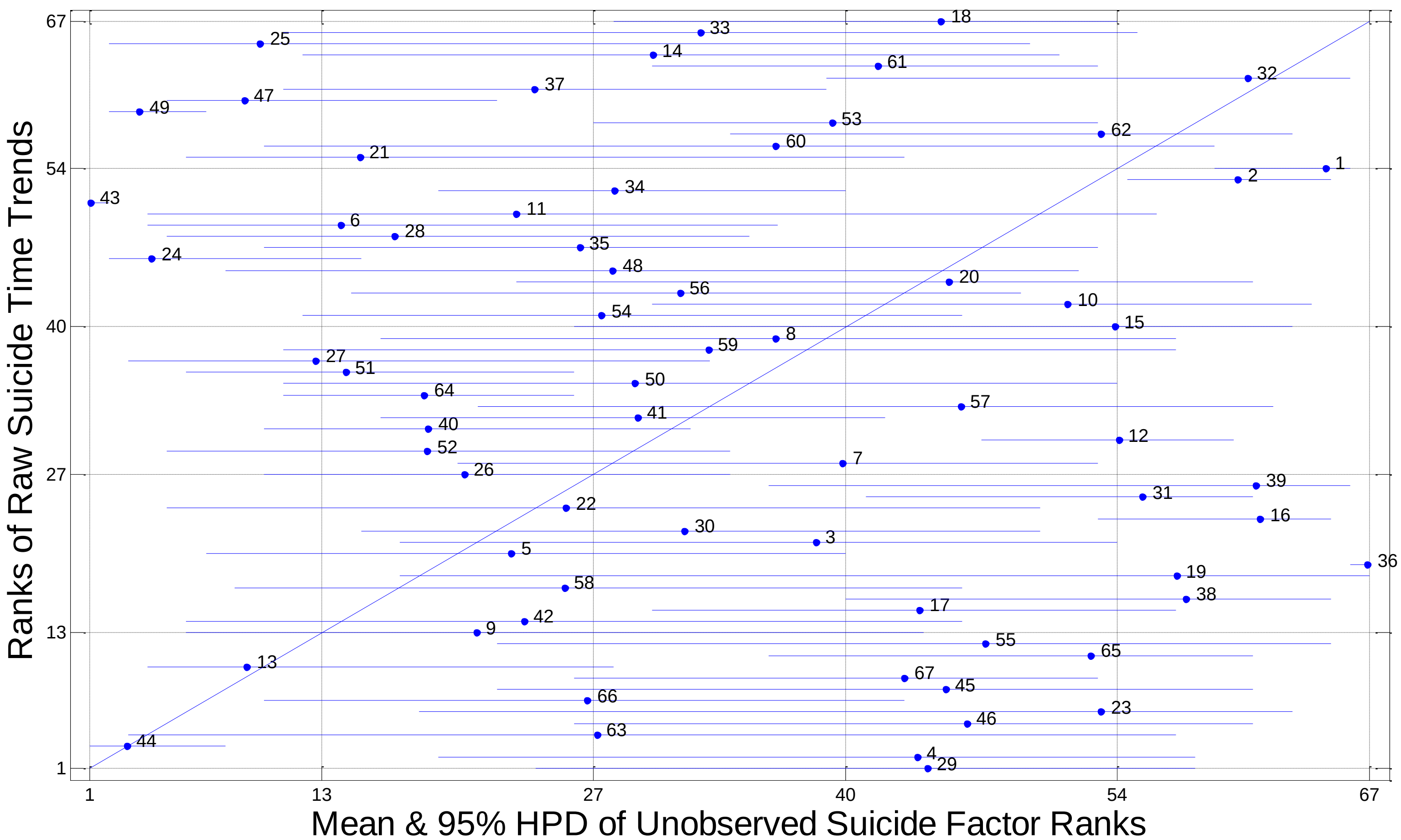



**Figure 9 (a). Florida - Ranks of Unobserved Suicide Propensity V.S. Ranks of Crude Suicide Time Trend**

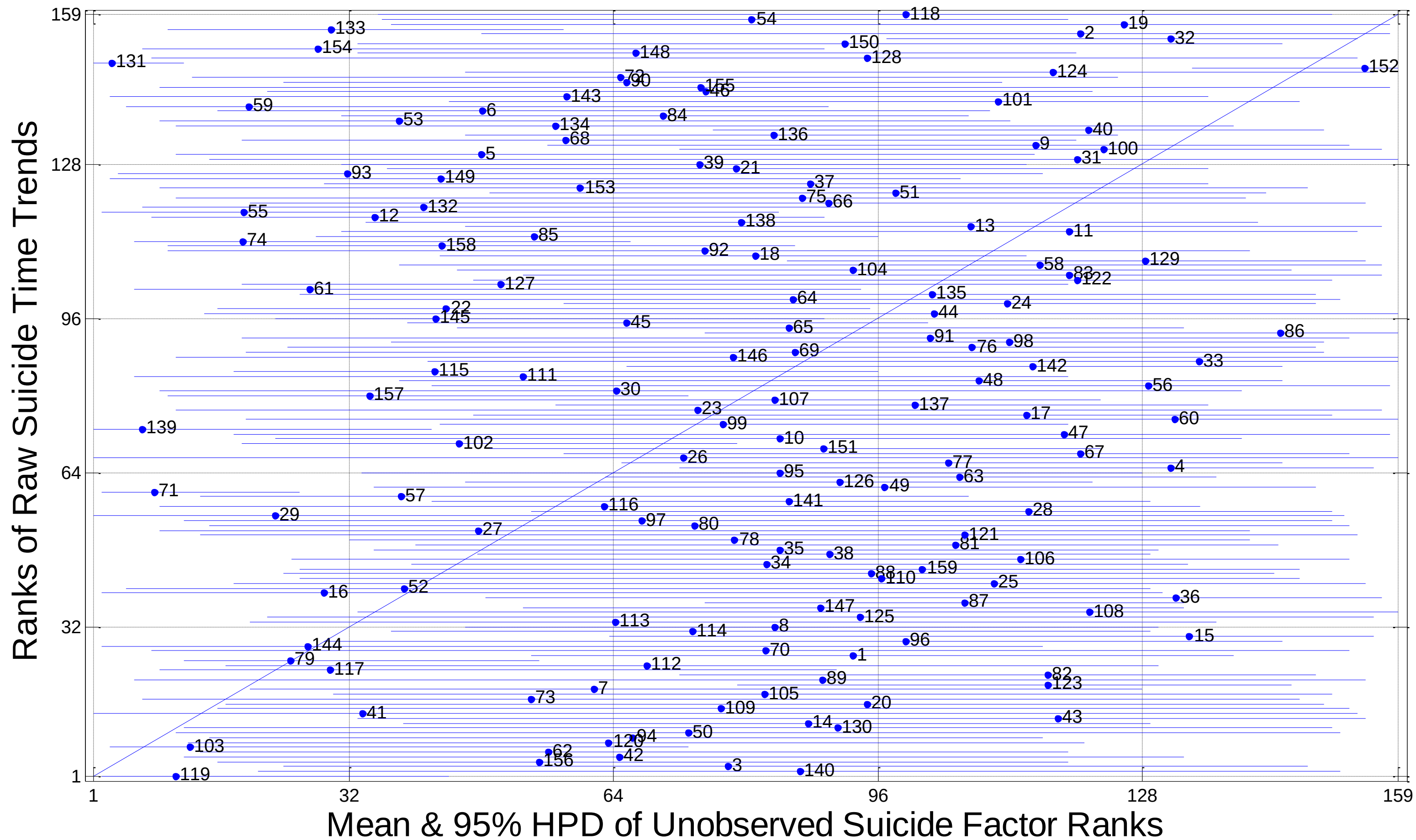



**Figure 9 (b). Georgia - Ranks of Unobserved Suicide Propensity V.S. Ranks of Crude Suicide Time Trend**

We rank counties in each state by the time trends of crude suicide rates as well.[73] The scatter plots of time trend ranks versus unobserved propensity ranks presented in Figure 9 and comparison between the maps (b) and (c) of Figures 7 and 8 show the discordance between these two ranks.[74] In other words, incorporation of a trend of rising or falling suicide rates in each county is not likely to make differences in the discordance found above when comparing the ranks of unobserved suicide propensity and the ranks of crude suicide rate.

These findings have valuable policy implications since the unobserved propensity is empirically proved to have a statistically significant effect on a county's suicide risk as discussed in Section 5.1. Public suicide prevention policies which solely target crude suicide rate or crude suicide time trend may be either ineffective or inefficient. Unobserved propensity should be considered together with the observable factors when such policies are implemented. As an example, Florida's efforts to provide proper educational facilities, public advertisement, medical treatment programs for depression, and stricter monitoring of the illegal possession of firearms and underage drinking would be better concentrated in counties like Miami-Dade as opposed to counties like Gilchrist and Holmes.

Finally, the maps present evidence for the spatial correlation of county suicide risk. Those counties that have similar ranks of unobserved propensities for suicide are clustered geographically. For example, Figure 7 shows that Miami-Dade (43) and Hendry (25), both of which are in the southern tip of Florida, have the highest unobserved suicide risks. The counties sharing a border with Miami-Dade or Hendry also have higher ranks of unobserved propensity toward suicide regardless of their crude suicide rates. Interestingly, high unobserved propensity

[73] We simply regress crude suicide rates on time for each county. We then decide the ranking of each county by taking the largest positive estimate as the highest rank and the greatest (in magnitude) negative estimate as the lowest rank.

[74] The estimated correlation coefficient between the two ranks is -0.1664 in Florida and 0.0369 in Georgia.

toward suicide spreads outward from southern Florida, but diminishes as it moves farther northward. Therefore, these high-risk counties not only tend to have a higher suicide risk themselves, but are also more likely to diffuse their risks into neighboring counties. Again, policies should be focused on counties similar to Miami-Dade and Hendry.

### 5.3 Probability to be the top 20 percent most risky counties

To convey more information regarding the uncertainty of the estimated ranks, we also compute the posterior probability for each county to be in the top 20 percent most risky counties based on the posterior distribution of unobserved propensity ($\delta$) ranks.[75] We compare these with the crude suicide rate ranks for each county in Figure 10. For Florida especially, a substantial number of counties show a discrepancy between their raw ranks and their posterior probability of being in the top 20 percent. The counties located in the bottom left of the graph have relatively higher crude suicide rates but lower probabilities of being in the top 20 percent. Counties in the top right of the graph have lower crude suicide rates but higher probabilities of being in the top 20 percent. Figure 10 supports the findings discussed in Section 5.2. In Florida, Miami-Dade (43) has a low crude suicide rate but a high posterior probability of being in the top 20 percent of most risky counties. In Georgia, Clarke also (29) has a low crude suicide rate but a high posterior probability of being in the top 20 percent.

We also map the probability of each county being in the top 20 percent of most risky counties in Figure 11. It is obvious that Miami-Dade in Florida and Clarke in Georgia show the same pattern discussed in Section 5.2. The risky counties in Florida are mostly located in the southern portion of the state, and the risky counties in Georgia are more often in the north. This enables us to identify another feature of the estimated spatial correlation. South Georgia borders

[75] The top 20 percent most risky counties are those with rank≤14th for Florida and rank≤32nd for Georgia.

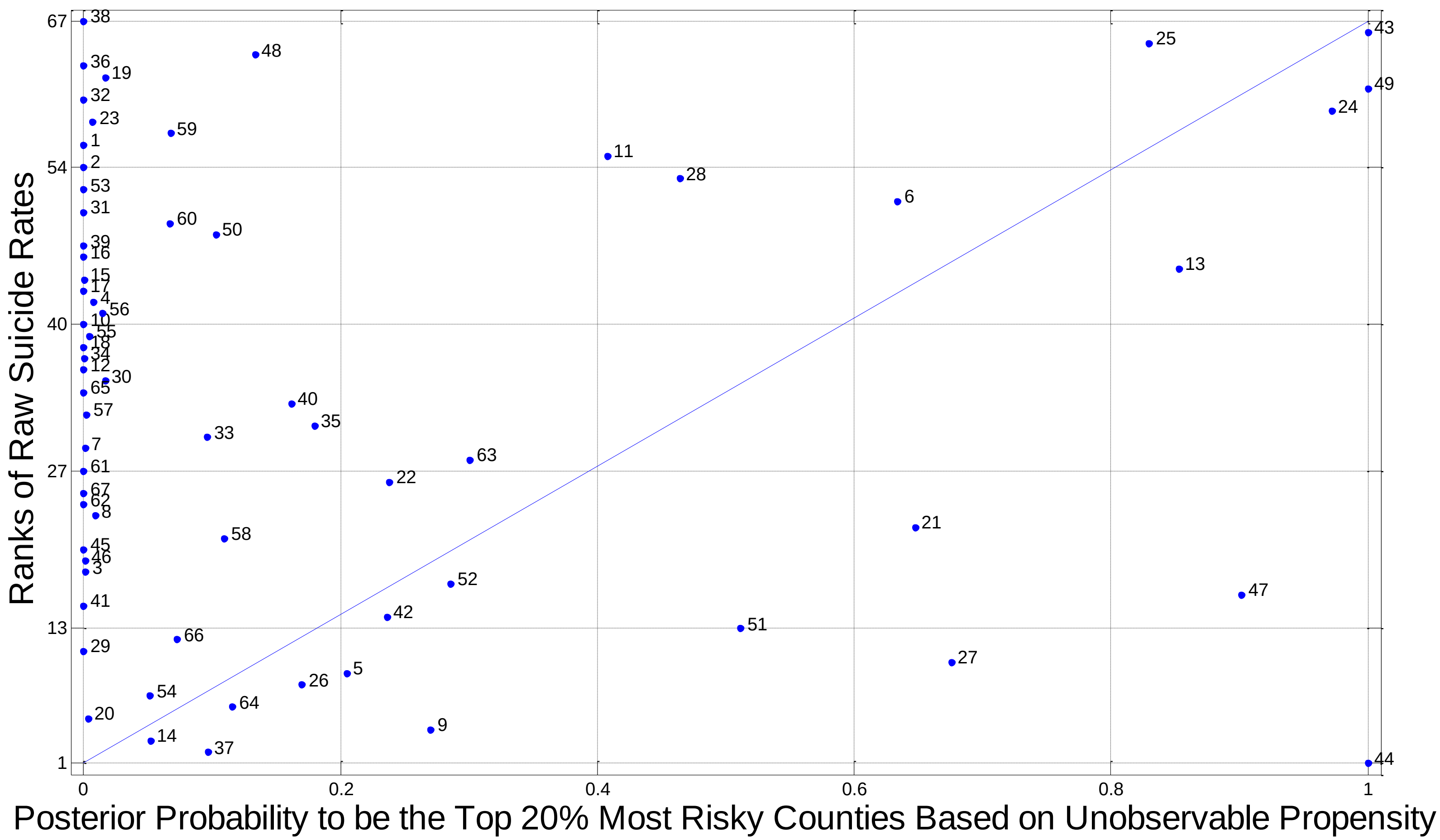



**Figure 10 (a). Florida - Posterior Probability to be the Top 20% Most Risky Counties V.S. Ranks of Crude Suicide Rate**

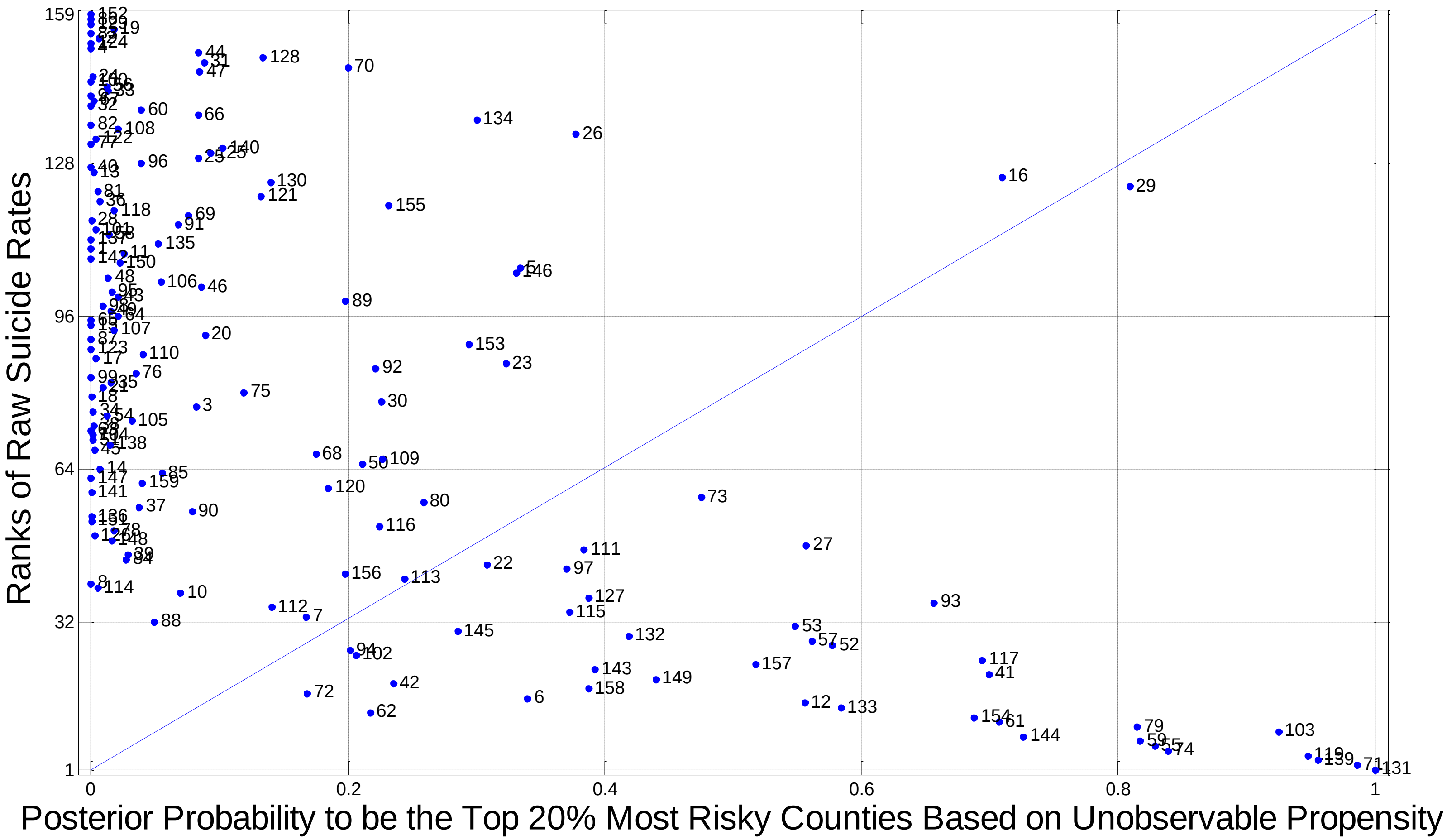
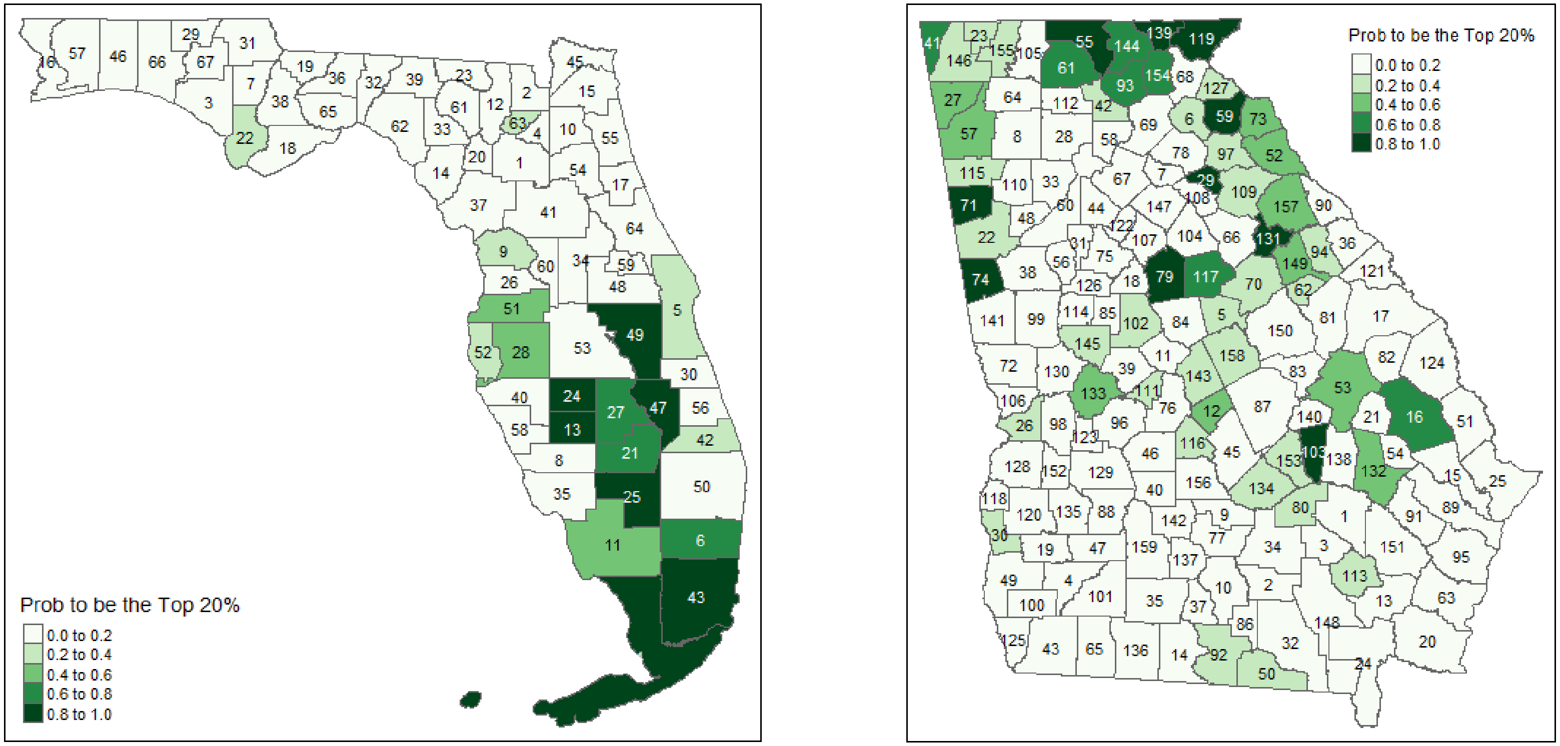



**Figure 10 (b). Georgia - Posterior Probability to be the Top 20% Most Risky Counties V.S. Ranks of Crude Suicide Rate**




**(a) Florida** **(b) Georgia**

**Figure 11. Maps of "Probability to be the Top 20% Most Risky Counties" based on Unobserved Propensity**

North Florida directly, and the spatial correlation of unobserved propensity toward suicide in the border counties is expressed in terms of light colors clustered around the borders of both states in Figure 11. The border counties across South Georgia and North Florida show similar characteristics regarding suicide, and are less likely to be in the top 20 percent most risky counties based on unobserved propensity.

**6. Conclusion**

A considerable amount of literature has analyzed the causes of suicide using data aggregated at large geographic levels. For example, national or sub-national level (e.g. the states in U.S. and NUTS-2 in Europe) analysis has been used extensively in previous literature. However, analysis within a large region is unlikely to capture sub-region-specific heterogeneity affecting suicide. If any omitted area heterogeneity is correlated with observables in the model, the empirical results will be biased. Estimating county-specific propensity with spatial dependence, we show that Florida and Georgia have different geographic patterns of suicides across counties even though the states share a border. In Florida, counties at higher risk of suicide are clustered in the south; but in Georgia, risky counties are more heavily clustered in the north. This implies that a considerable amount of previous suicide research ignoring sub-region-specific heterogeneity may provide misleading or invalid outcomes. Using county-level data and a hierarchical model incorporating spatially correlated county random effects, we are able to capture the unique unobservable suicide characteristics for each county.

The presence or absence of either sub-regional heterogeneity or time fixed effects can bring about different results in an empirical analysis of suicide. We find that the statistically significant effects of observable factors on suicide found in prior literature may be due to the exclusion of small area effects and time fixed effects. Without controlling for them, the true effect of unexplained county propensity and time trends may be hidden in observable factors. Therefore, policies focusing only on observable factors may rarely prove effective. Our empirical approach captures both county-specific effects and time trends which influence suicide mortality.

We also show that the unobserved county-specific propensity toward suicide is spatially correlated. The spatial dependence of county unobservable propensity has important policy implications. Our hierarchical model incorporating spatially correlated county random effects enables us to identify the counties which are not only likely at a greater risk of suicide themselves, but are also more likely to transmit their inclination to neighboring counties. Miami-Dade county in Florida and Clarke county in Georgia are particularly telling examples. Miami-Dade is one of the United States' most highly populated counties, and a common tourist destination for many Americans each year. It contains several cities and is also adjacent to the Atlantic Ocean. Those local area specific characteristics which tend to be spatially correlated should be considered in the analysis of suicide risk given their potential influence. Clarke county is home to the University of Georgia, implying that the mental health of friends and classmates living near one another may influence suicide decisions. Therefore, the mental state of college students should be adequately considered when structuring suicide prevention policy. To single out these and other similar counties for special treatment would perhaps be the most efficient policy. Government efforts targeting educational facilities, public advertisement, medical treatment for depression, and stricter monitoring of the illegal possession of firearms and underage drinking should be concentrated in such counties. Suicide prevention policies based solely on observables are likely to overlook counties similar to Miami-Dade and Clarke whose observable factors obscure their true risk.

While our study provides a substantial contribution to the literature, there are still limitations. Due to inaccessibility of similar mortality data for more states, our analysis is confined to Florida and Georgia. In addition, some potentially important variables are omitted in our analysis due to lack of data. For example, variables of home foreclosures, marital records, religion, and weather are not included in our estimation. With this said, it is likely that many of the omitted variable’s characteristics are subsumed by the unobserved county-specific propensity which we are able to capture in our model.

## Appendix A: Additional Tables and Figures for Essay 1

### Table 20. Falsification Test - Effect of the "Fake" GDL on Teenage Weight Status

| | (1) Random States | | (2) Random Years | |
|---|---|---|---|---|
| | **BMIZ** | **Pr(Overweight + Obese)** | **BMIZ** | **Pr(Overweight + Obese)** |
| **Entry** | 0.0147 | -0.0149 | -0.0537 | -0.0177 |
| | (0.0290) | (0.0134) | (0.0432) | (0.0236) |
| **Learner** | 0.0367 | 0.0027 | -0.0034 | 0.0185 |
| | (0.0245) | (0.0107) | (0.0278) | (0.0153) |
| **Night** | 0.0182 | 0.0046 | -0.0100 | -0.0020 |
| | (0.0191) | (0.0088) | (0.0300) | (0.0100) |
| **Combined** | 0.0018 | 0.0007 | 0.0067 | 0.0001 |
| | (0.0163) | (0.0076) | (0.0123) | (0.0050) |

Regressions are weighted by sampling weight provided in the YRBS and clustered at state level. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Models control for year fixed effects, state-age fixed effects, state linear trends, and age linear trends. There are 788,774 observations.

### Table 21. GDL Scores Assignment Schedules

| Items | Point Schedule |
|---|---|
| Minimum age for learner stage | 1 point for learner's entry age of 16 |
| Mandatory holding period | 2 points for ≥ 6 mo.; 1 point for 3-5 mo.; none for < 3 mo. |
| Minimum practice hours | 1 point for ≥ 30 hr.; none for less than 30 hr. |
| Nighttime curfew | 2 points for (before) 9 or 10 pm. 1 point for after 10 pm. |
| Passenger restriction | 2 points for ≤ 1 under-age passenger; 1 point for 2 passengers; none for 3 passengers. |
| Length of intermediate stage | 1 point if difference between minimum unrestricted license age and minimum intermediate age is 12 or more months; night driving and passenger restrictions are valued independently. |

Source: 2007 Insurance Institute for Highway Safety (IIHS)

## Appendix B: Additional Tables for Essay 2

**Table 22. Summary Statistics of Variables in Essay 2**

| Variables | Mean (St.D.) |
|---|---|
| ***Dependent Variables* [a]** | |
| Number of smoking days in the past 30 days | 2.878 (7.924) |
| Number of cigarettes per smoking day (among current smoker) | 4.800 (6.116) |
| Number of drinking days in the past 30 days | 1.951 (4.443) |
| Number of binge drinking days in the past 30 days | 1.537 (4.408) |
| | |
| ***GDL Restrictions* [b]** | |
| Probability of being below the minimum entry age | 0.209 (0.387) |
| Probability of being in the learner stage | 0.202 (0.365) |
| Probability of being subject to only a night curfew | 0.135 (0.326) |
| Probability of being subject to a night curfew along with passenger restriction | 0.157 (0.323) |
| | |
| ***Individual Covariates* [a]** | 0.501 (0.500) |
| =1 if female | 0.120 (0.325) |
| =1 if age 14 | 0.300 (0.458) |
| =1 if age 15 | 0.303 (0.460) |
| =1 if age 16 | 0.276 (0.447) |
| =1 if age 17 | 0.333 (0.471) |
| =1 if grade 9 | 0.300 (0.458) |
| =1 if grade 10 | 0.258 (0.438) |
| =1 if grade 11 | 0.108 (0.311) |
| =1 if grade 12 | 0.170 (0.375) |
| =1 if black | 0.138 (0.345) |
| =1 if Hispanic | 0.083 (0.276) |
| =1 if other race | |
| | |
| ***State Covariates*** | 48503.37 (7283.86) |
| Median household income ($) [c] | 6.283 (1.979) |
| Unemployment rate [d] | 1.622 (1.014) |
| Cigarette excise tax ($ / pack) [e] | 0.317 (0.298) |
| Beer excise tax (cent/gallon) [f] | 0.937 (0.244) |
| =1 if has state Zero Tolerance underage drunk driving law [g] | 0.233 (0.423) |
| =1 if has state tobacco-free campus law [h] | 2.878 (7.924) |

Data source: a. Youth Risky Behavior Surveillance System (YRBS);
b. The Insurance Institute for Highway Safety (IIHS);
c. The U.S. Census Small Area Income and Poverty Estimates (SAIPE);
d. The U.S. Bureau Labor Statistics (BLS) Local Area Unemployment Statistics;
e. The U.S. Tax Foundation and Department of Taxation of many states;
f. The National Highway Traffic Safety Administration (NHTSA);
g. State Tobacco Activities Tracking and Evaluation (STATE) System.

**Table 23. Regression Results on Smoking & Drinking across Different Specifications**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Individual Covariates | Y | Y | Y | Y |
| State Covariates | | Y | Y | Y |
| Year FE | Y | Y | Y | Y |
| State-Age FE | Y | Y | Y | Y |
| State Time Trends | | | Y | - |
| State-Age Time Trends | | | | Y |
| | | | | |
| ***# of Smoking Days*** | | | | |
| Entry | -0.3367 | -0.4149 | -0.2335 | -0.5894 |
| | (0.3783) | (0.3767) | (0.3228) | (0.6486) |
| Learner | 0.1446 | 0.1458 | 0.0033 | -0.1317 |
| | (0.1336) | (0.1139) | (0.1246) | (0.1737) |
| Night | 0.0513 | 0.0530 | -0.0379 | 0.2150 |
| | (0.1741) | (0.1657) | (0.1627) | (0.2172) |
| **Combined** | **-0.4540**** | **-0.4647**** | **-0.5568***** | **-0.1156** |
| | **(0.2108)** | **(0.1965)** | **(0.1918)** | **(0.2448)** |
| ***# of Cigarettes per Smoking Day*** | | | | |
| Entry | 0.8651*** | 0.7310** | 0.6301 | -0.1178 |
| | (0.3203) | (0.3461) | (0.4410) | (0.7321) |
| Learner | 0.4854** | 0.4459** | 0.2864 | 0.2257 |
| | (0.2246) | (0.2236) | (0.2240) | (0.3222) |
| Night | 0.0208 | 0.0192 | -0.0599 | -0.0057 |
| | (0.3049) | (0.2752) | (0.2943) | (0.3129) |
| **Combined** | **-0.0879** | **-0.1601** | **-0.2294** | **-0.4120** |
| | **(0.2078)** | **(0.1872)** | **(0.1488)** | **(0.3241)** |
| ***# of Drinking Days*** | | | | |
| Entry | 0.3204 | 0.2886 | 0.2484 | 0.3252 |
| | (0.2373) | (0.2163) | (0.1734) | (0.2528) |
| Learner | 0.0823 | 0.0834 | 0.0109 | 0.0247 |
| | (0.0614) | (0.0547) | (0.0496) | (0.0931) |
| Night | 0.0563 | 0.0347 | 0.0222 | 0.0549 |
| | (0.0863) | (0.0884) | (0.0849) | (0.1276) |
| **Combined** | **-0.0485** | **-0.0414** | **-0.0789*** | **-0.0162** |
| | **(0.0727)** | **(0.0658)** | **(0.0453)** | **(0.1118)** |
| ***# of Binge Drinking Days*** | | | | |
| Entry | 0.4700* | 0.4260* | 0.3090 | 0.3835 |
| | (0.2686) | (0.2565) | (0.2217) | (0.3892) |
| Learner | 0.1222 | 0.1376** | 0.0772 | -0.0391 |
| | (0.0784) | (0.0671) | (0.0615) | (0.1001) |
| Night | -0.0361 | -0.0567 | -0.0341 | 0.0173 |
| | (0.0921) | (0.0938) | (0.0926) | (0.1395) |
| **Combined** | **-0.1192** | **-0.1005** | **-0.1246**** | **-0.0234** |
| | **(0.0875)** | **(0.0771)** | **(0.0559)** | **(0.1143)** |

Regressions are weighted using the sampling weights provided by the YRBS. Robust standard errors in parentheses are clustered at the state-age level. *** p<0.01, ** p<0.05, * p<0.1.

Table 24. The Dynamic Effects of GDL Restrictions on Smoking and Drinking

| | (1) Smoking Days | (2) Cigarettes per Smoking Day | (3) Drinking Days | (4) Binge Drinking Days |
|---|---|---|---|---|
| **Entry** | | | | |
| t-1 | 0.2080 | -1.3121** | -0.3196* | -0.2850 |
| | (0.4955) | (0.5327) | (0.1821) | (0.1922) |
| t | -0.3948 | -0.1932 | 0.0708 | 0.1144 |
| | (0.4082) | (0.4433) | (0.1854) | (0.2491) |
| t+1 | -0.2200 | 0.2967 | -0.0472 | 0.0765 |
| | (0.4282) | (0.6751) | (0.1599) | (0.1787) |
| **Learner** | | | | |
| t-1 | -0.1571 | 0.1363 | -0.0042 | -0.0631 |
| | (0.2102) | (0.2301) | (0.0835) | (0.0836) |
| t | -0.1179 | 0.1014 | 0.0300 | 0.0014 |
| | (0.1460) | (0.2154) | (0.0661) | (0.0682) |
| t+1 | 0.3316 | 0.2764 | 0.0374 | 0.0536 |
| | (0.3108) | (0.3608) | (0.0811) | (0.0944) |
| **Night** | | | | |
| t-1 | 0.1150 | -0.0824 | -0.1655** | -0.2958*** |
| | (0.1962) | (0.1687) | (0.0741) | (0.0896) |
| t | 0.1972 | -0.0131 | -0.0114 | -0.0364 |
| | (0.1574) | (0.2451) | (0.0794) | (0.0856) |
| t+1 | -0.1507 | -0.3575** | -0.1854*** | -0.2251*** |
| | (0.1303) | (0.1684) | (0.0507) | (0.0514) |
| **Combined** | | | | |
| t-1 | -0.7870*** | -0.7737*** | -0.0853 | -0.3140*** |
| | (0.1939) | (0.2392) | (0.0588) | (0.0595) |
| t | -0.3833* | -0.3049* | -0.0656 | -0.0770 |
| | (0.1962) | (0.1814) | (0.0609) | (0.0612) |
| t+1 | -0.0895 | -0.0016 | -0.0967 | -0.0459 |
| | (0.1509) | (0.1864) | (0.0613) | (0.0603) |
| # Obs. | 952,807 | 159,959 | 969,364 | 957,774 |

Regressions are weighted using the sampling weights provided by the YRBS. Robust standard errors in parentheses are clustered at the state-age level. *** p<0.01, ** p<0.05, * p<0.1. The model controls for year fixed effects, state-age fixed effects, and state-specific time trends.

**Table 25. Calculation of Economic Significance of Combined Restriction on Youth Smoking and Drinking**

| | Estimated cumulative effects | 1991-2015 Increase in % of teenagers subject to combined restriction | 1991-2015 Reduction in risky behaviors | % of reduction in risky behavior due to the passenger restriction |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4) = (1) * (2) / (3)** |
| Smoking Days | -1.1654*** (0.3101) | 24.6% | 3.121 | **9.2%** |
| Cigarettes per Smoking Day | -1.0847*** (0.3151) | 24.6% | 2.273 | **11.7%** |
| Drinking Days | -0.1493* (0.0869) | 24.6% | 1.404 | **2.6%** |
| Binge Drinking Days | -0.3961*** (0.0762) | 24.6% | 1.327 | **7.2%** |

Source: Authors' calculation.

## Appendix C: Bayesian Algorithm and Additional Tables for Essay 3

To examine the determinants of suicide, we employ the following two-level hierarchical model with spatially correlated random effects. The conditionally autoregressive (CAR) specification is applied to allow for any spatial correlation (Besag 1974; Hogan and Tchernis 2004; Chamarbagwala and Tchernis 2010; Eibich and Ziebarth 2014).

$$\text{Level I:} \quad Y = X\beta + C\delta + \varepsilon \tag{2}$$

$$\text{Level II:} \quad \delta \sim N(0_N, \psi T) \tag{3}$$

For Level I: $Y$ is an $NT \times 1$ vector of $y_{it}$, with $i = 1, \dots, N$ and $t = 1, \dots, T$.[76] $X$ is an $NT \times K$ matrix of $x_{it}$ and $\lambda_t$. $\beta$ is a $K \times 1$ vector of regression coefficients. $C$ is an $NT \times N$ indicator matrix with $C_{it} = 1$ for county $i$ at any time $t$. $\delta$ is an $N \times 1$ vector of county random effects. $\delta$ represents unobserved county propensity toward suicide. $\varepsilon$ is the $NT \times 1$ vector of idiosyncratic error, such that $\varepsilon_{it} \sim iid\ N(0, \sigma^2)$.

For Level II: $\psi = (I - \omega R)^{-1}$, where $R$ is an $N \times N$ spatial correlation matrix，with $R_{ij} = 1$ if county $i$ and $j \neq i$ share a border. Otherwise $R_{ij} = 0$, and $R_{ii} = 0$. $\omega$ is the degree of spatial dependence. $T = I_N \tau^2$ measures the county variation in $\delta$ independent of the spatial correlation level.[77]

Using the Markov Chain Monte Carlo (MCMC) technique, we estimate the posterior distributions of the parameters: $\beta$, $\delta$, $\sigma^2$, $\omega$, and $\tau^2$. Our estimation uses 3500 total iterations,

[76] Suicide death is considered a Poisson random variable in prior Bayesian literature because of its rarity. Alternatively, we use average suicide rate as our dependent variable. This facilitates direct comparison with the results of our panel regressions, which is one of our paper's most important contributions. Additionally, the percentage of county-years without a suicide in our sample is only 2.9% in Florida and 15.6% in Georgia, implying that it is rather common.

[77] Our method is different from how prior literature incorporates spatial correlation. For example, a Bayesian hierarchical model constructed by Cheung et al. (2012) and Hsu et al. (2015) is that Standardized Mortality Ratio $\text{SMR} = \alpha + h_i + b_i$, or $\text{SMR} = X\beta + h_i + b_i$, where α is the overall level of relative risk, $h_i$ represents regional variation independent of spatial correlation, and $b_i$ indicates variation due to spatial dependence. $h_i + b_i$ is referred to as the error term. Our specification, however, separates the unobserved county propensity toward suicide (δ) from the error term ($\varepsilon$).

and the first 500 iterations are removed for burn-in. For each iteration, the steps of the estimation algorithm are summarized in Table 26. We use both a Gibbs sampling algorithm and a Metropolis-Hasting algorithm for $\omega$. Diffuse conjugate prior densities for each parameter are used in the estimation.[78] $\beta$ and $\delta$ are normally distributed while $\sigma$ and $\tau$ follow inverse gamma distribution. Specifically, as is described in Table 26, in step 1, we sample $\beta$ from $Y - C\delta = X\beta + \varepsilon$. In step 2, we sample $\delta$ from $Y - X\beta = C\delta + \varepsilon$. In step 3, we sample $\sigma^2$ from $Y = (X\beta + C\delta) + \varepsilon$. In step 4, we sample $\omega$ using a Metropolis-Hasting algorithm, where $\xi_1, \dots, \xi_N$ are the ordered eigenvalues of the spatial correlation matrix $R$, $\xi_1$ is the minimum eigenvalue, and $\xi_N$ is the maximum eigenvalue. In step 5, we sample $\tau^2$ from $\psi^{-\frac{1}{2}}\delta = U$, where $U \sim N(0, T)$.

[78] For example, a diffuse prior with mean of 0 and variance of 1,000 is used in step 1 for $\beta$.

**Table 26. Gibbs Sampling Algorithm for β, δ, σ², ω, and τ²**

| Step 1 | Prior Distributions | Posterior Distributions |
|---|---|---|
| $\beta$ | $N(b, B)$ | $N(a, A)$ |
| | $b = 0$ | $A = (B^{-1} + X^{'}X/\sigma^2)^{-1}$ |
| | $B = 1000$ | $a = A(bB^{-1} + X^{'}(Y - C\delta)/\sigma^2)$ |
| **Step 2** | **Prior Distributions** | **Posterior Distributions** |
| $\delta$ | $N(0_N, V_\delta)$ | $N(d, D)$ |
| | $V_\delta = \psi T$ | $D = (V_\delta{}^{-1} + C^{'}C/\sigma^2)^{-1}$ |
| | $\psi = (I - \omega R)^{-1}$, $T = I_N \tau^2$ | $d = D(C^{'}(Y - X\beta)/\sigma^2)$ |
| **Step 3** | **Prior Distributions** | **Posterior Distributions** |
| $\sigma^2$ | $IG(\alpha_0, \gamma_0)$ | $IG(\alpha_1, \gamma_1)$ |
| | $\alpha_0 = 0.001$ | $\alpha_1 = NT/2 + \alpha_0$ |
| | $\gamma_0 = 0.001$ | $\gamma_1 = (Y - X\beta - C\delta)'(Y - X\beta - C\delta)/2 + \gamma_0$ |
| **Step 4** | **Prior Distribution** | **Proposal Density** |
| $\omega$ | $\pi(\omega)$ | $q(\omega^t \| \omega^c) = \omega^c + u$, random walk |
| | $N(0, V_\omega) I(\xi_1^{-1} < \omega < \xi_N^{-1})$ | $u \sim N(0, \rho^2)$, where $\rho^2$is a tuning parameter |
| | The candidate $\omega^t$ is accepted with probability: $min\{1, \frac{f(\delta \| \psi^t, T)\pi(\omega^t)q(\omega^c \| \omega^t)}{f(\delta \| \psi^c, T)\pi(\omega^c)q(\omega^t \| \omega^c)}\}$ where $f(\delta \| \psi, T)\pi(\omega)$ is the target density of $\omega$ | |
| **Step 5** | **Prior Distributions** | **Posterior Distributions** |
| $\tau^2$ | $IG(\alpha_{00}, \gamma_{00})$ | $IG(\alpha_{11}, \gamma_{11})$ |
| | $\alpha_{00} = 0.001$ | $\alpha_{11} = N/2 + \alpha_0$ |
| | $\gamma_{00} = 0.001$ | $\gamma_{11} = (\psi^{-\frac{1}{2}}\delta)'(\psi^{-\frac{1}{2}}\delta)/2 + \gamma_{00}$ |

**Table 27. County Names and Numbers in Florida**

| # | Name | # | Name | # | Name | # | Name | # | Name | # | Name |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Alachua | 13 | Desoto | 25 | Hendry | 37 | Levy | 49 | Osceola | 61 | Suwannee |
| 2 | Baker | 14 | Dixie | 26 | Hernando | 38 | Liberty | 50 | Palm Beach | 62 | Taylor |
| 3 | Bay | 15 | Duval | 27 | Highlands | 39 | Madison | 51 | Pasco | 63 | Union |
| 4 | Bradford | 16 | Escambia | 28 | Hillsborough | 40 | Manatee | 52 | Pinellas | 64 | Volusia |
| 5 | Brevard | 17 | Flagler | 29 | Holmes | 41 | Marion | 53 | Polk | 65 | Wakulla |
| 6 | Broward | 18 | Franklin | 30 | Indian River | 42 | Martin | 54 | Putnam | 66 | Walton |
| 7 | Calhoun | 19 | Gadsden | 31 | Jackson | 43 | Miami-Dade | 55 | Saint Johns | 67 | Washington |
| 8 | Charlotte | 20 | Gilchrist | 32 | Jefferson | 44 | Monroe | 56 | Saint Lucie | | |
| 9 | Citrus | 21 | Glades | 33 | Lafayette | 45 | Nassau | 57 | Santa Rosa | | |
| 10 | Clay | 22 | Gulf | 34 | Lake | 46 | Okaloosa | 58 | Sarasota | | |
| 11 | Collier | 23 | Hamilton | 35 | Lee | 47 | Okeechobee | 59 | Seminole | | |
| 12 | Columbia | 24 | Hardee | 36 | Leon | 48 | Orange | 60 | Sumter | | |

**Table 28. County Names and Numbers in Georgia**

| # | Name | # | Name | # | Name | # | Name | # | Name | # | Name |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Appling | 31 | Clayton | 61 | Gilmer | 91 | Long | 121 | Richmond | 151 | Wayne |
| 2 | Atkinson | 32 | Clinch | 62 | Glascock | 92 | Lowndes | 122 | Rockdale | 152 | Webster |
| 3 | Bacon | 33 | Cobb | 63 | Glynn | 93 | Lumpkin | 123 | Schley | 153 | Wheeler |
| 4 | Baker | 34 | Coffee | 64 | Gordon | 94 | McDuffie | 124 | Screven | 154 | White |
| 5 | Baldwin | 35 | Colquitt | 65 | Grady | 95 | McIntosh | 125 | Seminole | 155 | Whitfield |
| 6 | Banks | 36 | Columbia | 66 | Greene | 96 | Macon | 126 | Spalding | 156 | Wilcox |
| 7 | Barrow | 37 | Cook | 67 | Gwinnett | 97 | Madison | 127 | Stephens | 157 | Wilkes |
| 8 | Bartow | 38 | Coweta | 68 | Habersham | 98 | Marion | 128 | Stewart | 158 | Wilkinson |
| 9 | Ben Hill | 39 | Crawford | 69 | Hall | 99 | Meriwether | 129 | Sumter | 159 | Worth |
| 10 | Berrien | 40 | Crisp | 70 | Hancock | 100 | Miller | 130 | Talbot | | |
| 11 | Bibb | 41 | Dade | 71 | Haralson | 101 | Mitchell | 131 | Taliaferro | | |
| 12 | Bleckley | 42 | Dawson | 72 | Harris | 102 | Monroe | 132 | Tattnall | | |
| 13 | Brantley | 43 | Decatur | 73 | Hart | 103 | Montgomery | 133 | Taylor | | |
| 14 | Brooks | 44 | DeKalb | 74 | Heard | 104 | Morgan | 134 | Telfair | | |
| 15 | Bryan | 45 | Dodge | 75 | Henry | 105 | Murray | 135 | Terrell | | |
| 16 | Bulloch | 46 | Dooly | 76 | Houston | 106 | Muscogee | 136 | Thomas | | |
| 17 | Burke | 47 | Dougherty | 77 | Irwin | 107 | Newton | 137 | Tift | | |
| 18 | Butts | 48 | Douglas | 78 | Jackson | 108 | Oconee | 138 | Toombs | | |
| 19 | Calhoun | 49 | Early | 79 | Jasper | 109 | Oglethorpe | 139 | Towns | | |
| 20 | Camden | 50 | Echols | 80 | Jeff Davis | 110 | Paulding | 140 | Treutlen | | |
| 21 | Candler | 51 | Effingham | 81 | Jefferson | 111 | Peach | 141 | Troup | | |
| 22 | Carroll | 52 | Elbert | 82 | Jenkins | 112 | Pickens | 142 | Turner | | |
| 23 | Catoosa | 53 | Emanuel | 83 | Johnson | 113 | Pierce | 143 | Twiggs | | |
| 24 | Charlton | 54 | Evans | 84 | Jones | 114 | Pike | 144 | Union | | |
| 25 | Chatham | 55 | Fannin | 85 | Lamar | 115 | Polk | 145 | Upson | | |
| 26 | Chattahoochee | 56 | Fayette | 86 | Lanier | 116 | Pulaski | 146 | Walker | | |
| 27 | Chattooga | 57 | Floyd | 87 | Laurens | 117 | Putnam | 147 | Walton | | |
| 28 | Cherokee | 58 | Forsyth | 88 | Lee | 118 | Quitman | 148 | Ware | | |
| 29 | Clarke | 59 | Franklin | 89 | Liberty | 119 | Rabun | 149 | Warren | | |
| 30 | Clay | 60 | Fulton | 90 | Lincoln | 120 | Randolph | 150 | Washington | | |

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# Vita

Qihua Qiu was born in Shanghai, China in May 1986. She entered college in September 2004 and received her Bachelor of Economics in June 2008 from Fudan University in China. After graduating from college, Qihua went to Ningxia Province, a remote mountain area, to work as a voluntary rural middle school teacher for one year. She went back to Fudan University in September 2009 and received her Master of Economics in June 2012.

In August 2012, Qihua entered the Department of Economics at Georgia State University for her doctorate degree study. Her major fields of interest are health economics, health policy, applied econometrics, and applied microeconomics. Her dissertation looked at the economics of risky health behavior and health outcomes, such as teenage obesity, teenage substance use, and suicide.  In addition, she have a list of working papers covering various topics (i.e. Human Development Index, income inequality, and zoonotic infectious diseases such as Leishmaniosis), applying advanced quantitative methodologies (i.e. Bayesian factor analysis), and shedding light on health policy decisions.