Does Telemedicine Save Lives? Evidence on the Effect of Telemedicine Parity Laws on Mortality Rates: A Replication and Extension of Chen and Dills (July 2024)

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I. Introduction

This paper replicates and extends *Does Telemedicine Save Lives? Evidence on the Effect of Telemedicine Parity Laws on Mortality Rates by Jiajia Chen and Angela K. Dills* as published in the Southern Economic Journal, July 2024. As the original paper did not include a replication package, all data were independently retrieved from cited sources, and the Stata code was developed independently. This paper bridges health economics and technology, two powerful forces shaping the future of healthcare.

The Federation of State Medical Boards defines telemedicine as "the practice of medicine using electronic communication, information technology, or other means between a physician in one location, and a patient in another location, with or without an intervening health care provider." (Federation of State Medical Boards, 2018) The World Health Organization defines eHealth as "the use of information and communication technologies (ICT) for health." (World Health Organization, 2018) Telemedicine, although with roots dating back to the late 1950s (Gujral, et al. 2025), is considered a recent technological innovation based on improved technology increasing the availability, use and effectiveness of telemedicine. Telemedicine or telehealth includes four types of activities: the use of real-time video conferencing between a patient and provider, transmitting images to medical specialists, remote patient monitoring, and mobile health apps. This technological progress drives economic growth through increased productivity and lower costs. In response to the improved technology, many states adopted telemedicine parity laws. Telemedicine parity laws require private health insurance plans, Medicaid, or both to provide coverage for telemedicine services to the same extent as in-person services. Thus, the term “parity” is used for the legal requirement for “equal” coverage.

The COVID-19 pandemic highlighted the need to understand how expanding telehealth affects health outcomes. In response, Medicare began covering over 135 telehealth services (Pifer, R.

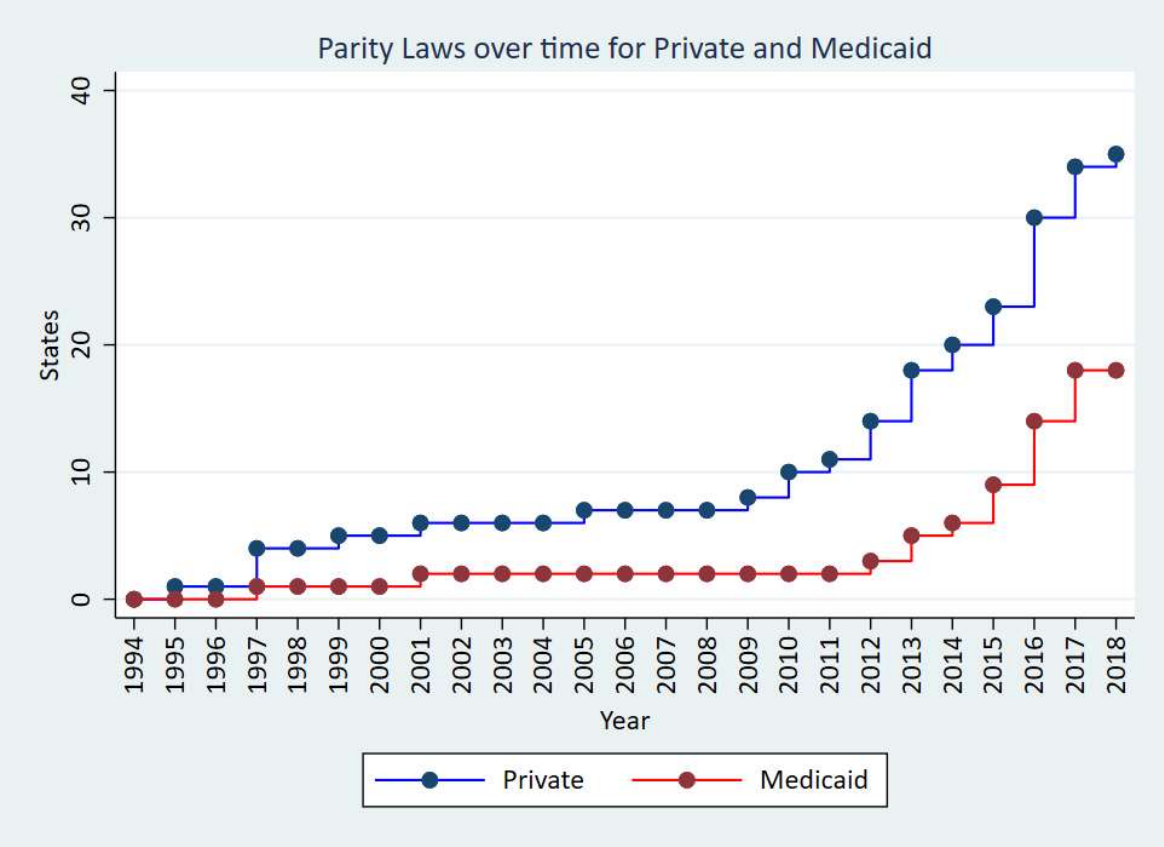
2020), and some major insurance companies waived patient cost-sharing, often under emergency state orders (Doiron, 2020). The use of live video visits between patients and providers increased dramatically during the pandemic (Drees, 2020).

This paper examines whether telemedicine parity laws improve patient outcomes. The analysis shows that these laws are associated with reduced mortality, especially from ischemic heart disease which is consistent with the original paper from Chen and Dills, 2024. Replicating the original analysis we will use difference-in-differences and event study methods. We will estimate effects across several causes of death likely to be impacted by telemedicine. (Parmar, et al., 2015) These include cerebrovascular diseases (CVD), diabetes mellitus (DM), influenza and pneumonia (I&P), ischemic heart disease (IHD), and suicide. We find convincing results across alternative specifications and falsification tests, supporting a causal link. In our subarea analysis, we find larger impacts are observed in urban fringe areas. Improved access to care, particularly in areas with limited provider availability, fewer uninsured residents, and better broadband drive these effects. We also find that parity laws reduce hospital utilization. Research as of the end of the analysis period found fewer delayed check-ups and lower hospital use in urban-nonmetropolitan areas, without evidence of increased costs. (Grecu and Sharma, 2019) For a modest extension to the paper, I estimate effects across malignant neoplasm (Cancer) and chronic lower respiratory disease (CLRD).

Figure 1 tracks the growth in the number of states enacting private telemedicine parity laws or Medicaid-related telemedicine parity laws. From 1999 through 2016, 26 states adopted private parity legislation, with most doing so after 2010. Five more states followed in 2017 and 2018. Today, most states have implemented some form of telemedicine parity law. According to the Public Health Institute/Center for Connected Health Policy, as of October 2025, only six states do not have

a telemedicine parity law: Alabama, Idaho, North Carolina, South Carolina, Wisconsin, and Wyoming. (CCHPCA, 2025)

FIGURE 1: Number of states with a telemedicine parity law over time (1995-2018).



II. Literature Review

In an area study in Minnesota, Garanin, et al. 2024 found that telemedicine intervention reduced the total number of all unplanned hospitalizations for heart failure by 36%. Their meta-analysis study also found telemedicine can improve access to healthcare, reduced hospital utilization and lower mortality rates, especially in intensive care and chronic conditions like heart failure. They find that patients with telemedicine support had heart failure hospitalizations of 78% of those without telemedicine support and had cardiovascular disease-related hospitalizations of

83% of those without telemedicine support. We will also analyze heart-related health outcomes, hospital utilization patterns, and the effects of telemedicine parity laws.

The analysis presented in this paper includes an analysis of subareas defined by urbanization ratings. McCormick, 2021 indicated in the United States there is an 11% shortage of neurologists and this shortage is expected to reach nearly 20% by 2025 with a greater problem for rural hospitals. Expanding telemedicine is essential for addressing healthcare disparities in underserved areas, where access to in-person care is often limited. Besides better clinical outcomes, telemedicine has shown to provide financial benefits by decreasing dependence on non-permanent physician coverage and minimizing costly transfers. (Zachrison et al., 2021) In rural hospitals facing a shortage of neurologists, teleneurology enables timely, expert intervention without requiring an on-site specialist. (McCormick, 2021)

People with diabetes, especially those with poor blood sugar control, are at higher risk from infections like the flu and COVID-19. Among the five causes of death examined in this analysis, diabetes is one of the outcome variables demonstrating impacts of the parity mandates. Aberer, et al. (2021) discuss the application of telemedicine and its importance in care of diabetes. According to the Canadian Agency for Drugs and Technologies in Health, guidelines recommend seeing a doctor every three months to check HbA1c levels, adjust treatment, and manage heart-related risks. However, many people with diabetes may not need to visit clinics in person if alternative tools for managing their condition are available. A 2019 meta-analysis that found that telemedicine significantly lowered HbA1c levels, especially among older adults with type 2 diabetes. And telemedicine programs lasting >6 months produced a significantly greater reduction in HbA1c levels (Techero et al. 2020).

Ischemic heart disease is one of the outcome variables demonstrating strong effects of the parity mandates (Chen and Dills, 2024) and will be a focus in this analysis. In a study of high-risk

cardiology patients by Woo, et al. clinical outcomes for individuals with coronary artery disease and/or heart failure who received telehealth care during the first six months of the COVID-19 pandemic (2020) were compared with those seen in person during the same period in 2019. Among patients aged ≥75 years, outcomes mirrored those of the broader group. (Woo, et al., 2023) Across both telehealth subgroups, there was no increase in cardiovascular event rates compared to their prepandemic counterparts. In fact, the overall outcome event rates were significantly lower in the telehealth group. Cardiovascular hospitalizations were significantly reduced in telehealth group. And emergency department visits also trended lower in the telehealth group.

Suicide is one of the three outcome variables that showed the most statistical significance of the effects of telemedicine parity laws in this paper. A recent study by Doupnik, et al. (2025) identifies suicide as a major public health concern in the United States, with nearly 50,000 deaths annually. They find emergency departments are increasingly functioning as the primary mental health care provider, with suicide-related visits rising 20% over the past decade and comprising 2% of all emergency department visits in 2020. Yet fewer than 25% of these patients receive a mental health evaluation during their visit. In response to the COVID-19 pandemic, emergency departments rapidly adopted telehealth to expand access to mental health services. Although not specific to suicide, this paper also analyzes hospital admissions and emergency room visits and telemedicine law effects.

Medical licensing requirements restricted the reach of telemedicine parity laws during the sample period for the original paper. Before the Covid-19 pandemic, healthcare providers were required to be licensed by the state where the patient was located (Federation of State Medical Boards, 2020). After our sample period (1999-2016) in 2017, the Interstate Medical Licensing Compact became operational. This made it easier for a physician to be licensed in a variety of states. (Chen and Dills, 2024)

III. Data

This study relies on multiple sources of data all publicly available online. County-level mortality data is used from selected states. Table 1 shows the categorization of states and inclusion or exclusion in the study. To ensure sufficient window of periods for evaluating estimates, our sample requires treated states to have at least four pre-policy years and three post-policy years.

TABLE 1: Categorization of States

State	Effective Date of Private Parity Law	Treatment Status	Data
Louisiana	*1995*	*Limited Pre Period*	*Excluded*
California, Oklahoma, Texas	*1997*	*Limited Pre Period*	*Excluded*
Hawaii	*1999*	*Limited Pre Period*	*Excluded*
Kentucky	*2001*	*Limited Pre Period*	*Excluded*
Georgia	2005	Selected Treated	treated = 1
New Hampshire	2009	Selected Treated	treated = 1
Maine, Oregon	2010	Selected Treated	treated = 1
Vermont	2011	Selected Treated	treated = 1
Maryland, Michigan, Virgina	2012	Selected Treated	treated = 1
Arizona, District of Columbia, Mississippi, New Mexico	2013	Selected Treated	treated = 1
Missouri, Montana	2014	Selected Treated	treated = 1
Indiana, Nevada, Tennessee	*2015*	*Limited Post Period*	*Excluded*
Alaska, Arkansas, Colorado, Connecticut, Delaware, Minnesota, New York	*2016*	*Limited Post Period*	*Excluded*
Nebraska, New Jersey, North Dakota, Washington	2017	Never Treated	treated = 0
Rhode Island	2018	Never Treated	treated = 0
Alabama, Florida, Idaho, Illinois, Iowa, Kansas, Massachusetts, North Carolina, Ohio, Pennsylvania, South Carolina, South Dakota, Utah, West Virginia, Wisconsin, Wyoming	No parity law at the time of study	Never Treated	treated = 0

Selected treated are states with at least four pre-policy years and three post-policy years.
Never treated did not have a parity law or had less than three post-policy years at the time of this study.

The study uses county-level mortality data from CDC's WONDER database to analyze overall and cause-specific death rates across geographic areas. All mortality data is publicly available from

CDC's WONDER database. (wonder.cdc.gov) For subarea analysis, the study applies the 2013 Urban–Rural Classification Scheme from the National Center for Health Statistics, which categorizes counties into metropolitan and nonmetropolitan areas across six levels. This classification is also available from CDC's WONDER database. The mortality data obtained was validated and is consistent with mortality rates in the original paper as shown in the tables provided in this paper.

County unemployment rates were obtained from the Local Area Unemployment Statistics (LAUS) from U.S. Bureau of Labor Statistics (BLS). Individual data files for each year from 1999 through 2016 are available from the bls.gov website.

Median household income and poverty rate come from Census Bureau's Small Area Income and Poverty Estimates (SAIPE). Individual data files for each year from 1999 through 2016 are available from the census.gov website.

Population density and provider information come from the Area Health Resources Files (AHRF). The data is available from the data.hrsa.gov website. Consistent with the original paper, I linearly interpolated data for 2008, which was missing from the raw files.

The status of state ACA Medicaid expansion was obtained from the Kaiser Family Foundation website. Percent Medicaid and percent Medicare data came from the Current Population Survey (CPS). This data is available from the census.gov and cps.ipums.org websites.

Percent black and percent white was obtained from the Decennial Censuses (2000 and 2010). Percent female, percent BA degree, and percent HS or below is from the 5-year American Community Survey Estimates (ACS, 2006–2010, and 2011–2015). This data is available from the census.gov website.

Hospital utilizations data was obtained from the American Hospital Association Annual Survey which includes hospital admission rate per 1000 population, emergency room visits per 1000

population, hospital inpatient days per 1000 population, and hospital outpatient visits per 1000 population.

The 2006 Health Insurance Mandates by state was obtained from the Council for Affordable Health Insurance. It summarizes about 80 different state health insurance benefit mandates measured in 2006, with each mandate weighted by percentage of added cost to the average health insurance policy. The second index measures regulations on providers in 2006 for each state. It covers about 30 different provider-related mandates using a similar weighting scheme. Manual calculations were needed to apply cost-range estimates (less than 1%, 1-3%, 3-5%, and 5-10%) to each health insurance benefit provided in the mandate.

Table 2 reports summary statistics for mortality rates and control variables. Column (1) presents descriptive statistics for states that never adopted private parity laws. Columns (2) and (3) split the sample into pre-policy and post-policy periods for treated states, while Column (4) presents statistics for treated states across all years. The sample is limited to at least 10 deaths per county for all causes mortality for the years 1999 through 2016. The independent variable of interest is the mortality rates. Because of this, it was important, and I was able to validate the mortality rates for all four subgroups in Table 2, matching the original paper from Chen and Dills, 2024. A total of 21 states, 1,255 counties, and 22,590 observations are used for the never treated states. A total of 14 states, 779 counties, and 14,022 observations are used for the selected treated states.

Our summary statistics in Table 2 show mortality rates are generally lower in treated states following policy enactment, whereas states without telemedicine parity mandates exhibit higher mortality rates across most causes. This is evident in the comparison of pre-policy and post-policy mortality rates among selected treated states (840.82 vs. 825.35) in Table 2. Counties in treated states tend to have lower population and provider densities, characteristics that may enhance the

potential benefits of telemedicine. In terms of economic indicators, median household income is approximately 2% lower in never treated states, although their poverty rates are about 1 percentage point lower. These time-varying factors, population, provider density, income, and poverty are included as controls in the regression analysis.

Table 2: Summary Statistics

	Never Treated States (all years)	Selected Treated States (pre)	Selected Treated States (post)	Selected Treated States (all years)
Mortality rate (per 100,000)				
All causes	894.67	840.82	825.35	835.37
Cerebrovascular diseases	51.67	50.62	42.08	47.63
Diabetes mellitus	26.22	24.94	24.19	24.67
Influenza and pneumonia	19.28	19.55	15.81	18.26
Ischemic heart disease	149.00	147.34	104.94	132.47
County-level statistics				
Suicide	12.12	12.69	13.86	13.11
Poverty rate	12.95	13.23	15.36	13.98
Percent black	12.76	16.29	19.78	17.52
Percent white	80.19	76.33	73.04	75.17
Percent female	51.00	50.95	50.97	50.96
Percent BA degree	17.99	17.23	18.34	17.62
Percent HS or below	43.40	42.59	40.48	41.85
Unemployment rate	6.11	5.91	6.63	6.16
Total active MDs (per 100,000)	266.99	253.81	261.01	256.35
Median age	38.43	37.38	37.68	37.48
Median household income	49318.68	47188.83	55635.35	50160.99
Population density in 2010	1,081.1			739.0
Counties short on PC providers in 2010	1,062			659
State-level statistics				
Percent Medicaid	14.6	13.4	17.5	14.9
Percent Medicare	16.8	15.4	16.9	15.9
Number of counties	1,255			779
Number of states	21			14
Number of observations	22,590			14,022

The sample is limited to at least 10 deaths per county for all causes mortality for the years 1999 through 2016. All means are weighted by county population each year.

IV. Methodology

A differences-in-differences regression model will be used with the cause-specific mortality rate as the dependent variable. The key independent variable will be an indicator at the state-year level for the adoption of a private telemedicine parity law. Telemedicine parity laws require health insurers to offer coverage and reimbursement for telehealth services that are equivalent to those for in-person medical care. The time frame of the data is 1999 to 2016, so the analysis will include 14 states that provide a sufficient window of periods for our pre- and post-policy estimates. The data and methodology will address the impact of telemedicine parity laws on both overall mortality rates and mortality rates associated with conditions commonly managed through telemedicine.

$$\ln(\text{Mortality Rate})_{ct} = \beta \cdot (\text{Parity Law})_{st} + \rho_c + \delta_t + X_{ct}' \cdot \tau + e_{ct} \quad \text{(Equation 1)}$$

where the dependent variable is the logged cause specific mortality rate in county c at year t. The variable of interest is the existence of a private telemedicine parity law in state s and year t. The equation includes county fixed effects (ρ_c) that control for differences in means of the log mortality rate across county. And year fixed effects (δ_t) that control for the overall mortality trend common to all counties. And time-varying county-level covariates (X_{ct}) that control for changes in county characteristics over time. These covariates include two state-level covariates, percent Medicaid population and percent Medicare population. The regression standard errors are clustered at the state-level to allow for arbitrary correlation across time and counties within each state.

To evaluate whether the common-trends assumption holds for our identification strategy, we conduct event-study analyses of mortality rates centered on each state's parity-policy adoption year. In these models, we extend Equation (1) by regressing mortality rates on a set of indicator variables representing the periods before and after each state enacted its policy:

$$\ln(\text{Mortality Rate})_{ct} = \sum_{\tau=-1}^{L} \beta_\tau \cdot (\text{Parity Law})_{st,\tau} + \rho_c + \delta_t + X_{ct}' \cdot \tau + e_{ct} \quad \text{(Equation 2)}$$

where the independent variable of interest (Parity Law)st,τ are event-time indicators. For states that never adopt a parity law, (Parity Law)st,τ indicators are always 0. The indicator (Parity Law)st,0 represents the year immediately before the policy takes effect, (Parity Law)st,1 represents the year the parity law takes effect, etc. Each βτ captures the treatment effect at event time τ relative to the omitted year for treated states and relative to all years for never-treated states. Endpoint restrictions are imposed so that $\beta_\tau=\beta_{-3}$ for all $\tau\leq-3$ and $\beta_\tau=\beta_3$ for all $\tau\geq3$. This means we pool all indicators for three or more years before treatment into a single "pre-treatment" category, and all indicators for three or more years after treatment into a single "post-treatment" category. The coefficient $\hat{\beta}_{-3}$ measures the difference in mortality rates at least three years prior to the adoption of the parity law relative to the underlying trend, while $\hat{\beta}_3$ measures the corresponding difference at least three years after adoption.

All the reported regression results find that estimates based solely on treated states are generally reliable, while those including never-treated states are less so. To clarify the identification strategy, we report regression results using two samples: (1) treated states only, and (2) both selected treated and never treated states. In the latter, we allow year fixed effects to vary by group to account for differing time trends. A series of regression tests are also examined as sensitivity, robustness and falsification tests. First, a sensitivity analysis is presented for the telemedicine parity law effects within the 35 to 64 age group mortality rates. Second, the robustness of telemedicine parity law effects to state-specific linear time trends. Third, falsification tests on the effect of telemedicine parity laws on other outcomes. Fourth, a subarea analysis of telemedicine parity law effects. And lastly, analysis of estimates of telemedicine parity law effects on hospital utilizations. As a modest extension to the original paper, additional analysis is provided on two alternate categories of causes of death, Malignant Neoplasm (Cancer) and Chronic Lower

Respiratory Disease (CLRD). All tables indicate level of statistical significance using the following indicators for p-value thresholds:

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

V. Analysis and Results

For our analysis, we start by estimating Equation (1) using the sample of 14 states that enacted private telemedicine parity laws between 2003 and 2014. By restricting the analysis to ever treated states, identification comes from variation in the timing of policy adoption (identified by treated=1 and parity_law=0 or 1). Panel A of Table 3 presents the results from this difference-in-differences specification. For context, we also report pre-policy means (both in logs and levels) for each outcome. Columns 2-6 summarize estimated effects on specific causes of death. Parity laws are associated with a 3.2% decline in mortality from diabetes mellitus (column 3), a 5.4% decline in ischemic heart disease mortality (column 5), and a 2.7% decrease in suicide mortality (column 6) although suicide is statistically insignificant. The estimated reduction in cerebrovascular disease mortality is smaller at 1.1% and statistically insignificant. The coefficient for deaths due to our 'all' category and influenza and pneumonia is positive and statistically insignificant. Panel B of Table 3 expands the sample to include additional control states and allows year fixed effects to vary between treated and never-treated counties. The resulting estimates and standard errors closely align with those in Panel A (DM at -3.9%, IHD at -5.7%, both statistically significant) and now suicide (-3.4%) also being statistically significant. Taken together, the evidence indicates that telemedicine parity mandates are associated with reductions in cause-specific mortality. One concern is that the all-cause mortality estimates are positive in our analysis, in contrast to the original paper. This discrepancy may stem from differences in statistical methodology.

TABLE 3: Impact of Parity Law on Mortality Rates

	All	CVD	DM	I&P	IHD	Suicide
Panel A – Selected treated states						
Parity law	0.008	-0.011	-0.032*	0.049	-0.054***	-0.027
	(0.006)	(0.016)	(0.017)	(0.055)	(0.017)	(0.017)
Log mortality rate (pre parity law)	6.73	3.92	3.22	2.97	4.99	2.54
Mortality rate (pre parity law)	840.82	50.62	24.94	19.55	147.34	12.69
States	14	14	14	14	14	14
Observations	13920	9502	5675	4701	12469	3292
Adjusted R^2	0.956	0.841	0.818	0.766	0.914	0.807
Panel B – Selected treated and never treated states						
Parity Law	0.005	-0.011	-0.039*	0.051	-0.057***	-0.034*
	(0.005)	(0.015)	(0.020)	(0.049)	(0.016)	(0.019)
Log mortality rate	6.78	3.94	3.26	2.96	5	2.51
Mortality rate	881.58	51.42	25.93	19.34	148.59	12.25
States	35	35	35	35	35	35
Observations	36191	24119	15795	13247	31866	9169
Adjusted R2	0.957	0.834	0.801	0.770	0.923	0.798

Standard errors in parentheses. Heteroskedasticity-robust SEs clustered by state. All regressions are weighted by county population, and control for county fixed effects, year fixed effects (regressions in Panel B allow control and treated states to have different year fixed effects), time-varying county-level covariates.

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

Abbreviations: CVD: cerebrovascular diseases; DM: diabetes mellitus; I&P: influenza and pneumonia; IHD: ischemic heart diseases.

The results in Table 3 focused primarily on mortality rates for the full population, which is viewed as the preferred sample. According to the Kaiser Family Foundation, 2019 individuals aged 65 and older are primarily covered by Medicare and many also maintain supplemental coverage through employer-sponsored insurance (30%), Medigap plans (29%), or Medicaid (22%). Chen and Dills, 2024 postulate telemedicine parity laws may encourage broader adoption of telemedicine beyond the insurance markets directly targeted by the legislation and this could result in spillovers among Medicare beneficiaries and in self-insured employer plans. As a robustness check, we estimate the main difference-in-differences specification using mortality rates for individuals ages 35–64. These results are reported in Table 4 and continue to show declines in deaths due to

ischemic heart disease and suicide when never treated states are included. Death counts are smaller for this age group, which leads to data suppression and a reduced sample and lower statistical power. To mitigate this limitation, the analysis aggregates deaths across the five cause-specific categories in column (7). For this combined outcome, we again find reductions in mortality following the adoption of telemedicine parity laws, consistent with the baseline results.

TABLE 4: Sensitivity analysis of telemedicine parity law effects with age 35-64 mortality rates

	All	CVD	DM	I&P	IHD	Suicide	Combined
Panel A – Selected treated states							
Parity law	0.004	-0.010	-0.013	0.084	-0.085***	-0.017	-0.038***
	(0.007)	(0.037)	(0.024)	(0.079)	(0.015)	(0.010)	(0.007)
Log mortality rate (pre parity law)	6.73	3.92	3.22	2.97	4.99	2.54	2.54
Mortality rate (pre parity law)	840.82	50.62	24.94	19.55	147.34	12.69	12.69
States	14	13	14	10	14	14	14
Observations	13178	1421	1576	385	6591	1732	9530
Adjusted R^2	0.924	0.845	0.825	0.728	0.866	0.797	0.870
Panel B – Selected treated and never treated states							
Parity Law	0.001	-0.004	-0.021	0.066	-0.085***	-0.021**	-0.040***
	(0.007)	(0.039)	(0.027)	(0.081)	(0.014)	(0.010)	(0.007)
Log mortality rate	6.78	3.94	3.26	2.96	5	2.51	2.51
Mortality rate	881.58	51.42	25.93	19.34	148.59	12.25	12.25
States	35	32	34	26	35	35	35
Observations	32602	4614	5074	1344	16518	5327	22897
Adjusted R2	0.907	0.814	0.794	0.698	0.841	0.774	0.853

Standard errors in parentheses. Heteroskedasticity-robust SEs clustered by state. All regressions are weighted by county population, and control for county fixed effects, year fixed effects (regressions in Panel B allow control and treated states to have different year fixed effects), time-varying county-level covariates. Combined includes the 5 selected mortality rates.

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

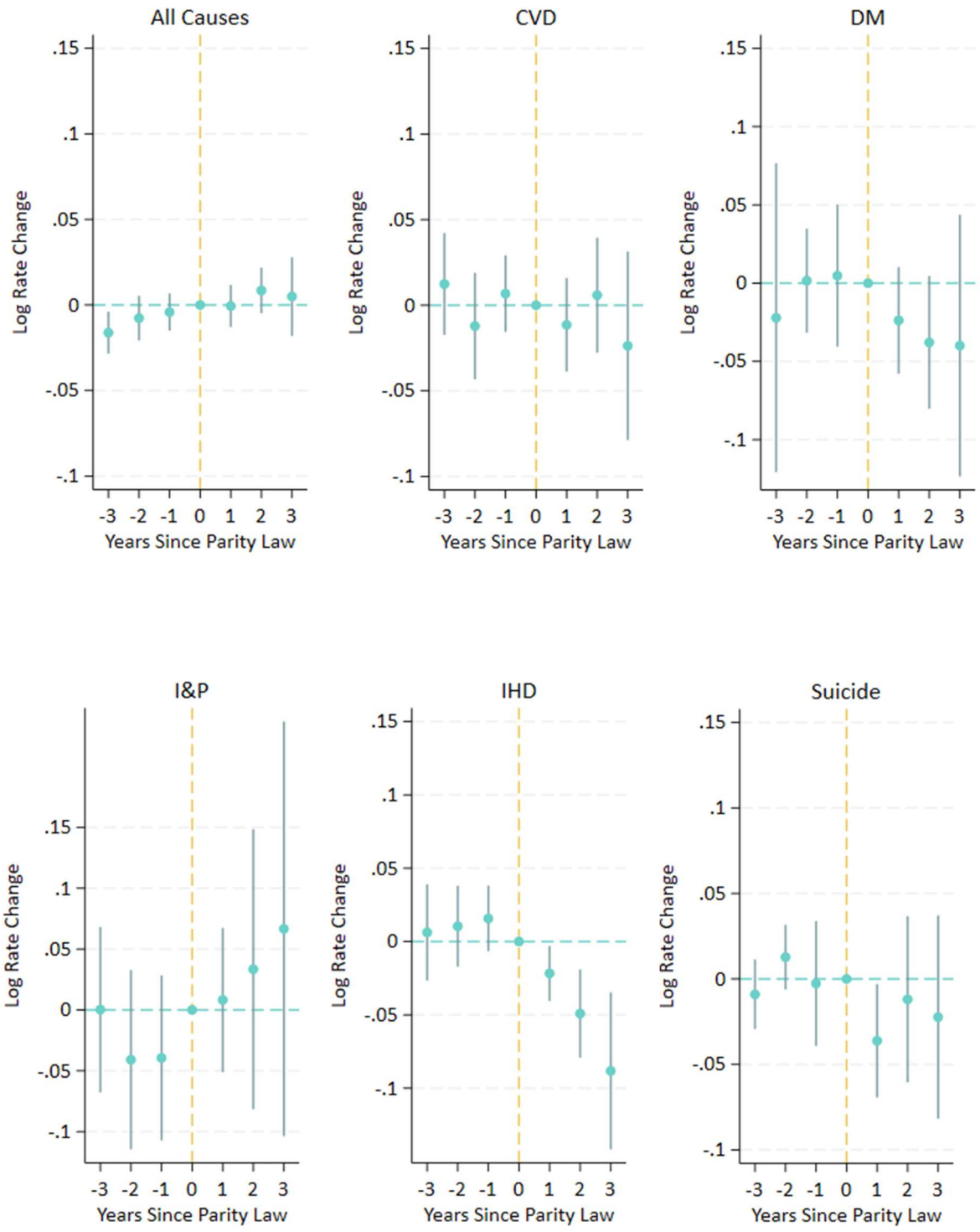
Next, we estimate the event study specification from Equation (2) using the same two samples as in the main analysis. The sample includes the 14 treated states with at least four years of pre-treatment data and three years of post-treatment data. Focusing on treated states enables comparisons among states that are arguably more similar to one another than to never treated states. Figure 2 plots the event study coefficients for the all causes mortality rate (top-left panel)

and for the cause-specific mortality rates most likely to be affected by increased access to telemedicine. The mortality rates for the six outcome variables hover around zero in the pre-treatment period, indicating that counties followed similar trends before parity laws took effect even though states adopted the policy in different years. The patterns align closely with the difference-in-differences estimates reported in Panel A of Table 3. For ischemic heart disease and diabetes mellitus, the event study coefficients indicate a growing policy effect in the years following adoption of the telemedicine parity law, with mortality rates much lower three or more years after the law takes effect. Cerebrovascular disease and suicide also display an immediate drop in mortality rates after the adoption of a law, and an overall lower mortality trend. The difference-in-differences estimates in Table 3 and the event-study results in Figure 2 indicate that state telemedicine parity laws are associated with reductions in mortality. A reasonable explanation is that these laws promoted the adoption of telemedicine services, which in turn increased the quantity and/or quality of care and ultimately improved population health. Although assessing the extent of provider adoption is challenging because major national health surveys such as the National Health Interview Survey, the Medical Expenditure Panel Survey, and the Behavioral Risk Factor Surveillance System did not include telemedicine questions during the period of the original study (Chen and Dills, 2024). Insurance claims data include telemedicine procedure codes, but these data are proprietary and therefore excluded from their research.

We have shown that cause-specific mortality rates declined after the adoption of a telemedicine parity law compared to control groups. Now we will evaluate the robustness of these estimates across different specifications and sample selections.

To evaluate the robustness of our findings, we first modify the baseline specification with key state-level health policies, including an indicator for ACA Medicaid expansions and two measures of health insurance mandates. Second, we incorporate state-specific linear time trends.

Figure 2: Event Study



The results presented in Table 5 show that most estimates remain similar in magnitude to those in Table 3. For the selected treated group, DM, IHD and suicide now have stronger coefficient estimates with suicide now being statistically significant. The consistency of the difference-in-differences estimates in Table 5 helps mitigate concerns about potential specification errors.

TABLE 5: Robustness of telemedicine parity law effects on state-specific linear time trends

	All	CVD	DM	I&P	IHD	Suicide
Panel A – Selected treated states						
Parity law	0.002	-0.017	-0.041*	0.034	-0.070***	-0.033*
	(0.006)	(0.020)	(0.022)	(0.058)	(0.013)	(0.018)
Log mortality rate (pre parity law)	6.73	3.92	3.22	2.97	4.99	2.54
Mortality rate (pre parity law)	840.82	50.62	24.94	19.55	147.34	12.69
States	14	14	14	14	14	14
Observations	13920	9502	5675	4701	12469	3292
Adjusted R^2	0.957	0.841	0.824	0.771	0.916	0.809
Panel B – Selected treated and never treated states						
Parity Law	0.005	-0.022	-0.032	0.016	-0.067***	-0.025
	(0.007)	(0.018)	(0.023)	(0.052)	(0.019)	(0.018)
Log mortality rate	6.78	3.94	3.26	2.96	5	2.51
Mortality rate	881.58	51.42	25.93	19.34	148.59	12.25
States	35	35	35	35	35	35
Observations	36191	24119	15795	13247	31866	9169
Adjusted R2	0.957	0.835	0.805	0.772	0.924	0.800

Standard errors in parentheses. Heteroskedasticity-robust SEs clustered by state. All regressions are weighted by county population, and control for county fixed effects, year fixed effects (regressions in Panel B allow control and treated states to have different year fixed effects), time-varying county-level covariates.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, we examine whether parity mandates influence outcomes unlikely to be affected by telemedicine services. As placebo or falsification tests, we focus on mortality from accidents and homicide, accident-related deaths are split into transport and non-transport categories. Accident mortality has a potential link to substance abuse which can be treated via telemedicine, so it may be an imperfect placebo. But any observed effects may reflect indirect pathways. Table 6 presents the falsification test results. There is no evidence that parity laws significantly reduce these

placebo outcomes, in fact all the parity law coefficients are positive. These findings lend additional credibility to the causal interpretation of our primary difference-in-differences estimates for the parity law effect on our selected mortality rates.

TABLE 6: Falsification tests – The effects of telemedicine policy laws on other outcomes

	Accidents (All)	**Accidents (Transport)**	**Accidents (Nontransport)**	**Homicide**
Panel A – Selected treated States				
Parity law	0.036***	0.023	0.021	0.014
	(0.010)	(0.022)	(0.013)	(0.039)
Log mortality rate (pre parity law)	3.71	2.78	3.2	2.36
Mortality rate (pre parity law)	40.85	16.12	24.5	10.56
States	14	14	14	14
Table 6 continued	**Accidents (All)**	**Accidents (Transport)**	**Accidents (Nontransport)**	**Homicide**
Observations	8989	4605	5874	1049
Adjusted R^2	0.814	0.847	0.815	0.917
Panel B – Selected treated and never treated states				
Parity Law	0.031***	0.027	0.019	0.004
	(0.010)	(0.020)	(0.015)	(0.041)
Log mortality rate	3.74	2.66	3.31	2.07
Mortality rate	41.9	14.35	27.47	7.9
States	35	35	35	35
Observations	22568	12555	15665	3190
Adjusted R2	0.793	0.864	0.787	0.901

Standard errors in parentheses. Heteroskedasticity-robust SEs clustered by state. All regressions are weighted by county population, and control for county fixed effects, year fixed effects (regressions in Panel B allow control and treated states to have different year fixed effects), time-varying county-level covariates.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Because telemedicine is intended to expand access, especially in areas with limited provider availability, we divide the sample based on county-level urbanization code. The categories include large central metropolitan, large fringe metropolitan, medium/small metropolitan, and nonmetropolitan counties. The large central metro contains counties in metropolitan statistical areas (MSAs) of one million or more population and contains all or part of a principal city of the

area. The large fringe metro contains the remaining counties (similar to suburbs) in MSAs of one million or more. The medium metro contains counties in MSAs of 250,000 to 999,999 population and the small metro contains counties in MSAs with populations under 250,000. Nonmetropolitan counties include micropolitan and noncore. The large central metro category is the most "urban" category, and the noncore category is the most "rural" category. (wonder.cdc.gov)

Observations are built at the urbanization code state–year level. For example, all large central metropolitan counties in Arizona in 2010. We focus on the three outcomes that showed consistent responses to parity laws in earlier analyses, diabetes mellitus, ischemic heart disease, and suicide mortality rates. Table 7 presents these results. For each outcome, we estimate three specifications. Columns (1), (4), and (7) include selected treated states only and use the same model specifications as in Panel A of Table 3. The number of treated states varies by area type because some states do not contain all four categories. Columns (2), (5), and (8) use the same model specifications as in Panel B of Table 3, allowing control and treated states to have different year fixed effects. Columns (3), (6), and (9) report estimates that instead allow for state-specific linear time trends. All other specifications are consistent with Equation (1). If telemedicine allows specialists located in urban areas to reach patients in less urban areas, we might expect larger benefits in those regions. Conversely, barriers such as lower broadband access or lower insurance coverage could limit benefits in nonmetropolitan counties. Caution must be used when interpreting the results from Table 7. Being conservative, the most consistent evidence of mortality reductions appears in large fringe metropolitan counties (suburban areas) for diabetes and ischemic heart disease (Panel B). We also find evidence of reductions in ischemic heart disease and suicide mortality in medium and small metropolitan areas (Panel C), and reductions in ischemic heart disease and diabetes mortality in nonmetropolitan areas (Panel D). Estimated effects are generally smaller and only two tests indicated statistical significance in large central metropolitan counties

TABLE 7: Subarea differences-in-differences estimates of telemedicine parity law effects

Panel A – large central metro

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	DM	**-**	**-**	**IHD**	**-**	**-**	**Suicide**	**-**	**-**
Parity law	-0.044	-0.079**	0.030	-0.070**	-0.027	-0.035	-0.011	-0.019	-0.022
	(0.027)	(0.030)	(0.037)	(0.027)	(0.045)	(0.027)	(0.038)	(0.041)	(0.027)
States	8	20	20	8	20	20	8	20	20
Observations	144	360	360	144	360	360	144	360	360
Adjusted R^2	0.914	0.888	0.902	0.977	0.981	0.990	0.886	0.914	0.920

Panel B – large fringe metro

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	DM	**-**	**-**	**IHD**	**-**	**-**	**Suicide**	**-**	**-**
Parity law	-0.059**	-0.082***	-0.056**	-0.066**	-0.056***	-0.037***	-0.039	-0.043	-0.001
	(0.023)	(0.025)	(0.024)	(0.020)	(0.015)	(0.013)	(0.034)	(0.030)	(0.039)
States	9	22	22	9	24	24	9	22	22
Observations	162	422	422	162	432	432	162	402	402
Adjusted R^2	0.794	0.800	0.835	0.950	0.959	0.971	0.815	0.904	0.907

Panel C – medium and small metro

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	DM	**-**	**-**	**IHD**	**-**	**-**	**Suicide**	**-**	**-**
Parity law	-0.032	-0.028	-0.034	-0.080***	0.081***	-0.034	-0.035	-0.043*	-0.049***
	(0.019)	(0.022)	(0.027)	(0.020)	(0.019)	(0.021)	(0.020)	(0.021)	(0.018)
States	13	33	33	13	33	33	13	33	33
Observations	234	594	594	234	594	594	233	590	590
Adjusted R^2	0.522	0.717	0.809	0.920	0.962	0.976	0.808	0.848	0.858

Panel D – nonmetropolitan

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	DM	**-**	**-**	**IHD**	**-**	**-**	**Suicide**	**-**	**-**
Parity law	-0.075**	-0.091***	-0.038	-0.014	-0.036***	-0.007	-0.016	0.001	0.031
	(0.032)	(0.029)	(0.033)	(0.014)	(0.013)	(0.013)	(0.030)	(0.030)	(0.033)
States	13	32	32	13	32	32	12	30	30
Observations	233	567	567	234	576	576	200	452	452
Adjusted R^2	0.482	0.496	0.541	0.950	0.956	0.969	0.573	0.588	0.587

Note: Column (1), (4), and (7) include treated states only. Panels are categorized following NCHS's 2013 Urban–Rural Classification Scheme. Column (2), (5), and (8) allow control and treated states to have different year fixed effects. Column (3), (6), and (9) instead control for state-specific linear time trends.

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

(Panel A). Overall, the subarea analysis suggests meaningful geographic heterogeneity in the effects of telemedicine parity laws, with the strongest and most consistent reductions in mortality occurring in suburban areas.

Our analysis shifts to the effects of parity laws on hospital utilization, with results reported in Table 8. Using data from the American Hospital Association Annual Survey, we analyze four measures of utilization including hospital admission rates per 1,000 population, emergency room visits per 1,000 population, inpatient days per 1,000 population, and outpatient visits per 1,000 population. Data is for community hospitals (all nonfederal, short-term general, and specialty hospitals whose facilities and services are available to the public) which represent 85% of all hospitals. Because these data are available only at the state-year level, we estimate state-year difference-in-differences models. Because the survey data ended in 2015, we exclude Missouri and Montana, two states that enacted parity laws in 2014, to maintain the requirement for at least three post-policy years.

All estimates in Table 8 are negative, indicating that telemedicine parity laws are associated with reductions in hospital utilization. This pattern may reflect improved health management in treated states or a substitution from in-person care toward telemedicine services. While these findings do not identify the underlying mechanisms, they do offer additional support for the view that telemedicine parity mandates generate meaningful improvements in population health, consistent with the mortality reductions as found in our previous analyses. Peters et al., (2021) reviewed randomized control trials of the effect of telehealth interventions on hospital use compared with usual care. They found compelling evidence that telehealth leads to reductions in the mean all-cause and condition-related hospitalizations, with 50 and 110 fewer hospitalizations per 1000 patients. And the all-cause hospital days overall decreased by 1.07 (95% CI −1.76 to −0.39) days per patient.

TABLE 8: Differences-in-differences estimates of telemedicine parity law effects on hospital utilizations

	(1)	(2)	(3)	(4)
	Hosp. Adm.	**EM Visits**	**IP Days**	**OP Visits**
Panel A – Selected treated States				
Parity law	-0.040***	-0.029	-0.020	-0.008
	(0.013)	(0.017)	(0.012)	(0.027)
Log mean of DV	4.74	6.06	6.44	7.62
Mean of DV	119.50	440.32	682.77	2228.92
States	12	12	12	12
Observations	204	204	204	204
Adjusted R^2	0.959	0.948	0.985	0.964

Standard errors in parentheses. Heteroskedasticity-robust SEs clustered by state. All models include county, year, and treated-by-year fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)	(3)	(4)
	Hosp. Adm.	**EM Visits**	**IP Days**	**OP Visits**
Panel B – Selected treated and never treated states				
Parity law	-0.041***	-0.030**	-0.022*	-0.010
	(0.012)	(0.013)	(0.011)	(0.023)
Log mean of DV	4.73	6.03	6.48	7.71
Mean of DV	116.78	425.86	688.98	2369.27
States	33	33	33	33
Observations	561	561	561	561
Adjusted R^2	0.960	0.917	0.978	0.951

Standard errors in parentheses. Heteroskedasticity-robust SEs clustered by state. All models include county, year, and treated-by-year fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Given the time-intensive nature of data extraction and transformation, I provide a modest extension of the original analysis. I examined two additional causes of mortality: malignant neoplasms (Cancer) and Chronic Lower Respiratory Disease (CLRD). The results, shown in Table 9, indicate that parity laws are associated with reductions in mortality for both conditions, but most tests are not statistically significant. Our test finds that only statistical significance is observed for CLRD in the combined sample of treated and never-treated states.

Cancer outcomes may be more appropriately evaluated over a longer period, given the extended treatment course and disease progression. For individuals with cancer, telehealth may be

particularly valuable for follow-up care and long-term monitoring, such as routine check-ins with providers. (Winstead, 2023) And in chronic respiratory failure, telemedicine includes both direct patient consultations via remote technologies and indirect interactions, such as wireless transmission of patient data to clinical teams, remote adjustment of treatment protocols, and continuous monitoring via wearable sensors and smartphone applications. (Shah et al., 2021) Shaw, et al. finds these capabilities can reduce the need for in-person visits and overnight hospital stays, thereby lessening the burden on patients. Moreover, more frequent and proactive monitoring may help prevent exacerbations and reduce hospitalizations. (Shah et al., 2021)

TABLE 9: Impact of Parity Law on Mortality Rates (Cancer & CLRD)

	(1)	(2)
	Cancer	**CLRD**
Panel A – Selected treated States		
Parity law	-0.004	-0.018
	(0.006)	(0.012)
Log mean of DV (pre)	3.82	5.26
Mean of DV (pre)	45.47	191.76
States	14	14
Observations	13,255	9,306
Adjusted R^2	0.895	0.887

Standard errors in parentheses. Heteroskedasticity-robust SEs clustered by state. All models include county, year, and treated-by-year fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(1)	(2)
	Cancer	**CLRD**
Panel B – Selected treated and never treated states		
Parity law	-0.006	-0.027**
	(0.006)	(0.011)
Log mean of DV	3.86	5.31
Mean of DV	47.66	201.99
States	35	35
Observations	33,695	23,546
Adjusted R^2	0.906	0.880

Standard errors in parentheses. Heteroskedasticity-robust SEs clustered by state. All models include county, year, and treated-by-year fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

VI. Conclusion

The regression analysis and results presented in this paper closely align with those of Chen and Dills (2024). The parity law coefficients are not exact matches, but they are consistent in sign (negative) and statistical significance for our selected causes of mortality which indicate modest declines in mortality rates following the adoption of these state telemedicine parity laws. The tests were significant primarily for ischemic heart disease and diabetes, with the strongest effects in metropolitan fringe areas. Telemedicine reduces travel time and office/hospital visit costs which benefits patients with mobility or transportation barriers or with limited availability to local healthcare providers.

Using a differences-in-differences regression and event study analysis, my analysis finds that telemedicine parity laws are associated with reduced mortality. Mortality rates for ischemic heart disease (5.7% lower) and diabetes (3.9% lower) for the entire sample using all ages were the most promising through all the tests. Also, suicide was statistically significant with a 3.4% decrease for the entire sample using all ages. The largest declines occur in areas on the fringes of large metropolitan regions for these three causes of death. Many states continue updating telemedicine policies and federal rules remain under debate, but these results are strong evidence that requiring coverage for telemedicine lowers mortality rates.

This economic research is important as it provides a causal link between telemedicine parity laws and a decline in mortality rates. The subarea analysis helps identify vulnerable populations, areas with fewer healthcare providers. This research also provides statistical evidence that telemedicine parity laws reduce hospital admissions and usage. In summary, this economic research is important because it provides healthcare providers and policy makers with evidence-based information to make informed decisions that provide better health outcomes.

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