The Effects of Education on Mortality: New Evidence from Compulsory Schooling Laws

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Abstract

We investigate the effects of compulsory schooling laws on long-run mortality in the United States. We make two main contributions to this literature. First, we utilize individual level data from vital statistics records, which allow us to examine the age of death, both for all causes and for specific causes of death, in both OLS and unconditional quantile regression specifications. Second, we expand upon recent research which suggests that the effects of compulsory schooling laws on educational attainment and income are strongest in areas with higher relative teacher salaries. Our results suggest that an extra year of required schooling increases life expectancy, with the largest gains occurring for at older ages of death. We also find substantial heterogeneity across causes of death. Finally, we find that the gains in life expectancy occur mainly in states with higher teacher salaries, while educational attainment and increases life expectancy in states with higher than median quality schools while remaining unchanged, or even falling, in states with lower quality schools.

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1 Introduction

One of the most confounding empirical relationships in health economics is the causal relationship between educational attainment and mortality. Since the canonical study of Grossman (1972) posited a bidirectional relationship between education and health, researchers been attempting to verify these predictions. A landmark study of this relationship, Lleras-Muney (2005), used changes in compulsory schooling laws (CSLs) in the United States as instruments for educational attainment. She documented a strongly positive, causal effect of education on mortality rates. But more recently, a number of studies suggest that the results in Lleras-Muney (2005) are sensitive to changes in the sample period or construction of mortality rates (e.g. Mazumder, 2008; Clark and Royer, 2013; Black et al., 2015). The persistent debate represents an important puzzle from both a theoretical and policy standpoint: can education meaningfully improve longevity?

To provide insight into this important issue, we make two contributions to the literature. First, instead of calculating mortality rates, we use in our main analyses age of death from the National Vital Statistics System mortality files. These data enable the exploration of new dimensions of the effect of education on mortality, specifically, the novel application of unconditional quantile regression to examine the distributional effects of education on mortality. Second, we build on recent work by DeCicca and Krashinsky (2020) which finds that CSLs only increase reported educational attainment in states with relatively higher relative teacher salaries. By contrast, students who were educated in states with lower relative teacher salaries did not exhibit meaningful changes in educational attainment in response to CSLs. Thus, prior studies that analyze a pooled sample of all states may suffer from locally weak instruments, which generate imprecise estimates.

We find that CSL-induced educational attainment does lead to longer life expectancy for both men and women. Examining the results across the distribution of age of death, the results at the mean hide significant heterogeneity across the age of death distribution. We find these effects are driven by increases in longevity among the oldest individuals, and we also find significant heterogeneity by cause of death. For example, while we see a statistically significant effect of CSLs on age of death from suicide, unconditional quantile regressions reveal an large increase in life expectancy for the oldest individuals. Next, we examine the cause of death results by gender and document heterogeneity in the effects of CSLs on age of death. Finally, we bifurcate states into those

with above-median relative teacher salaries and those with below-median relative teacher salaries. Here we find that CSLs in the above median teacher salary states lead to increased educational attainment, in line with DeCicca and Krashinsky (2020). We also find substantially larger effects of CSLs on life expectancy for the states with relatively high teacher salaries.

Examining the effects of schooling laws on mortality across the distribution of deaths is important because it elucidates the precise channel through which education impacts mortality. Grossman (1972) posited that increased educational attainment may increase health through a number of different channels. First, education increases income, which allows consumers to afford more healthcare. Second, increased education also increases consumers knowledge and thus may increase the productivity of healthcare. Finally, the increased income from higher education increases individuals' utility from a longer life. It is plausible that many of these factors vary at different ages and the effects of CSLs on mortality may differ at different ages.

The rest of this paper is organized as follows. Section 2 reviews the previous literature on the use of CSLs as an instrument for educational attainment for the pecuniary returns to education, the literature examining CSLs and health outcomes, and finally the broader literature examining the relationship between education and health. Section 3 describes our data sources for mortality data, educational attainment, and compulsory schooling laws. Section 4 outlines our methods, which entail two sample two stage least squares regressions and reduced form uncontitional quantile regressions. Section 5 outlines our results, and finally Section 6 concludes.

2 Literature Review

Our paper touches on a few large areas of economic research. First, we build on studies which examine the returns to education and instrument for educational attainment with CSLs. Second, we contribute to studies in this area that are specifically interested in using CSLs to identify a plausibly causal relationship between education and health, as well as a broader literature seeking to examine the causal relationship between education and health, both in the United States and across the world. Below we summarize each of these literatures.

2.1 The Effects of Compulsory Schooling Laws on Education and Income

One of the most-studied and important policy questions in empirical economics is the relationship between education and income. Because the impact of education on health is generally assumed to at least partially operate through an income channel, any discussion about the impact of education on health revolves around a more fundamental question about the effect of education on income. A series of instrumental variables are used to estimate the causal nature of this effect, and CSLs are a prominent instrument within this literature. From Angrist and Krueger (1991) to Oreopoulos (2006a,b), most early studies that use CSLs find that they have a strong effect on educational attainment, and the resulting increase in education causes a positive and significant increase in income.

But more recently, the positive effect of compulsory schooling on income has been called into question. Studies using non-U.S. data find small or insignificant returns to education induced by changes in CSLs – some examples include Pischke and von Wachter (2008) with German data, Devereux and Hart (2010) with British data, and Grenet (2013) with French data. Particularly striking is Stephens and Yang (2014), which use U.S. Census data to show that the inclusion of school quality measures and region-specific trends negates any positive IV effects of education on earnings generated by changes in CSLs. Together, all of these studies cast doubt on the efficacy of CSLs in changing income or any other outcome measures, such as health, that are impacted by income.

However, a recent paper within this literature raises the possibility that CSLs in the U.S. may have still been effective within certain states, even after accounting for school quality and regional trends. DeCicca and Krashinsky (2020) show that states with comparatively higher relative teacher salaries exhibit positive and significant effects of compulsory schooling laws on educational attainment and result in positive and significant IV returns to education. By contrast, states with lower relative teacher salaries exhibit weaker effects of compulsory schooling laws on educational attainment, and negligible and insignificant IV returns to education. This would suggest that any examination of the effect of compulsory schooling laws on outcome measures like health must also be bifurcated by states along this same dimension. Specifically, if compulsory schooling laws impact health through an income channel, then a proper analysis of this effect requires that the sample is

bifurcated into states with and without efficacious compulsory schooling laws.

2.2 The Effects of Compulsory Schooling Laws on Health

Much of the economic interest in the relationship between education and health outcomes begins with Grossman (1972), who theoretically predicts that higher educational attainment could influence health. Grossman's model predicts that higher education could influence health though higher income or higher levels of health-related knowledge that allows individuals to more efficiently interact with the health-care system. However, Grossman's model also predicts that higher health levels may also increase education or that both health status and education may be affected by a third factor, for example discount rates or ability. Indeed, there is a well-documented association between education and health in Grossman (2015) and Kitagawa and Hauser (1968).

To disentangle the association between schooling and health and arrive at plausibly-causal relationships between educational attainment and health, many papers utilize CSLs as an exogenous shifter of educational attainment. Lleras-Muney (2005) pioneered this approach, creating simulated mortality rates using the one percent public use U.S. Census Samples from 1960, 1970, and 1980. In her headline results, Lleras-Muney (2005) finds that a one year increase in educational attainment reduces 10-year mortality rates by about seven percentage points. Glied and Lleras-Muney (2008) use two-sample two stage least squares techniques and data on cause-specific mortality from Vital Statistics and find that compulsory schooling laws have a larger impact on causes of death where there have been recent medical advances. However, subsequent research finds this relationship to be fragile to changes in the sample or estimation strategy. For example, Mazumder (2008) uses five percent U.S. Census samples from 1970 and 1980 as well as data from the 1990 and 2000 U.S. Censuses in her analysis, and these additional, larger data sources markedly reduce the relationship between education and mortality. Similarly, Black et al. (2015) incorporate Vital Statistics death records in a GMM framework to reduce measurement error in the estimation of the original cohort size and again find a much weaker relationship between education and later-life mortality. Results surrounding other health conditions have also arrived at mixed results. Earlier work by Oreopoulos (2007) and Mazumder (2006) suggest that education, instrumented for by compulsory schooling laws, increased various health measures such as self-reported physical or mental health disabilities and self-reported health. However, more-recent findings in Fletcher (2015) document a much weaker

relationship using AARP data and a wide variety of health-conditions.

2.3 Other Research into Education and Health

Researchers have also studied the effects of compulsory schooling laws in other countries. While Clark and Royer (2013) do not find an effect of compulsory schooling reforms in Britain on health outcomes, other research have found positive relationships. Gathmann et al. (2015) study Europe and find that compulsory schooling reforms implemented in the 20th Century reduce mortality for men, but not for women. Fischer et al. (2013) find that compulsory schooling reforms in Sweden reduce mortality even at young ages and the magnitude of the reduction grows until ages 55-60, and Lager and Torssander (2012) find that later compulsory schooling laws implemented as a quasi-experiment in Sweden reduced all-cause mortality as well as cancers, heart disease in women, and external causes for men.

Papers also examines other exogenous shifters of education to examine the relationship between education and health. Notably, Buckles et al. (2016) use the Vietnam draft as an instrument for increased college education and find a positive relationship between education and later-life mortality, concentrated in reductions in heart disease and cancer deaths. Aaronson et al. (2021) document the effects of the Rosenwald Schools on African American education and later-life mortality.

3 Data

We utilize three main sources of data for this paper; (1) data from the National Vital Statistics Death Certificates between 1981 and 2004; (2) data from the 1980 Census; and (3) information on compulsory schooling laws and other related policies collected by Stephens and Yang (2014).

3.1 National Vital Statistics Death Certificates

To measure mortality, we use the Vital Statistics mortality data between 1981 and 2019. This data contains information from death certificates, covering all deaths in the United States during each year. The information recorded on the death certificate includes demographics of the deceased individual, such as race, gender, state-of-birth, and the cause of death. We restrict the sample to individuals born in the lower 48 contiguous states between the years of 1905 and 1954. Previous

work by Lleras-Muney (2002) finds that compulsory schooling laws were not effective at raising the educational attainment of African Americans, so we restrict our focus to White individuals. Finally, we restrict our attention to deaths of individuals aged 50 and older. We do this to limit the effects of selection into our sample, as individuals born in 1905 will have to reach age 75 to be recorded in the 1980 NVSS data. The mortality data also contain ICD-9 codes, which are grouped into 34 codes for the years 1981-1998 and then 39 codes from 1999-2004. We use these to group causes of death into 11 causes: heart disease, COPD, liver disease, diabetes, stroke, cancer, infections, accidents, homicides, suicides, and other causes.[1]

3.2 Census Data

We use the IPUMS 1980 Census 5% sample, collected from Ruggles et al. (2022), to estimate the size and average educational attainment of each state-of-birth by year-of-birth by gender cohort as of 1980.[2] This particular wave of the Census is similar to the data used by previous analyses of compulsory schooling laws, including Acemoglu and Angrist (2000), Stephens and Yang (2014), and Lleras-Muney (2005). We restrict the sample in the Census to the same characteristics as above, examining white individuals born between 1905 and 1954 in the lower 48 contiguous states. We follow Acemoglu and Angrist (2000) and Stephens and Yang (2014) in coding years of education.

3.3 Compulsory Schooling Laws and Educational Quality

To capture measures of school quality, we use data assembled by Card and Krueger (1992) on three annual measures of state-level school quality: relative teacher earnings, pupil-teacher ratios, and term length. Relative teacher earnings in each state are determined by comparing the average teacher salary paid in a given state to the average manufacturing wages paid in that same state, while the other two variables are measured in the standard way. Data on compulsory schooling laws were compiled by Oreopoulos (2006b); the laws dictate the earliest age at which an individual may cease their educational training. From this, we create two indicators, one for if a student is

[1] We group the 34 code recodes as follows: heart disease (140 to 180), cancer (40 to 110), accidents (330 to 340), suicide (350), infections (10, 20, 30, and 230), liver disease (260), diabetes (120), stroke (200), COPD (240), and homicide (360). We group the 39 code recodes as follows: heart disease (19 to 22), cancer (4 to 15), accidents (38 to 39), suicide (40), infections (1, 2, 3, and 27), liver disease (30), diabetes (16), stroke (24), COPD (28), and homicide (41).

[2] We do not use earlier or later Census samples because we want to measure the effects of CSLs on educational attainment immediately before our mortality data commences.

required to attend school until age 16, and one for if a student is required to attend school until age 17 or higher. We merge these indicators as of the year the individual turned 14 years old.

4 Methods

One drawback to the NVSS Death Certificate data is that it does not consistently contain individuals' educational attainment. To address this drawback, we use both two-sample two stage least squares regressions as well as reduced form regressions to examine the effects of CSLs on educational attainment and mortality and the direct effects of CSLs on mortality.

4.1 Two Sample Two Stage Least Squares

To structurally examine the relationship between education and health, we use two-sample two-stage instrumental variables estimation (TS2SLS). In the first-stage, we regress completed years of education from the 1980 Census sample on the years of required schooling:

$$ED_{icsy} = \pi + \pi_2 CSL16_{sy} + \pi_3 CSL17_{sy} + \gamma_i + \sigma_s + \theta_{cy} + \epsilon_{iscy}. \tag{1}$$

In equation (1), ED_{icsy} is the reported years of educational attainment for individual i born in state s and Census Region c in year-of-birth y. The independent variable of interest, $CSL16_{sy}$ and $CSL17_{sy}$ measure the drop out ages for individuals born in state-of-birth s in year-of-birth y. We include an indicator, γ_i, for whether an individual is female. Finally, we include a set of dummies for state-of-birth (σ_s) and Census region$\times$birth year (θ_{cy}). We follow previous papers in this area, e.g. Lleras-Muney (2002) and Stephens and Yang (2014), and cluster our standard errors at the state-of-birth by year-of-birth level.

In the second stage, we predict the effects of education on the age of death using the results from the first stage:

$$AD_{iscy} = \gamma + \gamma_2 \widehat{ED}_{iscy} + \gamma_i + \sigma_s + \upsilon_y + \tau_q + \theta_{cy} + \epsilon_{isyq}, \tag{2}$$

4.2 Reduced Form OLS and Unconditional Quantile Regression Specifications

In addition to the TS2SLS specifications, we examine reduced form specifications to examine the total effect of CSLs on later-life mortality. We first estimate OLS specifications which are similar to equation **??**:

$$Age_{icsy} = \alpha + \alpha_2 CSL16_{sy} + \alpha_3 CSL17_{sy} + \gamma_i + \sigma_s + \theta_{cy} + \epsilon_{iscy}. \tag{3}$$

The key difference is that the dependent variable is the individual's age of death, Age_{icsy}.

We also leverage the continuous nature of the age of death variable available in the death certificate data to examine the effects of CSLs on age-of-death across the distribution of ages using unconditional quantile regression (Firpo et al., 2009). Unlike OLS, quantile regression calculates the effect of independent variables on a dependent variable at a specific quantile of the dependent variable. Here, this means estimating the reduced form effect of CSLs on age of death across different quantiles of the ages of death.

Firpo et al. (2009) develop unconditional quantile regression using the recentered influence function (RIF),

$$RIF(y; \nu(F_Y)) = \nu(F_Y) + IF(y; \nu(F_Y)). \tag{4}$$

Here $\nu(F_Y)$ is a statistic measured on the distribution of the random variable, y, and $IF(u; \nu(F_Y))$ is the influence function, a measurement of the influence of an observation on $\nu(F_Y)$. When the statistic of interest is a quantile, q_θ, the influence function can be written as,

$$IF(y; q_\theta) = \frac{\theta - 1[Y \leq q_\theta]}{f_{Y(q_t heta)}} \tag{5}$$

and then the recentered influence function is

$$RIF(y; q_\theta) = q_\theta + \frac{\theta - 1[Y \leq q_\theta]}{f_{Y(q_\theta)}}, \tag{6}$$

where $1[Y \leq q_\theta]$ is an indicator variable for whether the dependent variable is above or below quantile θ and $f_{Y(q_\theta)}$ is the probability density function of the dependent variable evaluated at quantile θ. Firpo et al. (2009) show that the partial effects of covariates on the dependent variable

Y at each quantile can be estimated from a regression using the RIF as the dependent variable. The implementation of unconditional quantile regression is relatively straightforward. First, the density of the dependent variable is estimated using a kernel or similar method. Second, the unconditional partial effects can be estimated through a regression of the RIF on the covariates.[3]

We also leverage the death certificate data to examine the TS2SLS and reduced form results separately by causes of death. Building on the work of Glied and Lleras-Muney (2008), we postulate the effects of education on health may differ both across the causes of death and across the distribution of ages of death within each cause of death.

In order to examine the effect of CSLs on educational attainment and mortality accounting for the advancements in DeCicca and Krashinsky (2020), we bifurcate our sample into two sets of states: those with above-median relative teacher salaries, and those with below-median teacher salaries. To accomplish this division, the average relative teacher salary ratio was computed across all birth cohorts for each state of birth in our data. Once this average was computed for each state of birth, the states were then ranked on the basis of this state-specific average ratio from highest to lowest, and then divided into roughly two equal subsamples: states in the lower half of this distribution (which were categorized as "Lower than Median" states) and states in the upper half of this distribution (which were categorized as "Higher than Median' states). Figure 1 shows the states which fall above and below the median relative teacher salary value. The key result from this division is to document how individuals born in "Higher than Median" states exhibited higher average levels of education and earnings compared to those in "Lower than Median" states, and this was not related to differences in divorce rates or unemployment rates. DeCicca and Krashinsky (2020) demonstrate that this result was primarily due to differing impacts of compulsory school laws between the two groups: only individuals exposed to compulsory schooling laws in the "Higher than Median" states exhibited significant effects of compulsory schooling laws on education, which led to significant IV returns to education for only this group; this result will be discussed in further detail later in this paper, along with its connection to differences in mortality patterns for the two subsamples.

[3]We use the R Package `rif` to estimate the recentered influence function and then the `fixest` package to run regressions.

4.3 Event Study Specifications

Finally, we use event studies to test the parallel trends assumptions underlying the first stage and reduced form regressions as well as examine the dynamics of the effects of CSLs on educational attainment and mortality. To this end, we modify equation 1:

$$ED_{icsy} = \beta + \beta_2 CSL16_{sy} + \sum_{j=-n}^{k} \beta_{3,j} CSL17_{syj} + \gamma_i + \sigma_s + \theta_{cy} + \epsilon_{iscy}. \tag{7}$$

We also estimate similar models for the reduced form specificaitons, replacing educational attainment with age of death:

$$Age_{icsy} = \delta + \delta_2 CSL16_{sy} + \sum_{j=-n}^{k} \delta_{3,j} CSL17_{syj} + \gamma_i + \sigma_s + \theta_{cy} + \epsilon_{iscy}. \tag{8}$$

Here, we replace $CSL16_{sy}$ with an indicator for a dropout age of at least 16 years, so that this indicator does not turn off when the event study indicators turn on. We also create dummy variables for the age at which a state enacts a dropout age of at least 17. We treat the law passing at age 4, the year before the individual likely entered school, as the omitted category. We plot the coefficients for 10 years before and after this omitted period.

5 Results

5.1 OLS Results

We begin by showing the results of first stage, reduced form, and TS2SLS regressions. As previous work by Stephens and Yang (2014) shows that the economic returns to education using CSLs as instruments are not robust to the inclusion of Census Region by year fixed effects, we start by showing how this new specification affects our results. Following DeCicca and Krashinsky (2020), we also show results bifurcated by states above and below the relative median teacher salary.

Results to be added later.

5.2 Event Studies

Results to be added later.

5.3 Unconditional Quantile Regression Results

Next, we show results reduced form unconditional quantile regressions for the dropout age of at least 17. We begin in Figure 2, showing quantile regression results for both genders, then men and women.

The results vary across genders. While the increases in age of death in the OLS regressions seem uniformly spread across the age of death distribution, this hides heterogeneity within each gender. For men, coefficients are generally small and not statistically significant for the lowest 25% of the distribution, while the coefficients become positive, large, and statistically significant above the median. These correspond to ages of death in the mid 70s or older. However, for women the coefficients evolve differently across the distribution of ages of death. Here, a dropout age of at least 17 has the largest effects at the lower quantiles while the effects are smaller and not all statistically significant at the 5% level for the upper quantiles.

Next we disaggregate results by cause of death, first for all genders in Figure 3 through 5. Figures 6, 7, and 8 show results disaggregated by gender, with results for men in blue and women in pink. The solid line and shaded area show the quantile regression coefficients and 95% confidence intervals, while the dashed lines show the OLS coefficient and 95% confidence interval for comparison.

Figure 3 shows results for accidents, cancers, COPD, and diabetes, Figure 4 shows results for heart disease, homicide, infections, and liver disease, and Figure 5 shows results for strokes, suicides and other causes. Loosely grouping the results, we find relatively constant reduced form effects of CSLs on age of death for cancers and the catchall category of other causes, results that are largest for the oldest individuals for accidents, diabetes, heart disease, infections, and suicide, and results that are largest for the youngest ages of death for COPD, liver disease, and strokes.

Examining the results for specific genders, we find that some causes of death appear similar across genders in Figures 6, 7, and 8. In particular, COPD, diabetes, infections, and strokes show similar reduced form effects of CSLs on mortality across genders. A few causes show markedly different effects for both men and women. For example, the constant effect of CSLs on heart disease for men contrasts to an increasing relationship for women. Suicides show a much larger effect of CSLs for men at the upper parts of the age distribution for men, while the results are more muted for women.

Next, we investigate whether the quantile regression results vary based on relative teacher salaries. Figure 9 shows results from these models, plotting the coefficients ant 95% confidence intervals across the distribution of ages of death for a dropout age of at least 17. For both genders, results are largest for the lowest and highest ages of death for above median teacher salary states. For below median states, CSLs do not increase the age of death, but rather decrease the age of death at the very lowest and highest quantiles. However, there are again large differences by gender. For men, the effect of CSLs on age of death increases steadily across the age of death distribution for above median states, while showing little relationship in below median states. For women, the results are starkly apparent in the lowest and highest quantiles for above median states while showing little relationship across all but the highest ages of death in the below median states.

In Figure 10 through 12, we show disaggregated results split by above vs. below median relative teacher salaries by cause of death. Examining the specific causes of death, broadly we see increased ages of death, with the largest increases in life expectancy occurring for the oldest. Many causes show sharp differences between the two groups of states, especially at older ages of death, for example accidents, COPD, cancers, diabetes, heart disease, strokes, suicide, and the residual category of other causes.

6 Conclusion

The way in which education impacts mortality is a key idea that is essential for both the health economics literature as well as related policy initiatives. If there is no relationship between these two measures, then educational investments have no bearing on public health; but if education causally improves health, then it represents a significant, additional policy dimension for improving individual well-being. To date, there has been no clear agreement about the exact nature of this relationship, because credible studies have found highly divergent causal effects of education on mortality. This persistent disagreement represents a substantial shortfall in the literature, as well as a severe limitation in the way in which educational policy initiatives should be guided.

To address these problems, this study presents several novel pieces of evidence to provide a new perspective on the causal effect of education on mortality. First, we demonstrate that changes in mortality rates resulting from education are not similar across the entire population of the United

States. Populations who exhibited meaningful education-induced changes in mortality rates were born in states with binding compulsory schooling laws, while those who did not exhibit meaningful changes were born in states whose compulsory schooling laws were not binding. This suggests that there exists a flaw in the standard approach of pooling all states together to analyze the causal effect of education on mortality, because this process would include states whose changes in educational attainment were not exogenous. We note that this type of approach could give rise to divergent estimates of the effect of education on mortality, which are evident in the literature.

By focusing our analysis on the states with changing mortality rates, we document a significantly positive, causal effect of education on mortality; our reading of the literature is that the estimated magnitude of this effect is well within the reasonable range of expected values. Furthermore, we apply a novel econometric approach by using an unconditional quantile regression on new data to explore the distributional dimension of this effect, and we find that it is concentrated in the upper range of the distribution. Specifically, education improves the longevity of the oldest individuals in the population. Lastly, we examine specific causes of death and demonstrate that the effect of education is wide-ranging in this regard: additional education made individuals less likely to be affected by a large set of potential causes of death.

Overall, this evidence helps to address a significant disagreement within the Health Economics literature by showing the specific ways in which education impacts mortality, and by identifying a problem that has plagued prior studies on this topic. Further, this evidence represents a credible way to advise public health initiatives: mandating higher levels of additional education can impact mortality, but only if these mandates are properly enforced by local governments. If enforcement is sufficient, education can have positive effects on the upper end of the longevity distribution, and can help to mitigate certain causes of death.

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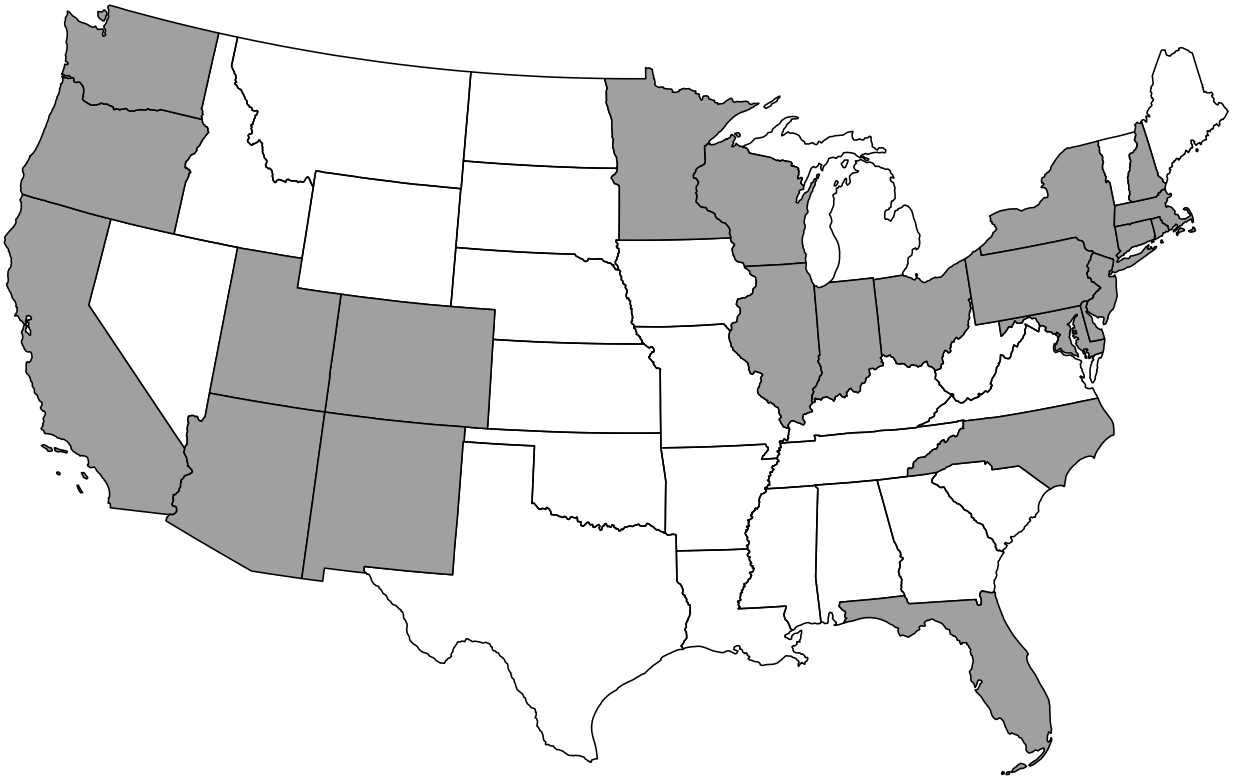
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Pischke, S. and T. von Wachter (2008). Compulsory schooling and labour market institutions in Germany. Review of Economics and Statistics 90(3), 592–598.

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Stephens, M. and D.-Y. Yang (2014). Compulsory education and the benefits of schooling. American Economic Review 104(6), 1777–92.

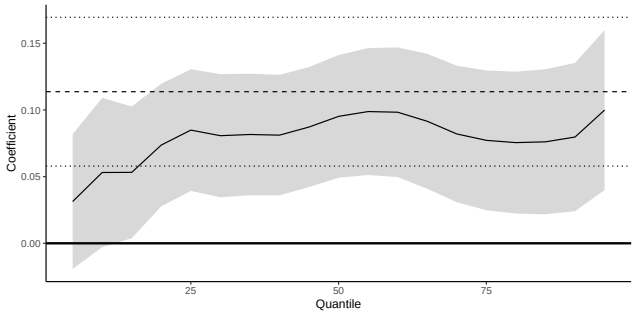
Figure 1: Map of States with Average Relative Teacher Salaries Above vs. Below Median Value



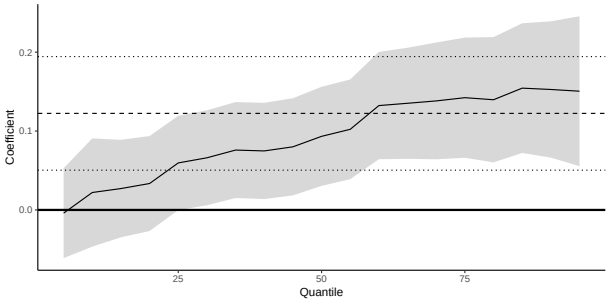
Notes: Data from Card and Krueger (1992).

Figure 2: Reduced Form Quantile Regressions
Both Genders

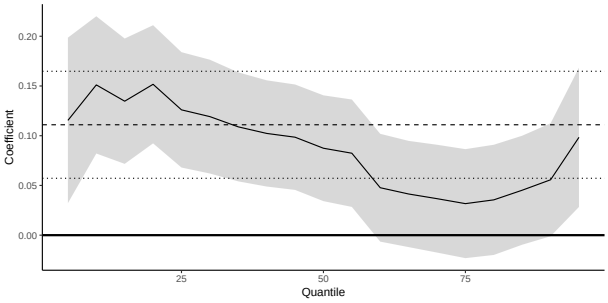
(a) All Genders



(b) Men

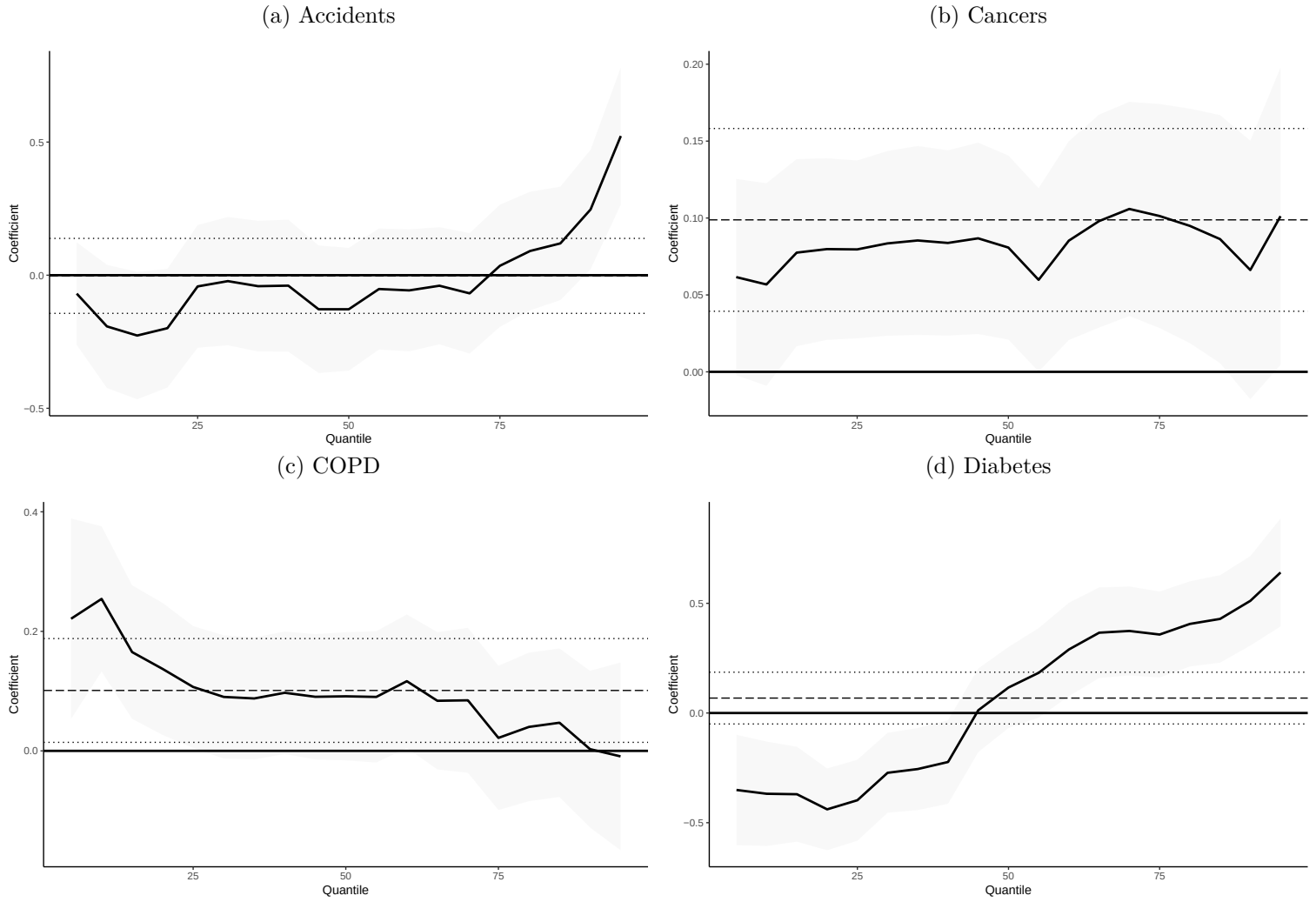


(c) Women



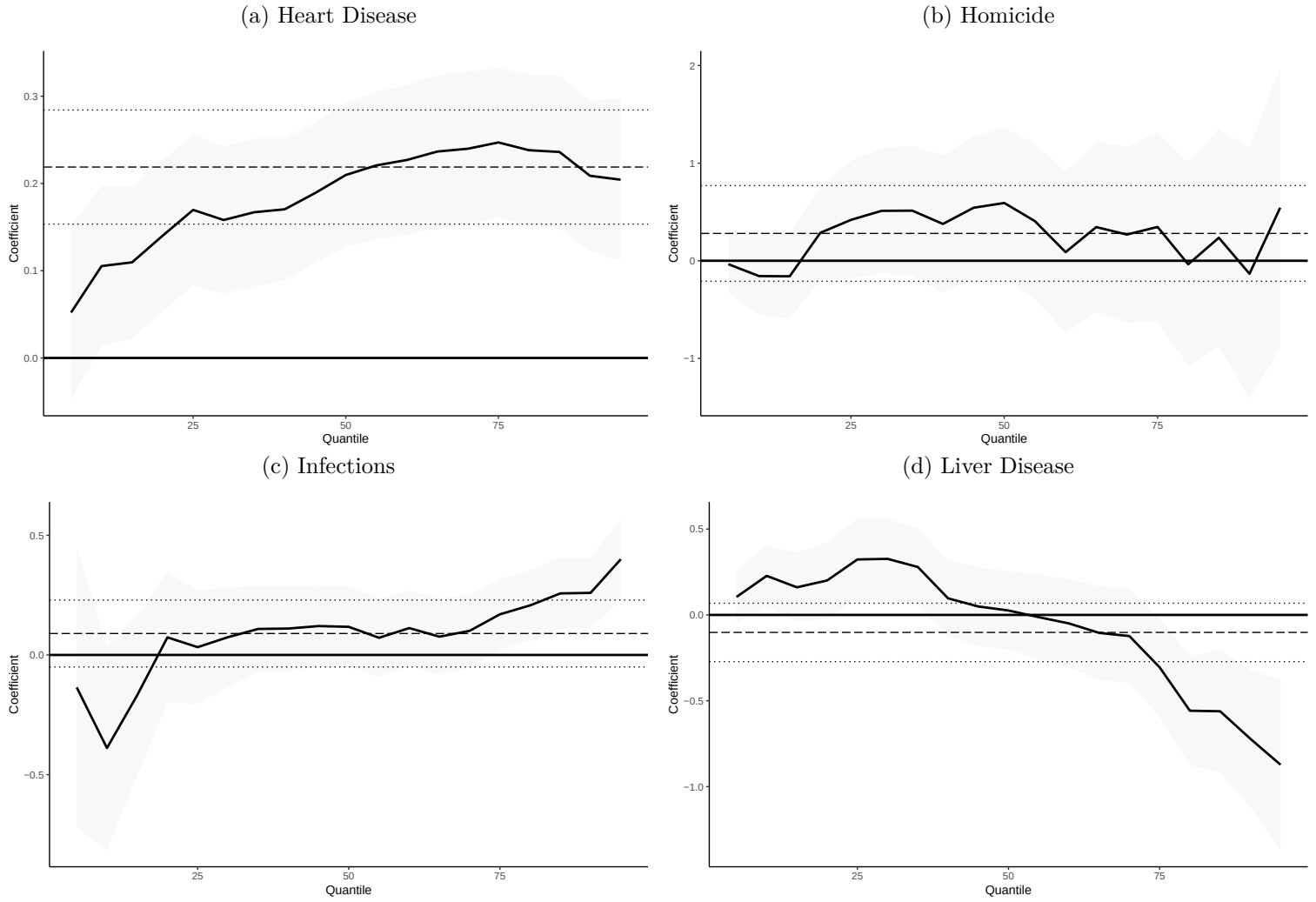
Notes: The red line and shaded area represents the coefficients and 95% confidence interval for the above-median states, while the blue line and shaded area represents the coefficients and 95% confidence interval for the below median states. The dashed lines in each color represent OLS coefficients and 95% confidence intervals.

Figure 3: Reduced Form Quantile Regressions: Specific Causes of Death



Notes: The black line and shaded area represents the coefficients and 95% confidence intervals for the quantile regressions while the dashed lines represent OLS coefficients and 95% confidence intervals.

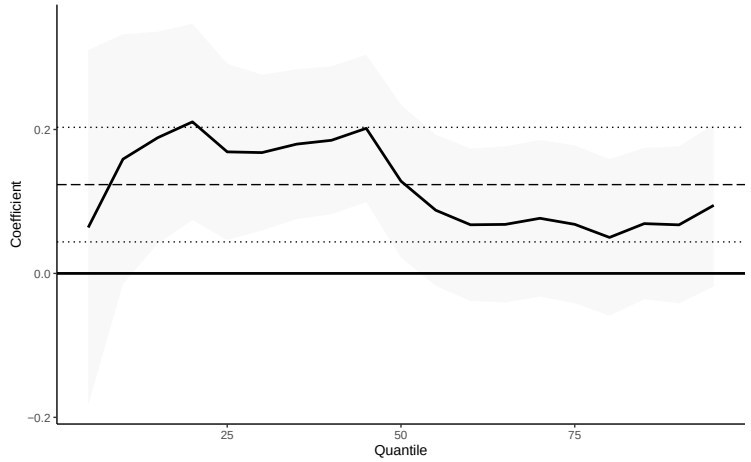
Figure 4: Reduced Form Quantile Regressions: Specific Causes of Death



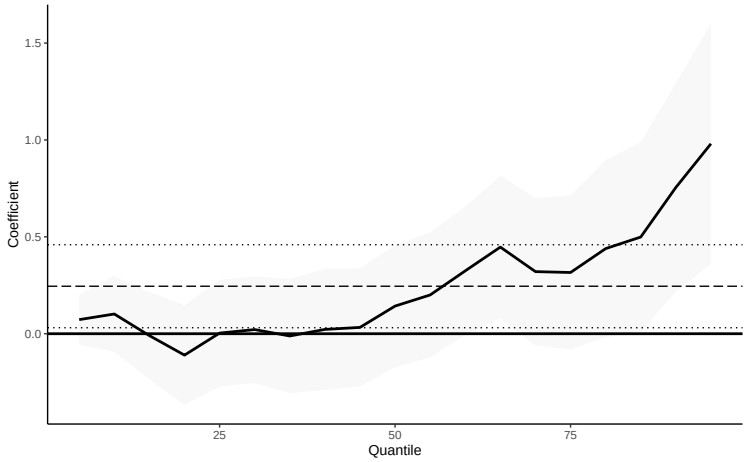
Notes: The black line and shaded area represents the coefficients and 95% confidence intervals for the quantile regressions while the dashed lines represent OLS coefficients and 95% confidence intervals.

Figure 5: Reduced Form Quantile Regressions: Specific Causes of Death

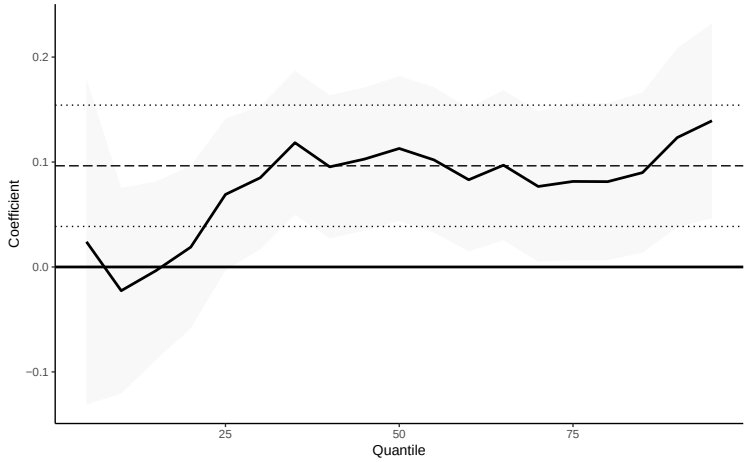
(a) Stroke



(b) Suicide

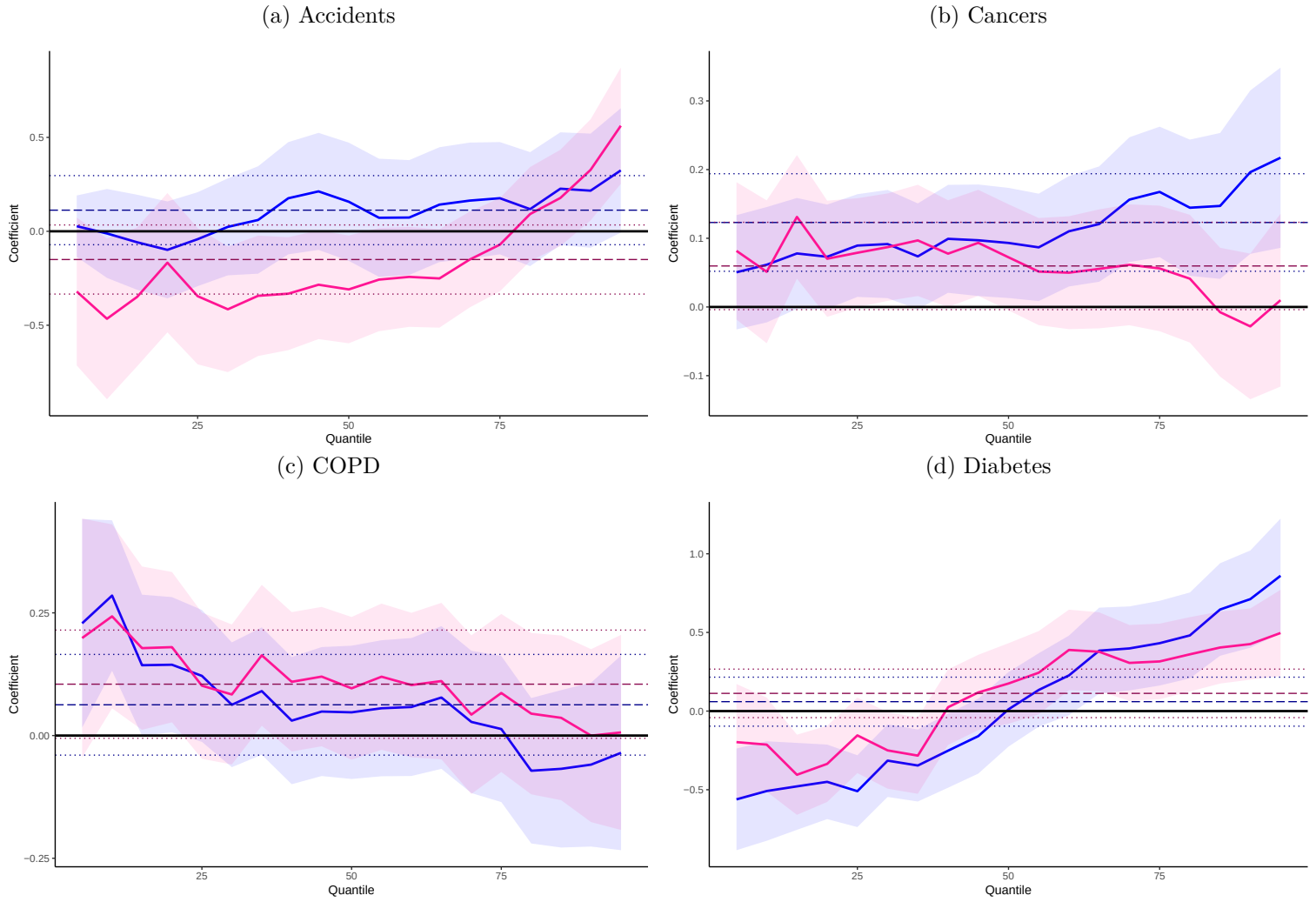


(c) Other Causes



Notes: The black line and shaded area represents the coefficients and 95% confidence intervals for the quantile regressions while the dashed lines represent OLS coefficients and 95% confidence intervals.

Figure 6: Reduced Form Quantile Regressions: Specific Causes of Death by Gender

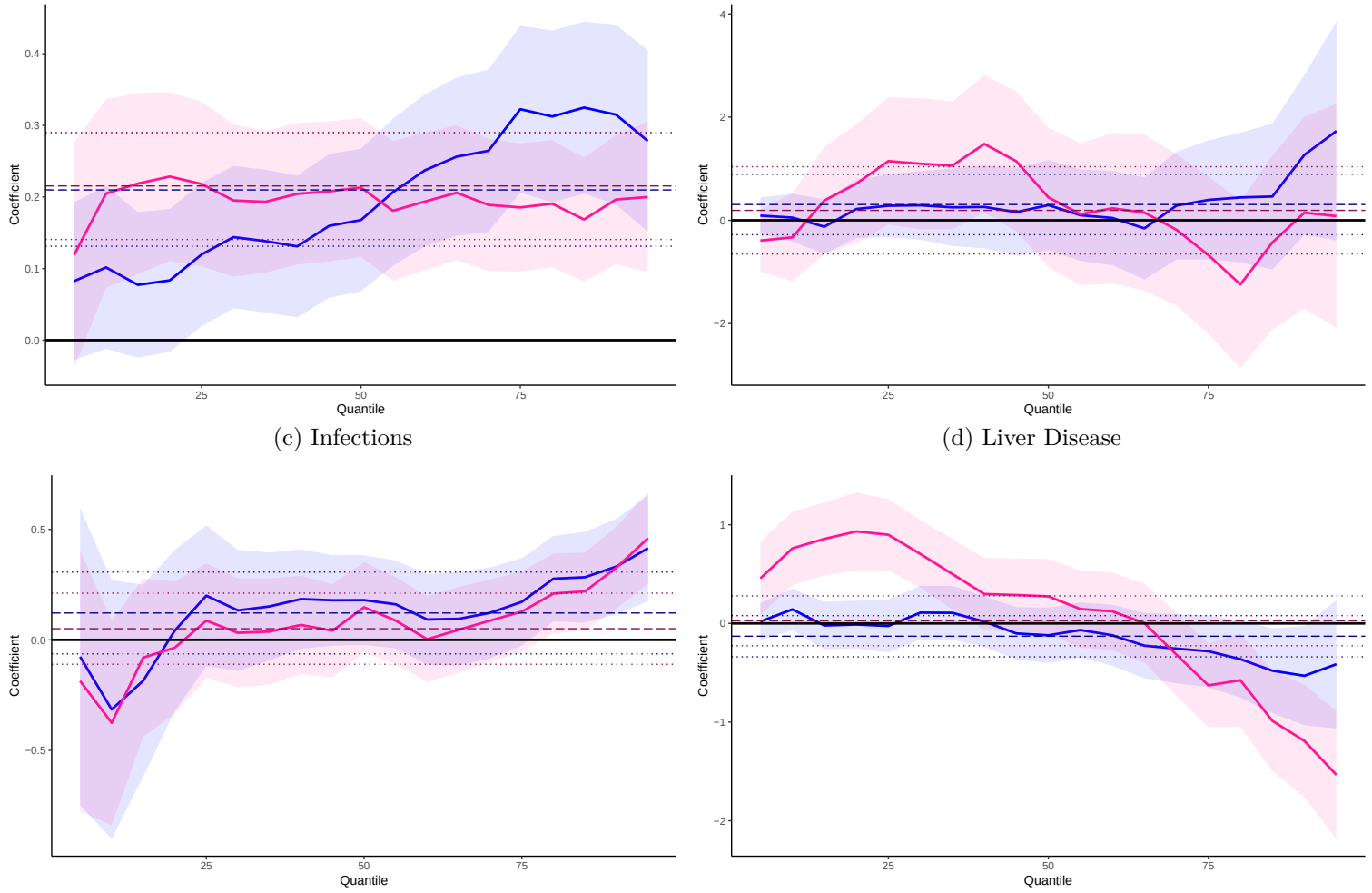


Notes: The blue line and shaded area represents the coefficients and 95% confidence interval for men, while the pink line and shaded area represents the coefficients and 95% confidence interval for the women. The dashed lines in each color represent OLS coefficients and 95% confidence intervals.

Figure 7: Reduced Form Quantile Regressions: Specific Causes of Death by Gender

(a) Heart Disease

(b) Homicide



(c) Infections

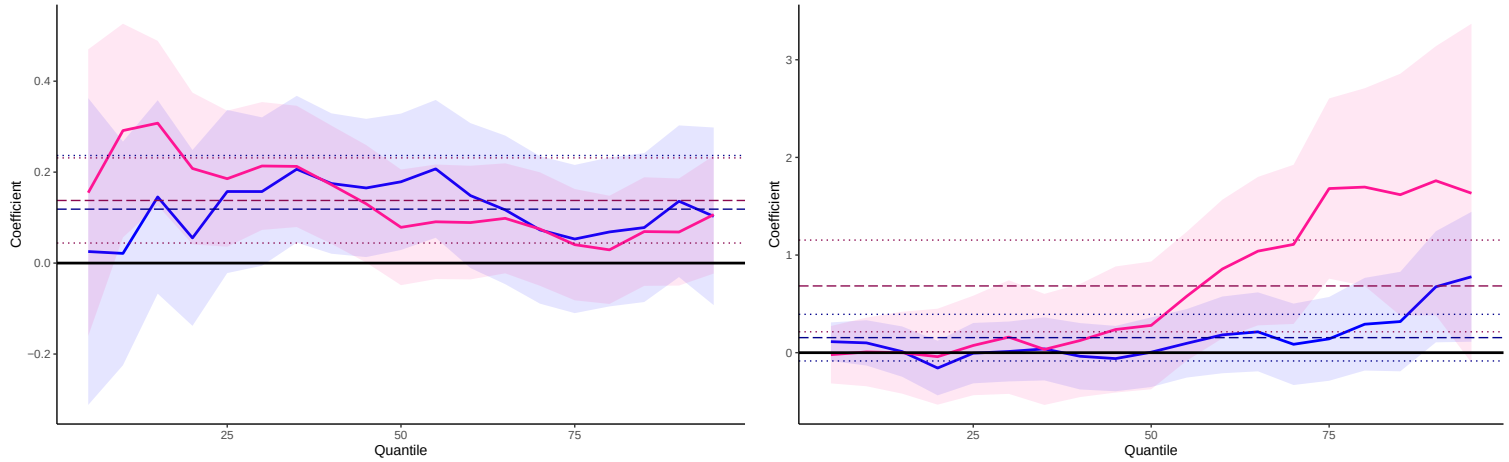
(d) Liver Disease

Notes: The blue line and shaded area represents the coefficients and 95% confidence interval for men, while the pink line and shaded area represents the coefficients and 95% confidence interval for the women. The dashed lines in each color represent OLS coefficients and 95% confidence intervals.

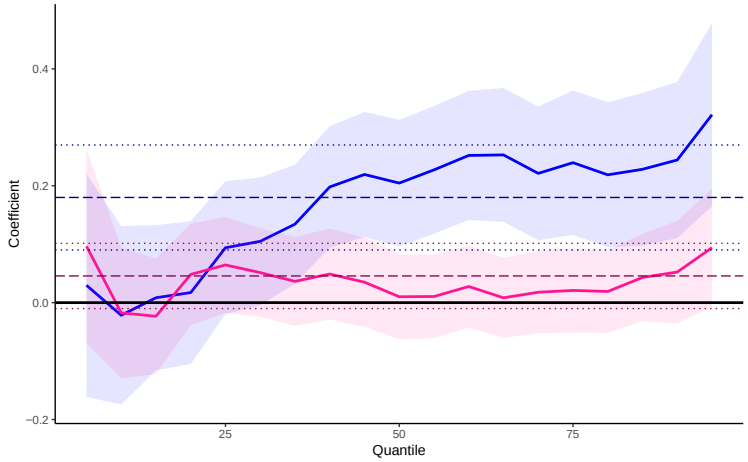
Figure 8: Reduced Form Quantile Regressions: Specific Causes of Death by Gender

(a) Stroke

(b) Suicide



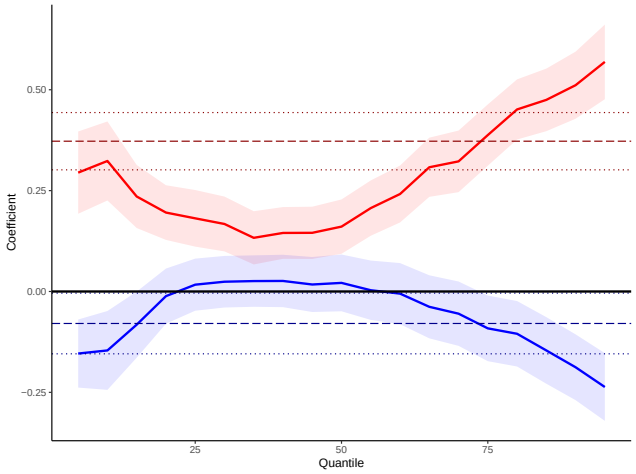
(c) Other Causes



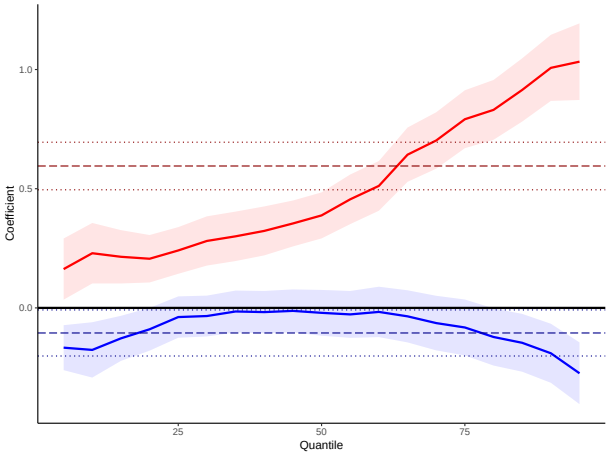
Notes: The blue line and shaded area represents the coefficients and 95% confidence interval for men, while the pink line and shaded area represents the coefficients and 95% confidence interval for the women. The dashed lines in each color represent OLS coefficients and 95% confidence intervals.

Figure 9: Reduced Form Quantile Regressions
Above vs. Below Median Relative Teacher Salary

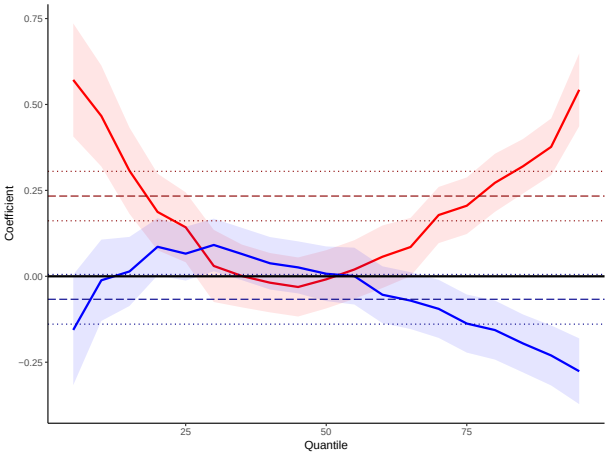
(a) All Genders



(b) Men

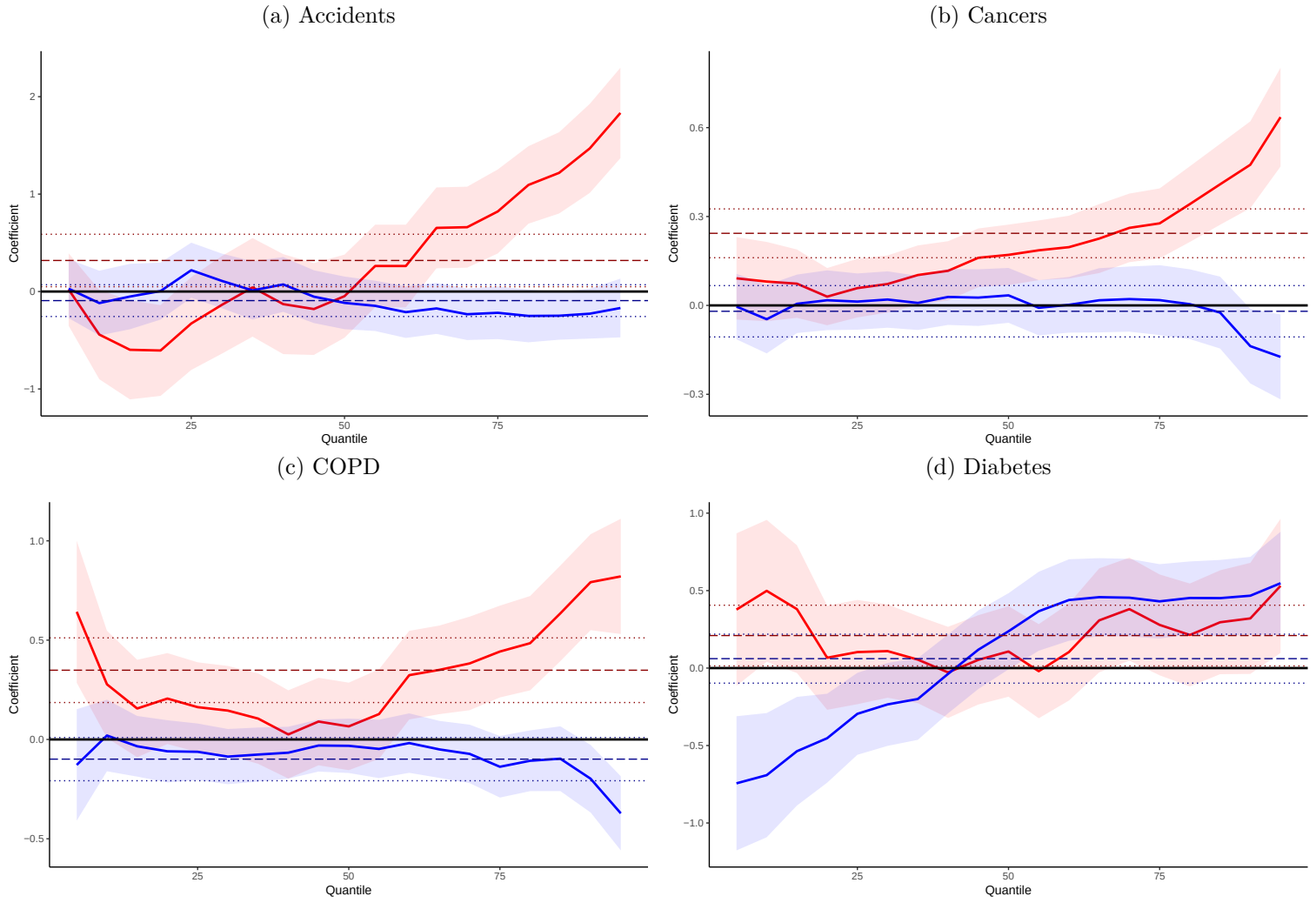


(c) Women



Notes: The red line and shaded area represents the coefficients and 95% confidence interval for the above-median states, while the blue line and shaded area represents the coefficients and 95% confidence interval for the below median states. The dashed lines in each color represent OLS coefficients and 95% confidence intervals.

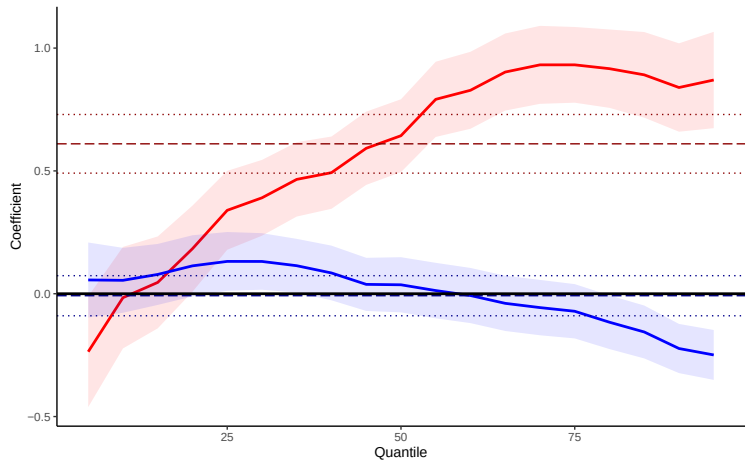
Figure 10: Reduced Form Quantile Regressions: Causes of Death
Above vs. Below Median Relative Teacher Salary



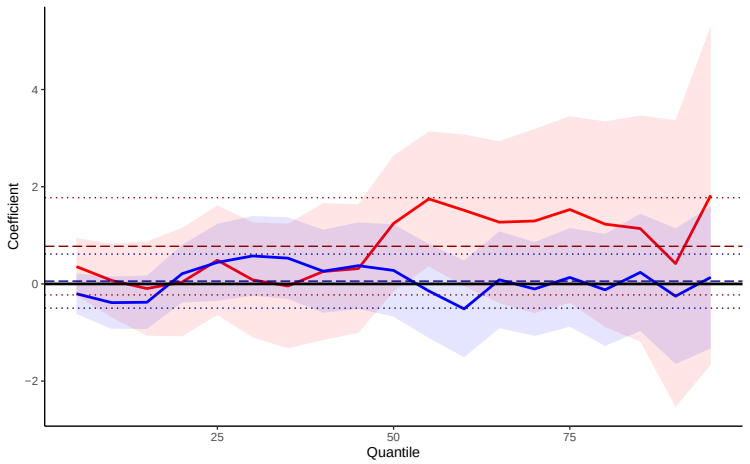
Notes: The red line and shaded area represents the coefficients and 95% confidence interval for the above-median states, while the blue line and shaded area represents the coefficients and 95% confidence interval for the below median states. The dashed lines in each color represent OLS coefficients and 95% confidence intervals.

Figure 11: Reduced Form Quantile Regressions: Causes of Death
Above vs. Below Median Relative Teacher Salary

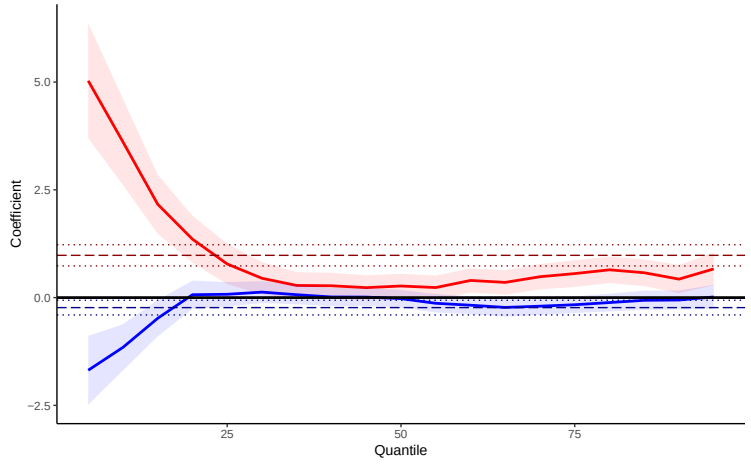
(a) Heart Disease



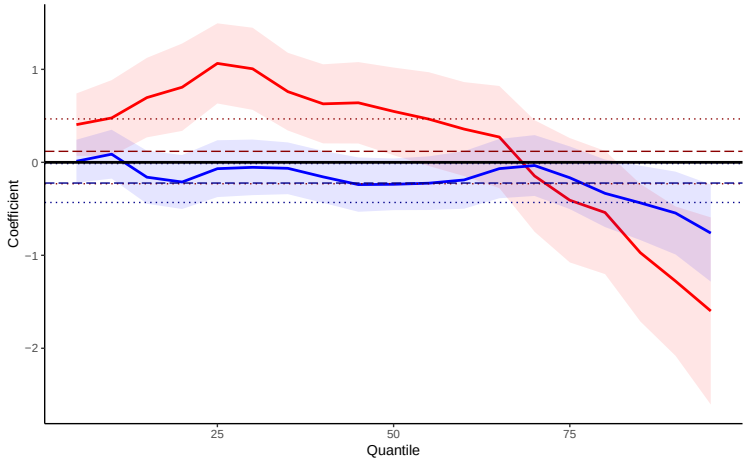
(b) Homicide



(c) Infections



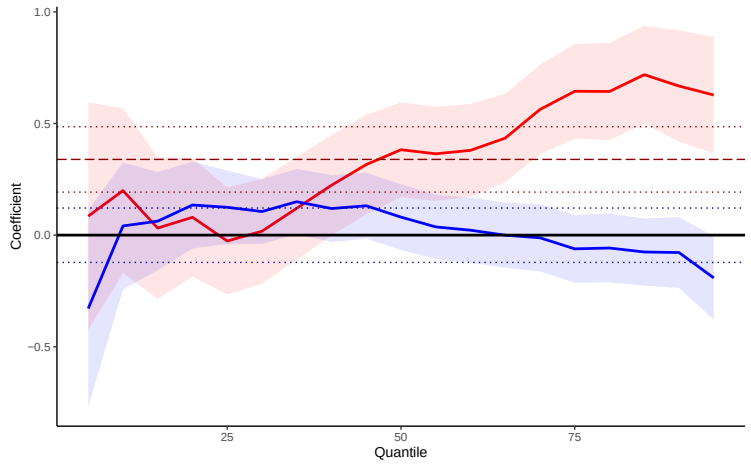
(d) Liver Disease



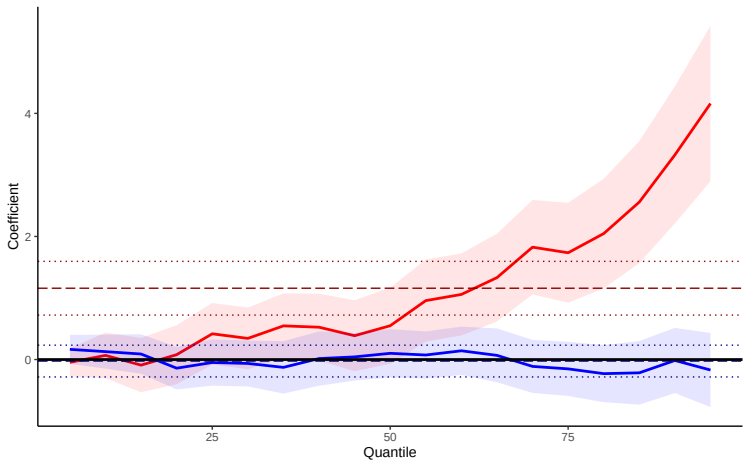
Notes: The red line and shaded area represents the coefficients and 95% confidence interval for the above-median states, while the blue line and shaded area represents the coefficients and 95% confidence interval for the below median states. The dashed lines in each color represent OLS coefficients and 95% confidence intervals.

Figure 12: Reduced Form Quantile Regressions: Causes of Death
Above vs. Below Median Relative Teacher Salary

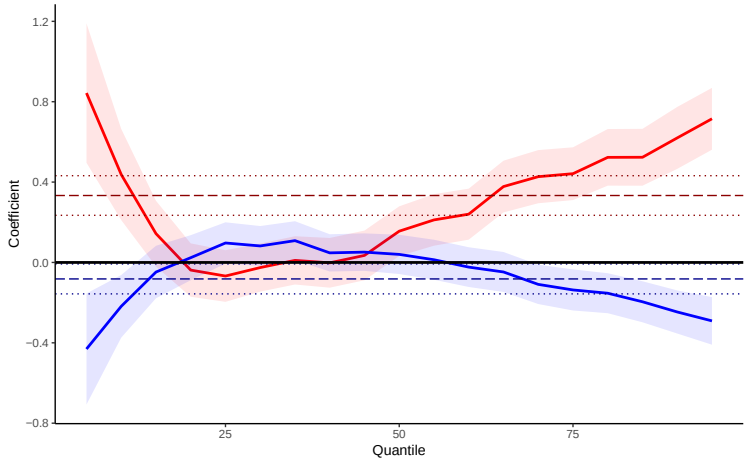
(a) Stroke



(b) Suicide



(c) Other Causes



Notes: The red line and shaded area represents the coefficients and 95% confidence interval for the above-median states, while the blue line and shaded area represents the coefficients and 95% confidence interval for the below median states. The dashed lines in each color represent OLS coefficients and 95% confidence intervals.