The Impact of Telehealth Parity Laws on Health Expenses*

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October, 2022

Abstract

Telemedicine is becoming increasingly popular as a way of providing remote medical care to patients. COVID-19 has pushed providers, patients, and payers into widespread adoption of telehealth. While there is extensive literature on how telemedicine impacts utilization of medical care at the individual level, little is known about how it affects aggregated medical expenditures. Using the staggered implementation of Telehealth Parity Laws (TPLs), I conduct difference-in-differences (DiD) analysis on aggregated state-year expenditure data (1991-2014). I find that the passing of TPLs decreased total healthcare expenses by 3.9%, hospital care expenses by 3.0%, and physician service expenses by 5.9%. I also observe steady increases in both the empirical value and statistical significance of the effects 1 year down the road from implementation. After the 4th and subsequent years of implementation, reductions in total, hospital and physician health expenses categories are estimated to be 6.8%, 6.4%, and 9.4%, respectively.

Key words: telehealth, parity laws, health expenses

*I thank my advisor Daniel Dench for his guidance throughout the development of the paper. Also, special thanks to Tibor Besedes, Brantly Callaway, David Cutler, Danny R. Hughes, Benjamin Raymond, and Maxwell Rosenthal for helpful comments and feedback. All errors are my own.

1 Introduction

Health care expenditures in the United States have substantially increased over the past decades. According to the National Center for Health Statistics (2021), the National Health Expenditures (NHE) share of Gross Domestic Product (GDP) has increased from 12.1% in 1990 to 17.8% in 2018, and this ratio is projected to raise to almost 20% by 2030 (Centers for Medicare & Medicaid Services, 2022), with an average growth speed of 5.1% per year. Progress made by the health care system always centers around availability and cost reduction. Among all, virtual communication has been increasingly used due to the convenience it provides. According to American Hospital Association (2019), 76% of U.S. hospitals had fully or partially implemented a computerized telehealth system by 2017, an effort that was only accelerated during the breakout of the COVID-19 pandemic that made telehealth ubiquitous. However, the effects of telehealth on health care cost are still inconclusive. The accessibility brought by telehealth may lower health expenses by decreasing overhead costs, or it could increase expenses due to overuse. Since very little is known about the economic effects of telehealth, it is hard to evaluate whether telehealth is an efficient alternative and complement to in-person healthcare services.

In this paper, I examine the effects of telehealth on health care expenses by means of a state level policy shock: the implementation of telehealth parity laws (TPLs), through which states require private health insurers to expand the coverage of health service to telehealth. The exogenous variations in the timing of policy implementation across states during 1991 to 2014 enable me to utilize difference-in-differences models to pursue a plausible causal relationship between telehealth parity laws and changes in state-level health cost. Using the data from the State Health Expenditure Accounts (SHEA), I start from estimating the overall effects on total medical expenditure, hospital care cost, and physician & clinical service spending. Next, I perform event studies for these three categories, respectively, to explore the dynamic effects. I further validate the causality between TPLs and the shifts in health care expenses in three ways: reduction of bias by using improved identification methods, consideration of the variation of TPLs across states, and distillation of the effects of TPLs from contemporary polices.

My study shows that the telehealth parity laws (TPLs) are successful at reducing health expenses. I find that the implementation of the parity laws (TPLs) decrease total health care expense per capita by 3.91%, and reduced costs in hospital care and in physician & clinical service by 2.96% and 5.93%, respectively[1]. These results are robust to a variety of alternative estimations. For example, results reported by Callaway & Sant'Anna estimation (Callaway and Sant'Anna, 2020) suggest larger significant reductions of health care expenses by 5.00%, 6.00%, and 7.16% in each category, respectively.

[1] these estimates are obtained when the first 2 years after adoption are taken as transition years to avoid bias and clutter.

Furthermore, I find the effects of TPLs on health expenses to snowball, becoming larger and more statistically significant with each passing year from the effective year. Results from event studies indicate that telehealth parity laws began to cause a uniform decrease in total health expenses approximately right after implementation across all specifications, with effects beginning to be sustainably pronounced and statistically significant after 3 years. This effect is basically mirrored by the pattern seen in hospital care and physician & clinical services spendings. After four or more years, the TPLs can be shown to significantly lower the total health expenses including hospital care and physician & clinical services by 6.97%, 6.44%, and 9.42%, respectively, which are reaffirmed by alternative estimators.

A detailed examination of telehealth parity laws further validated my results. Considering the nuances of TPLs across states, I categorize the parity laws into 3 different types: coverage parity, payment parity, and cost-shifting protection. I focus on the coverage parity laws since it is the movement that essentially removes the barriers for patients to using telehealth services. My results suggest that the coverage parity laws decrease the total health expenses including hospital care and physician & clinical services per capita by 5.51%, 3.94%, and 8.49%, respectively, which is slightly lower than, while still consistent, with the primary results.

My results are also robust when I disentangle the effects from similar laws in Medicaid, and become more pronounced when I distinguish the TPLs from other contemporary efforts in improving healthcare delivery. That is, without the impact of Medicaid TPLs, the private TPLs decrease total health expenses including hospital care and physician & clinical services per capita by 3.70%, 2.35%, and 5.64%, respectively. Restricting the contemporary healthcare delivery policies by testing earlier adopters, I find more prominent reductions of 5.58% - 6.77%, 4.93% - 6.80% and 7.45% - 8.22% in total health care, hospital care and physician & clinical services spendings, respectively.

My study makes a number of important contributions to the literature. First, it provides novel and strong evidence that policies encouraging virtual communication usage would reduce healthcare spending at an aggregated state level. While a set of papers have examined the cost efficiency of telehealth, they either focused on specific diseases (McCue et al., 1997; Armstrong et al., 2007; Kirkizlar et al., 2013; Richter et al., 2015; Frederix et al., 2016; Langarizadeh et al., 2017; Kini, 2019), or performed analyses on relatively small samples like in a local community Marx et al. (2018) or hospital Wicklund (2019). As far as I know, I am the first to study the impact of telehealth on health care expenses at an aggregate level. Secondly, my study dissects more clearly the details on telehealth parity laws by a careful review of the content and history of TPLs of each state, which were only vaguely mentioned in previous studies. This effort not only revises several implementation years provided by the ATA state Telemedicine Toolkit (American Telemedicine Association, 2017) that are referenced by almost all other research using TPLs (Dills and Chen, 2018; Grecu and Sharma, 2019; Harvey et al., 2019; Cornaggia et al., 2021), but also provides additional policy facts that could be used by later researchers to check the exclusive effects of TPLs on other variables of interests. Finally, I leverage improved multiple identification methods to reduce bias from taking the early treated group as control (Goodman-Bacon, 2018), which has never been done by previous research adopting TPLs as policy shocks to estimate its effects (Dills and Chen, 2018; Grecu and Sharma, 2019; Harvey et al., 2019; Cornaggia et al., 2021). Unlike their papers employing traditional staggered DiD designs and event study, my study closely references Cengiz et al. (2019), Callaway and Sant'Anna (2020), and Abadie and Gardeazabal (2003) and Donald and Lang (2007), and further utilize stacked clean control estimation, Callaway & Sant'Anna's estimation, and synthetic control estimation, to provide more robust applications for further policies studies on public health.

2 Background: Telehealth Parity Laws

Telehealth in the United States is currently regulated by laws and regulations at both the federal and the state levels (Yang, 2016). Specifically, the federal government mainly focuses on regulating Medicare reimbursements, while states are in charge of scheming out the laws governing commercial insurers as well as their local Medicaid. As a result, the insurance restriction, coverage, and reimbursement of different payers for telehealth have different characteristics.

Prior to the COVID-19 pandemic, Medicare programs could only compensate for live video services with originating sites in designated rural areas and with restrictions on providers, except in Alaska and Hawaii, where store-and-forward services are also covered (Centers for Medicare & Medicaid Services, 2019).

Private insurance mandates are affected by the telehealth parity laws (TPLs) enacted by the state legislatures. Until 2019, 36 states and D.C. have passed private telehealth parity laws (American Telemedicine Association, 2019). Overall, the private parity laws are quite uniform across states. On the one hand, the language used in specifying the scope of telehealth service shows a similarity among states, that most define telehealth as "interactive audio, video, or other electronic media used for the purpose of diagnosis, consultation, or treatment". On the other hand, there are less restrictions in state-level laws for reimbursing telehealth. As noted by the American Telemedicine Association (2016), 24 states out of the 29 that have passed parity laws before 2016, have no technological, patient setting, or provider restriction. The consistency in the service scope of telehealth and in the rarity of restrictions against telehealth applications among states lays a good foundation for estimating the effect of the TPLs. Details of TPLs of each state have been provided in Appendix Table A1.

My research aims to determine the effect of TPLs on health expenses, for which data by state is available between 1991 and 2014. Therefore, the TPLs implemented before 2014 are carefully examined and mapped out in Figure 1. Per the ATA State Telemedicine Toolkit (2017), there are 23 states that have implemented the telehealth parity laws on or before 2014. Among them, 3 states have been excluded from my treated sample since their TPLs became effective in 2015 [2]. In addition, the effective years of 9 other states have been revised according to each state's legislation [3].

As shown in Figure 1, there are 19 adopting states as well as D.C. in my sample. Telehealth pioneers such as Louisiana and Texas required reimbursement parity as early as the 1990s, and there are 5 states having passed the law before 2000. Another 6 states enacted the TPLs between 2001 and 2010, and 9 states included TPLs between 2011 and 2014. Figure 1 also shows that there is no observable connection between states which passed the TPLs, that for each of the time-spans labeled, states passing the TPLs spread to at least 3 regions of the Northeast, the Midwest, the South, and the West. The staggered and scattered adoption of parity laws formed a quasi-experiment that made it possible to study the effects of telehealth adoption by comparing the health expenses between the treatment group (19 adopting states and D.C.) and control group (31 states without parity laws by 2014) over time.

Considering the fact that most Medicaid programs include telehealth services earlier than private TPLs in most states, to isolated the effect of private TPLs on health expense, I also include Medicaid coverage for telehealth into one of the specifications to confirm the robustness of my primary results. In Appendix Table A2 , I list the chronology of when states incorporated telehealth services into their Medicaid reimbursement programs. Unlike the conformities in Medicare and in TPLs, the coverage for telehealth services by state Medicaid are much more heterogeneous in terms of forms of service, and specific provider and patient restrictions. According to the (Center for Connected Health Policy, 2020b), in addition to the fact that all states and D.C. have reimbursed for some type of live video telehealth services in Medicaid by 2019, there are 18 states that reimburse for store-and-forward services and 21 states that reimburse for remote patient monitoring. Among them, many states set restrictions on patient location (e.g. require a patient to be located in rural Health Professional Shortage Areas) and on what services and providers are eligible, to limit the utilization of telehealth to delivering services already in their Medicaid telehealth reimbursement policies (Center for Connected Health Policy, 2020a). In the robustness check section, I ignore the restrictions and take all kinds of Medicaid coverage for telehealth to be the same, which aims to provide a conservative estimation of TPLs' effects.

[2] the 3 excluded states are Arizona (eff. 1/1/2015, by Ariz. Laws 2013, c70,§ 4), New York (eff. 1/1/2015, by N.Y., S.B. 7852) and Tennessee (eff. 1/1/2015, by Tenn. Acts 2014, c. 675, § 1).

[3] the 9 states for which the effective year was revised are California (from 1996 to 1997, by Stats 1996, c. 864, § 6), Hawaii (from 1999 to 1998, by Haw. Laws 1998, c 278, §2), Kentucky (from 2000 to 2001, by Ky. Acts 2000, c. 376, § 7), Colorado (from 2001 to 2002, by Colo. Laws 2001, c. 300, § 3), Georgia (from 2006 to 2005, by Ga. Laws 2005, c. 82, § 3), Oregon (from 2009 to 2010, by Or. Laws 2009, c. 384, § 2), Virginia (from 2010 to 2011, by Va. Acts 2010, c. 222), Missouri (from 2013 to 2014, by Mo. Laws 2013, S.B. 262), and Montana(from 2013 to 2014, by Mont. Laws 2013, c. 164, § 1).

My study also takes the nuances in TPLs into analysis. The most foundational form of TPLs is coverage parity, which requires health plans to cover a health care service delivered via telehealth if the insurer would cover the same service as if it were provided during an in-person consultation[4]. As shown in Appendix Table A1, some states use language prohibiting private health plans from excluding a medical service solely because the service is provided through telehealth/ telemedicine. The others require that health insurance plans provide coverage for telemedicine services to the same extent that the services would be covered if they were provided through in-person consultant.

In addition to coverage parity, some states further include payment parity and cost shifting protection in their TPLs. Payment parity refers to the situation where a state law expressly addresses payment and reimbursement rates for telehealth services as compared to in-person health care. For some states, the language used is *at the same reimbursement rate*. For other states, the reimbursement language sets a ceiling, or floor. Cost-shifting protection refers to the situation where the state law prohibits a health plan from charging any greater deductible, co-payment, or coinsurance amount than what would be applicable if the same health care was provided through face-to-face diagnosis, consultation, or treatment. Details of payment parity and cost-shifting protections amongst states are provided in Appendix Table A3 and Appendix Table A4, respectively. In the robustness check section, I control for different kinds of parity laws to validate my estimated effects.

3 Identification Strategy

3.1 Binary Indicator DiD

To identify the effects of state adoption of telehealth parity laws on health expenses, I apply the staggered difference-in-differences (DiD) strategy that builds on plausibly exogenous variation in the timing of policy adoption across states, as the baseline specification for estimating the effect of TPLs. Additionally, as observed and suggested by Mazumder and Miller (2014), Maxwell et al. (2011),Hu et al. (2018),Miller and Wherry (2019), and McKenna et al. (2018) [5], I consider the first two years post implementation as transition

[4] under the same concept, private telehealth parity laws are used as service parity by some associations like CCHP

[5] in the study of Mazumder and Miller (2014), the Massachusetts health reform (also known as Romneycare) saw a nearly immediate decrease in health care spending after implementation in the percentage of the population that is uninsured but only 2 years later were the effects on debt, or delinquent large hospital bills (bills that are $5,000 or greater) evident in a positive manner. In Maxwell et al. (2011), it is noted that the effects on access to healthcare to minorities and traditionally underserved communities were significant and pronounced three years after the same bill's passing in 2006. The Affordable Care Act, widely known as Obamacare, was shown by Hu et al. (2018) to reduce collections and bankruptcies in a significant way only 3-4 years after the act was passed in 2010. Before that, the effects were minimal but growing with time. Similar, Miller and Wherry (2019) notes that 4 years after implementation, the primary effects the Affordable Care Act towards increasing health coverage become significant and apparent. In fact, some financial analysis techniques will consider the first two years post implementation as transition years that are more accurately categorized as pre-implementation than post-implementation (McKenna et al., 2018).

years for the effects to manifest. The regression model takes the following two-way fixed effect (TWFE) form:

$$Log(Expense)_{st} = \alpha_s + \lambda_t + \delta^{DD} TPL_{st} + \gamma' X_{st} + \epsilon_{st} \tag{1}$$

where $Log(Expense)_{st}$ is the natural logarithm of health expense per capita, measured at the state-year level. To be specific, I primarily focus on exploring the effects of telehealth parity laws on the total health expense, and its two main elements: the costs of hospital care and physician & clinical services care. α_s and λ_t are state and year fixed effects, which absorb all time-invariant state-level characteristics and health expense trends that are common to all states; TPL_{st} is a binary indicator set to 1 when 2 years after a state passes TPLs and 0 prior, and therefore, the estimated coefficient $\widehat{\delta^{DD}}$ is the primary parameter of interest in my study, which is the estimation of causal effects of TPLs on state level health expenses. X_{st} is a vector of time-varying state-level controls intended to mitigate confounding events and correlated omitted variables, and as a baseline estimation, I include only one control variable: the natural logarithm of GDP per capita of each state (Fuchs, 2013; Robinson et al., 2017).

3.2 Event Study DiD

The key requirement that lies behind the DiD strategy above is the parallel trend assumption, that compared to the control states, there is nothing unobserved in the treated states that is changing between the pre- and post- treatment periods that also squares up the health expenses. Since the counterfactual is not available, I adopt the event study DiD to test whether the treated group and control group are comparable in dynamics in the pre-treatment period, which aims to provide evidence for examining the parallel-trend assumption.

The event study DiD estimation also provides the dynamic effects in response to the TPLs, which unravel how improved access to health services affect patient/client behavior and health outcome yearly after the TPLs' treatment. It is quite possible that the reduction is yet to be statistically significant or we may even observe an increase in health expenses at one or two years after the treatment, due to the growth in medical care utilization (Grecu and Sharma, 2019). However, I assume that the expenses will lower significantly in the following years due to the saved hospital cost.

To evaluate the parallel trends assumption between the treatment and control groups with differential timing, and to estimate the degree to which the post-TPL treatment effects are dynamic, I use the following event study form that includes leads and lags into the DiD specification (Miller et al., 2019):

$$Log(Expense)_{st} = \alpha_s + \lambda_t + \sum_{k=-4}^{4} \delta_k I[t - t_s^* = k] + \gamma' X_{st} + \epsilon_{st} \tag{2}$$

where indicator variable $I[t - t_s^* = k]$ measures the time relative to the implementation year, t_s^*, of the adoption of TPLs in each state, and is zero in all periods for untreated states. An endpoint restriction was created so that for $t - t_s^* = -4$ for any $t - t_s^* \leq 4$ and $t - t_s^* = 4$ for any $t - t_s^* \geq 4$. The omitted category is $k = -1$, which is 1 year before the TPLs policy adoption. Therefore, each estimate of δ_k provides the change in health expenses in treated states relative to the untreated states during year k, as measured from the year '4 or more years' prior to the TPLs effective year. If health expenses for treated and control states are trending similarly prior to the TPLs adoption, the estimated coefficients associated with event times $k = -3$ to $k = -2$ are expected to be close to zero and not statistically significant; and if the dynamic effect is as assumed, the results aligning with event times $k = 1$ to $k = 4$ are expected to be negative and rising in terms of value and significance level.

3.3 Alternative Estimators

3.3.1 Alternative DiD Estimators

Because my identification strategy comes from a staggered DiD strategy with two-way fixed effect (TWFE) form, a potential concern is its usage of early treated units as control units, as pointed out by emerging literature (Goodman-Bacon, 2018; Baker et al., 2021). To alleviate this concern, I perform two alternative empirical specifications to disentangle the effect from early adopters, both of which attempt to compare the treated units to a "clean" set of control units, to make sure that the early treated units would not generate bias by being included into the estimation of later treated groups.

The stacked clean control approach (Cengiz et al., 2019) solves the problem in TWFE by creating separate data sets associated with the event of interest(passing of TPLs). That is to say, for each of the 20 treated states from 1991 to 2014, a separate data set is generated, and in each of these data sets, only the target state g and states that were never treated within a 9-year panel(4 years before, and 4 years after) by event time are included. The policy effect therefore is estimated by staking these 20 estimates via the equation:

$$Log(Expense)_{stg} = \alpha_{sg} + \lambda_{tg} + \sum_{k=-4}^{4} \delta_k I[t - t_s^* = k] + \gamma' X_{stg} + \epsilon_{stg} \tag{3}$$

where the newly added g subscript indicates both the event and data set.

Callaway & Sant'Anna Estimator The stacked regression approach uses OLS variance-weighting, which may still generate biases in the estimate of average treatment effect. Therefore, I follow the methodology of Callaway and Sant'Anna (2020) that weighs data by propensity scores. Those observations from the control group sharing similar characteristics would be weighted up. The key concept in Callaway and Sant'Anna

(2020) is the group-time average treatment effects, $ATT(g,t)$, which are the average treatment effects in period t for the group of units first treated in period g. Assuming parallel trends conditional on covariates and overlapping in propensity scores, the non-parametric estimator for a group ATT by time is:

$$ATT(g,t) = E[(\frac{G_g}{E[G_g]} - \frac{\frac{\hat{p}(X)C}{1-\hat{p}(X)}}{E[\frac{\hat{p}(X)C}{1-\hat{p}(X)}]})(Y_t - Y_{g-1})] \tag{4}$$

where G_g is a binary variable equal to 1 when a unit is first treated in period g. $E[G_g]$ measures how many units are treated in this group; $p_g(X)$ is the propensity score calculated as $p_g(X) = P(G_g = 1|X, G_g{+}C = 1)$, that which is the probability of being first treated in period g conditional on covariates and either being a member of group g or not participating in the treatment in any time period. C is a binary variable equal to 1 for individuals in the control group, so when $G_g = 1$, $C = 0$ and vice versa.

3.3.2 Synthetic Control Method

A critical concern in my identification strategies is the possibility of heterogeneous trends in the absence of TPL treatment, since the counterfactual units are unobservable. To alleviate this concern, I include the state and year fixed effects to control for the potential effects that are constant within a state over years, or are constant across all states within each year; also, I present the results from event study DiD and alternative DiD estimators to test whether the treated states and control states are comparable in pre-treatment period. However, it is not possible to traverse all differential trends since many state characteristics are unobservable. Therefore, I apply an alternative empirical method, the synthetic control method which is unlike previous estimators which require the parallel trend assumption, to examine impact of telehealth parity laws.

The primary idea of the synthetic control method is to generate a more appropriate counterfactual unit by comparing the similarities between a treated unit and a group of control units across outcome and explanatory variables over the pre-treatment period. As a result, by a data-driven optimization algorithm, the proper units in the control group are selected, the appropriate weights to be attached to each unit are decided, and finally, a synthetic counterfactual unit is produced for each treatment state in the form of a weighted combination of the chosen control states. Then the effect of the treatment can be estimated by comparing the value of the outcome variable of the treatment unit and its corresponding synthetic counterfactual unit over the post-treatment period.

I perform the synthetic control method mainly by five steps. First, I take one state at a time from the treatment pool (i.e. 1 out of the 20 states adopting TPLs) and construct its corresponding donor pool, which includes the 31 never treated states and the yet to treated states throughout 5 years after the treated state's TPLs shock year or 2014, the end year of my available data, whichever comes first. In the second step, I synthesize the counterfactual unit for the selected state by using the constructed donor pool, which is a standard Abadie SC approach (Abadie and Gardeazabal, 2003). The matching variables here are the outcome variable, health expenses, and the control variable as was in my main specification, the GDP per Capita. Having compared the post-treatment difference of health expenses between the treated state and its counterfactual, the t-value of the averaged treatment effect is calculated and saved for further use[6]. Thirdly, for inference purposes, I perform the placebo tests for the selected treatment state. To this end, I generate a synthetic counterfactual for each donor unit using the rest of the donor units as potential controls, and compute the t-values of treatment effects from the placebo experiments (i.e. placebo effects). In the fourth step, I repeat the last 3 steps for every state in the treatment pool. Finally, I draw up the t-value distributions of the treatment effects, placebo effects, and most importantly, the comparison of these two effects. I calculated where the central t-values of treatment effect places in the distribution of t-values of placebo effects (Donald and Lang, 2007). I assume the TPL effect on treated units is significant in respect to the effects on the donor units, so the effect on the treated states would at the left of the 10th percentile of the distribution of placebo effects.

Another potential concern in my identification strategy is the endogeneity problem, which arises from the fact that there are other health care delivery models, which may or may not be directly related with telehealth, that also increase access to healthcare, for example, the Urgent Care Centers (Meille, 2021). This endogeneity problem would worsen my result if the other health care improvements happened in the later years of my study frame, when the treated units are more widespread across the United States.

I validate my results in two ways. First, I control for telehealth related polices, namely the increasing inclusion of telehealth coverage in Medicaid, into my specification, to disassociate their effects on health expense. Second, for the other indirectly related policies, I performed three more tests by restricting my time period to 2010, 2011 and 2012, after which the other healthcare delivery forms have grown rapidly. In these cases, only the states that have adopted the telehealth parity laws in and before 2010, 2011 or 2012 would be taken as treated units.

My estimation should be interpreted as a conservative lower-bound estimate of the TPLs' effect on health expenses for two reasons. First, I include states like Louisiana (which limits to the original site physician only) and Colorado (which has geographical restrictions) that limit the covered application in their policy provisions. Second, variances in coverage parity exist among the laws, and the coverage parity of some states (prohibiting private health plans from excluding telehealth) are weaker than the others (in regards to requiring private health plans to provide coverage for telehealth to the same extent as is provided by in-person health care). By including these weakly treated states in the treatment group, I would underestimate

[6] my analysis is done in Stata using the synth software package developed by Abadie et al. (2011)

the effect of TPLs.

4 Data

4.1 Data Source

My study involves three sets of information: health expenses, telehealth parity laws, and other state resident information. The State Health Expenditure Accounts (SHEA, 1991-2020) data provides official state-level variation in healthcare spending in the United States. My study is focused on the years before the Affordable Care Act's (ACA) Medicaid expansion, so I limit the original data to 2014. As a subset of the National Health Expenditure Account (NHEA), the SHEA data are estimated by the Office of the Actuary (OACT) in the Centers for Medicare & Medicaid Services (CMS), who utilize the same methodology for all states and all years to generate two sets of consistent estimates: the health care expenditures by state of provider, and health care expenditures by state of residence. As explained by Centers for Medicare & Medicaid Services (2017), the residence-based expenditures are converted from the provider-based data, and adjusted using information on health care expenditure flows or patterns between states.

I choose the health care expenditures by state of residence for two reasons. First, using the provider-based estimates would cause bias, since the observed cost reduction between TPLs adopting states and non-adopting states, may result from patients' flow to and pay to non-adopting states. However, I can mitigate this bias by using residence based estimates, which reflect all health care costs made by the residents of a state, regardless of where the care was provided. Second, I use residence population to calculate per capita health spending and GDP. Therefore, choosing resident-based estimates is more appropriate due to the alignment in caliber.

The total health expense data from SHEA are estimated at the Personal Health Care (PHC) level, which includes all health care goods and services consumed, and excludes government administrative cost, government public health activities, and investment in research and structures & equipment (Centers for Medicare & Medicaid Services, 2017). The total health expense data is further decomposed into the nine sub categories, namely hospital care[7], physician and clinical services[8], other professional services, dental services, home health care, prescription drugs and other non-durable medical products, durable medical products, nursing home care, and other health, residential and personal care (Centers for Medicare & Medicaid Services, 2018). In my research, I mainly focus on exploring how the TPLs affect the total health expenses, spendings on hospital care, and physician and clinical services, two categories which combined, account for over 60%

[7] expenditures for all services providing to patients and billed by the hospital;

[8] include spendings for services provided in establishments operated by Doctors of Medicine (M.D.) and Doctors of Osteopathy (D.O.), outpatient care centers, plus the portion of medical laboratories services that are billed independently by the laboratories;

of total expenditures.

The information on the telehealth parity laws of each state come from local legislative documents. Taking the TPLs as a policy shock, I mainly focus on screening out the earliest effective date and statutes describing how private insurers should include telehealth into their coverage and reimbursement plan. With the help of Casetext, I start from the current TPLs of each state, carefully reviewed its revision history, and traced back to the original local laws or acts including TPLs, which have always been recorded by local legislation.

As introduced in Section 2, I identify a state as in the treated group once it passes coverage parity laws. I focus on coverage parity for inclusion in the treatment group since it is the deciding factor which removes the barrier of using telehealth for patients by requiring that private insurers not exclude telehealth services. To solve the concern that the effects estimated might be upward then, I further refine the TPLs into coverage parity (details are presented in Appendix Table A1), payment parity (Appendix Table A3), and cost-shifting protection (Appendix Table A4) for each state, which is done through a careful examination of the collected TPLs statutes.

A typical concern here is that the modification of TPLs over time may lead to bias. I dispel this concern in two ways: first, revisions are always effective on and after 2014, which is the last year of my study period; second, revisions are aimed at improving instead of impairing the benefits of the insurant who uses telehealth[9]. Therefore, leaving the revisions of TPLs may cause underestimation, but would not give rise to mismatch from control group to treatment group.

I have also collected the coverage policy for telehealth by state Medicaid programs to further validate my results. However, unlike the private insurer TPLs that have been clearly filed by local legislation, records of telehealth coverage policies in Medicaid programs are documented dispersedly, and many of original policies are not publicly available anymore. For example, rather than in local laws and legislative acts, the telehealth policies of some states can only be found in specific manuals (e.g., Maine, Sorth Carolina and North Carolina), Medicaid Bulletins (e.g., Michigan, and New York) and/or reports from the CMS (Centers for Medicare and Medicaid Services). Appendix Table A2 lists the earliest data and source of reachable records. Since difficulties in traceability happened mainly in control states, I argue that the robustness check is still effective, that if there are any policy shocks of Medicaid telehealth laws that happened earlier than listed, my results and significant level would have been weakened by these unobserved effects. In other words, if my results are solid under current robustness check, it would not be less reliable under the checks with early records.

Annual state-level demographic measures are obtained from different sources. To compensate for the potential effect of economic development on health expense, I use Gross Domestic Product (GDP) per

[9] for example, Hawaii includes the payment parity in 2014 in their TPLs, to augment their prior coverage parity.

capita as a control variable (Fuchs, 2013; Robinson et al., 2017). The Gross Domestic Product (GDP) data is obtained from the U.S. Bureau of Economic Analysis (BEA), and resident population data is from the U.S. Bureau of Census (and further aggregated by the Federal Reserve Bank of St. Louis). This population data is also used to calculate per capita health care spendings.

In addition, to check whether there are geographical or socioeconomic differences between the adopting states and the non-adopting states that may have endogenously created a change in health care expenses, I also calculate population-weighted density for each state with census data from counties (U.S. Bureau of the Census, 2012) using the method by Ottensmann (2018), and include some basic demographic characteristics, namely gender ratio, ethnic ratio (including Hispanic and non-Hispanic), age group breakdown, fraction of persons 25 years old and over with at least a high school degree, and fraction of population with at least a Bachelor's degree. All but the education attainment data are obtained from Bridged-Race Population Estimates of the CDC's WONDER online database, and the education attainment data are collected from the Digest of Education Statistics by National Center for Education Statistics.

4.2 Summary Statistics

Table 1 presents the descriptive statistics of 50 states and D.C. in 1991 and 2014. Column (1) is the variable means for the full sample, which is further separated into control group (column (2)) containing states that did not adopt telehealth parity laws by 2014, and treatment group (column (3)) of states that did eventually adopt TPLs by 2014.

Across all states, the averaged total health care expense per capita in 1991 is \$2601.54, in which hospital care spending is \$1077.79, physician & clinical services spending is \$649.35, and other spending is \$874.40 per capita basis. These expenses in each category increased to \$8336.81, \$3331.72, \$1860.54 and \$3144.55, respectively, in 2014. During both periods, health care expenditures in non-adopting states are either higher(total, physician & clinical services, and others) or similar (hospital care) to their counterparts in adopting states, and the ratios of health care expenses to GDP per capita are consistently higher among patients residing in states that did not adopt TPLs, relative to those residing in the adopting states.

Across most observable characteristics, there are no significant pre-existing differences between adopting states and non-adopting states, as reported in coloumn (4) [10]. The notable exceptions are with regards to race/ethnicity: residents in adopting states are substantially less likely to be white or aged over 65 years, than residents in non-adopting states. Furthermore, I perform a probit regression for the first (1991) year to test whether there are endogenous driving forces for states to adopt telehealth parity laws. As reported

[10] I also ran tests for other pre-treatment years, 1992-1994. The significance levels are similar to the results here, in that only 'white' and 'age 65+' have p-Values lower than 0.1.

in Appendix Table A5, the concern on the exceptions, race white and age over 65, could be dispelled, and there are no obvious state characteristics endogenously propelling a state to adopt TPLs.

5 Estimation Results

I first report the preliminary results by the staggered difference-in-differences specification in Equation 1. As shown in Table 2, the adoption of TPLs decreases the total health care spending significantly by 3.91% (column (1)), the cost of hospital care by 2.96% (column (2)), and the expenses of physician & clinical services significantly by 5.93% (column (3)), when a 2-year transition period has been included[11]. While further checking the pretrends by the event study estimation using Equation 2, I find that prior to the implementation of parity laws, the treated states potentially showed linearly increasing trends when compared to the control states (column (1)-(3) of Table 3). Therefore, I use state-specific linear trends estimates to account for these observed trends, and results are reported in Table 4. Having adjusted linear trends among states, the estimates indicate that the adoption of TPLs significantly decreased total health care expense by 2.75% over the long run, including hospital care expenditure by 1.39%, and a more pronounced reduction of 3.7% in the spending of physician and clinical services.

To gain a better understanding of the dynamic effects of TPLs, the relationship between the years passed since the enaction of TPLs and health care spending has been plotted in Figure 2. Additionally, Figure 2 plots the estimated coefficients and their 95 percent confidence intervals. First, across all three categories, there is no significant difference in spending at the 5 percent level between adopting and non-adopting states prior to the implementation of telehealth parity laws (estimates are reported in Table 3). This result not only lends strong support to the parallel trend assumption, but also suggests that there were no heterogeneous trends in health expense with regards to the adoption of TPLs prior to the policy shock.

Figure 2(a) shows that the implementation of TPLs leads to a sustained decrease in per capita total health care expense. Especially 3 years post implementation, the trend of decreasing healthcare costs becomes increasingly obvious. This suggests that the effects of the TPLs, while immediate from its adoption, is cumulative in nature. Specifically, the estimates in column (1) of Table 3 demonstrate that a 1% decrease in total healthcare expense can be expected 2 years after a state passes a parity law, which leads up to a 3.16% statistically significant reduction in the subsequent year, and a 6.79% significant decline after 4 years from when parity laws have been adopted.

The dynamic effects of TPLs on hospital care and physician & clinical services have also been plotted, which I present in Figure 2(b) - (c). The progressive reductions in hospital care and physician & clinical

[11] estimates without considering lag effects and with 1-year lag effect have been reported in Appendix

services are meaningful, since these two account for over 60% of total health care cost. Similar to the dynamic effects on total expenditure, overall decreasing trends are observed. As reported in column (2) of Table 3, the effects on lowering hospital care spending grows to a significant 6.44% after 4 or more years have passed after adoption. Effects on the expense of physician & clinical services are intensifying (Table 3, column (3)), such that a significant 4.33% drop was observed 3 years after TPLs adoption, and a further significant 9.42% reduction could be expected after 4 years. Figure 3 presents the dynamic effects of TPLs while having the state-specific linear controlled, in which the declining trends are even more consistent, and the effects get statistically significant sooner, although the estimates (reported in Appendix Table A7) are smaller than the primary results.

6 Robustness Check

My results, that the effects of telehealth parity laws gradually increase in magnitude becoming statistically significant 3 years after adoption, are robust to a wide range of alternative specifications and robustness checks. In the following section, I first validate my results by using three alternative estimators to dispel the concerns lying behind my methodology; then I ratify that the variations in telehealth parity laws among states would not affect my results; finally, I take the development of other healthcare delivery models into consideration, in which I manifest that my results are robust both when controlling for the expansion of Medicaid telehealth coverage, and when I restrict my sample to earlier adopters to avoid the entangled effects from other contemporary polices.

6.1 Alternative Empirical Estimates

The results from estimation of the stacked clean control approach by Equation 3 are plotted in Figure 4(a)-(c), which show that my primary results are quite robust. Specifically, for total health care spending, the TPLs increasingly reduce healthcare spending after being adopted, and start to play a sustainably significant role three years after adoption. In addition, in the 4th year, a 3.48% drop can be expected (Appendix Table A8, column (1)). Along with the total health care spending, the effects of TPLs on lowering cost on hospital care and physician & clinical services are also found to intensify with time (Appendix Table A8, column (2)-(3), respectively).

Figure 5(a)-(f) present the results aggregated from the Callaway & Sant'Anna estimator by Equation 4[12]. Once again, it proves that my primary results are robust by providing a similar trend of decreasing health care expenditures with the effect beginning on the first year post implementation and gradually increasing,

[12] my analysis is done in R using the CS estimation package developed Brantly Callaway and Pedro H.C. Sant'Anna

regardless of whether the control groups are consist with states that not yet been treated (Figure 5(a)-(c)), or states that never got treated (Figure 5(d)-(f)) by TPLs. Estimates show (Appendix Table A9) that a larger, 1.63% significant decrease in total expense can be expected 2 years after a state passes TPLs; and a similar, 3.53%, significant drop can be observed in the third year. Since it is not expedient to use the CS estimator to approximate the effect after 4 or more years as a lump, I extend the study period for another 3 years, in which a statistically significant 7.56% decrease in the 6th year, and a statistically significant 8.14% reduction in the 7th year can be seen. Though the statistical significance is not immediately strong, nor would that be typically expected for newly implemented healthcare policies, the effects of TPLs on hospital care and on physician & clinical services costs are quite impressive in that 2.18% and 4.57% statistically significant reductions in cost were observed in the 3rd year in these two categories, respectively. Increasing in magnitude throughout the years, these effects grew to a statistically significant 6.03% and 12.18% in the 7th year.

Based on event studies, the overall effect on each cost category is reported in Table 5. In alignment with the TWFE specification, I take the 2nd year after policy shock as the 1st post-treatment year, to avoid clutter/background from transition years. Table 5 presents greater and more significant effects of TPLs on all three cost categories, and reductions of 5% (column (1)), 6% (column (2)), and 7.16% (column (3)) have been estimated, regardless of whether the control group consists of never treated states or not yet treated states, which once again provides evidence that my primary results are quite robust.

Finally, Appendix Figure A1(a)-(i) plots the results of the synthetic control method, which is selected to release the restriction on parallel trend assumption, and to take the uniqueness of a state into consideration by specifically creating counterfactual units. Appendix Figure A1(a)(d)(g) shows that the distribution of t-values of TPLs effect on treated states is left-skewed, and moving further towards left when lag effects are considered; while the distribution of t-values of TPLs effect on the placebo states, is relatively centralized, as shown in Appendix Figure A1(b)(e)(h). When I put these two kinds of figures together, I find that the median t-value of treatment effect on the treated group is at the left of the 15th percentile of the distribution of placebo effects (Appendix Figure A1(c)(f)(i)), which are slightly higher than the preferable 10th percentile, but still suggests a strong effect resulting from the implementation of TPLs.

6.2 Refined Telehealth Parity Laws

I also take the heterogeneity among TPLs into consideration. Due to detailed variances in the language of statutes that states use, I further refine the parity laws of each state into three categories: coverage parity that requires private health plans to cover a health care service delivered via telehealth if the insurer would cover the same service provided during an in-person consultation, payment parity that refers to the situation in which a state law expressly addresses payment and reimbursement rates for telehealth services in comparison to in-person health care; and cost-shifting protection which refers to the situation in which the state law prohibits a healthcare plan from charging any greater deductible, copayment, or coinsurance amount that would be applicable if the same health care was provided through face-to-face diagnosis, consultation, or treatment.

Table 6 lists the specific laws that each state adopted. During 1991-2014, there are 19 states as well as the D.C. which have enacted coverage parity laws; 4 states have passed the payment parity laws; and 7 states plus the D.C. have released the cost-shifting protection laws. Among all, the state of Virginia and Missouri are the only 2 states that have adopted all three laws.

In line with my main identification strategy, I add two more dummy variables to the staggered DiD specification to estimate the effect of each law:

$$Log(Expense)_{st} = \alpha_s + \lambda_t + \delta_1^{DD} CP_{st} + \delta_2^{DD} PP_{st} + \delta_3^{DD} CsP_{st} + \gamma' X_{st} + \epsilon_{st} \tag{5}$$

where CP_{st}, PP_{st} , CsP_{st} are all binary indicators set to 0 before the second year after a state passes coverage parity, payment parity, or cost-shifting protection, and 1 afterwards. Therefore, the coefficients, δ_1^{DD}, δ_2^{DD}, and δ_3^{DD} are the estimated effects of coverage parity, payment parity, or cost-shifting protection on health care, respectively.

Table 7 presents results using the Equation 5. The estimated effects of coverage parity laws on total health expense is -0.0551, which is slightly higher than my primary estimate of -0.0391, and still statistically significant. In addition, coverage parity reduced the spending of hospital care by 3.94%, which is slightly higher than my prior estimate of 2.96%. The estimated effect on reducing cost on physician & clinical services, 8.49%, is greater as well, comparing to the estimate of 5.93% in Table 2. In summary, the results obtained by refined TPLs are consistent with my main results.

6.3 Contemporary State Policies

My results are still robust when controlling for the effect of Medicaid telehealth coverage, which may potentially cause endogenous problems and bias my result. Figure 6 demonstrates the distribution of Medicaid telehealth coverage compared to private parity laws by 2014; 17 out of 51 states have required coverage in both private health plans and in Medicaid; 3 states have private TPLs only, 25 states have Medicaid telehealth coverage only, and 6 states have never been treated by any of these laws or policies. The detailed data is listed in Table A2.

I add one more dummy variable to my original DiD specification to disentangle the effect of Medicaid from my previous result:

$$Log(Expense)_{st} = \alpha_s + \lambda_t + \delta_1^{DD} TPL_{st} + \delta_2^{DD} Medicaid_{st} + \gamma' X_{st} + \epsilon_{st} \tag{6}$$

where $Medicaid_{st}$, is a binary indicator controlling for the adoption of telehealth coverage in Medicaid that equals one 2 years after a state includes the coverage of telehealth in their Medicaid plan, and 0 prior. And therefore, its effect is reflected by the coefficient, δ_1^{DD}.

Panel A in Table 8 presents results using Equation 6. The estimated effect of TPLs on total health expenditure is a significant -3.7% (column (1)), which is slightly lower than my primary result of -3.91%, but still statistically significant. It is quite possible since many of my previous controlled variables (state not adopting TPLs) already include the coverage of telehealth in Medicaid, which leads to a slightly upward effect of TPLs. In addition, the adoption of TPLs show similar effects on reducing the spending on hospital care by (column (2), 2.35% comparing to 2.96%), and physician & clinical services (column (3), 5.64% compared to 5.93%), which are consistent with my main results.

Finally, my results are robust when controlling for other contemporary healthcare delivery polices. During the later stage of my study period, many other kinds of healthcare delivery models were introduced. For example, the number of centers has increased steadily from 2013 (Urgent Care Association, 2020). Therefore, I test for early adopters to validate my results by restricting the study period to 2012, 2011, and 2010, respectively. Having been estimated by the same specification, Equation 1, my results once again show robustness.

Panel B in Table 8 demonstrates the effect of TPLs on these earlier adopters. The adoption of TPLs significantly reduced the total health spending by 5.58%, 6.16% and 6.77% (column (1)) when I restricted the study frame to 2012, 2011, and 2010, respectively. These results are more pronounced and consistent with my primary results. In addition, the TPLs exhibit more pronounced effects on reducing the cost of hospital care, and physician & clinical services. To be specific, the telehealth parity laws significantly lowered the cost of hospital care by 4.93%, 5.79% and 6.80% (column (2)) when I restricted the study frame to 2012, 2011, and 2010,respectively; and significantly decreased the expenses of physician & clinical services by 7.45%, 7.83%, and 8.22% (column (3)) in these three years.

To validate the effects from early adopters, I also perform stacked clean control for a shorter sample period: 1991-2009, when the first 10 adopting states have passed TPLs. Figure 7 plots the estimated coefficients for 4 years before and after the passing of TPLs, and their 95 percent confidence intervals. In addition the declining trends that are consistent with prior event studies, more immediate and stronger effects are indicated compared to my primary results, that I find statistically significant declines in total and hospital care expenses only one year after the adoption of TPLs. On the third year, effects are estimated to be 5.7%, 4.71%, and 7.1% (Appendix Table A10) reductions on total, hospital care, and physician & clinical service expenses, respectively.

7 Potential Mechanism

My study provides strong evidence that the public polices encouraging the usage of virtual communication help ramp down aggregated health care expenditures, which could be resulting from bargaining between insures and providers, or from the fact that people are overall getting healthier by timely treatment thus needing less medical services in the long run.

Overall, offering telehealth services would create larger profit margins for providers. The increased profit margin could come from at least two directions. Firstly, the reduction of patient flow to the hospital in favor of digital services reduces hospital overhead costs associated with in patient visits, such as number of staff and consumable goods needed during these visits, which, according to Frakt (2011), accounted for 30% of hospital overall costs and with outpatient costs adding an additional 9%. Secondly, the convenience afforded to the patient of being able to be seen by a doctor without going to the hospital reduces the rate of no-show patients, thus reducing the financial loss to the hospital from missed appointments. According to Gier (2017), a nation-wide 30% no-show rate at a cost of $150 billion dollars a year have been estimated for the overall US healthcare system. However, Erdogan et al. (2018) summarized that the no-show rate for telemedicine from 2 different studies converged on only 11-12%. These extra profits leave some space for insurers to negotiate with providers. Especially, some small providers would utilize this as a bargaining chip, accepting a drop in prices in exchange for cooperation with insurers with large market shares (Roberts et al., 2017).

For insurers, they will bargain for lower prices with providers when they have the leverage to do so (Ho, 2009). Being required to cover telehealth service into their plans, insurers know that it becomes cheaper to maintain a network of providers which provide telehealth services and along with it, the cost advantages of such. This would prompt competing providers to also adopt telehealth in order to incorporate such cost advantages, further reducing the cost on the insurer while those hospitals that do not may find themselves too expensive and out of network. The synchronized effect is a gravitation towards telehealth and reduced cost across the board for an increasing number of hospitals in states that employ TPLs. This explains why a reduction of aggregated health care expenditures can be observed after the passing of private telehealth parity laws with the effect becoming more notable as time passes.

Another reason generating this reduction is likely to be an increase in the general health of the population. Patients who might otherwise have brushed aside small health concerns in their early stages off-put by the hassle of going to the hospital (which often includes time off from work, long drives, difficult parking and long wait times) can now seek help from the comfort and convenience of their homes or even offices whenever they feel the need. Oftentimes, diseases caught early on have much better outcomes and require far less and less expensive methods of intervention than if diagnosed in advanced stages, which are a major driver of healthcare costs.

8 Conclusion

The breakout of COVID-19 has unprecedentedly expedited the popularization of telehealth service. My paper provides new evidence on the potential power that telehealth has to lower the health care expenses. I find that after only about 2 years of accumulation, the impact of telehealth becomes statistically significant. What's more, from there on out, the cost saving effects widened between the treated and control groups as did the statistical significance along with them.

Specifically, my study shows that the passing of the parity laws significantly decreased total health care expense per capita by 3.91%[13], a result which is valid to a variety of robustness checks that resulted in a range of statistically significant reductions of 2.75-5.0% on total health expenditure per capita. Furthermore, the implementation of TPLs has also reduced expenditure in hospital care and in physician & clinical service by 2.96% and 5.93%, respectively, though the significance levels of hospital care expense reductions are less prominent due to a further delayed effect to later years.

One area which merits more attention is the dynamic effect achieved by the laws due to stronger policy implementation. I found that despite an initial effect on healthcare costs that somewhat varies by specification, parity laws began to cause a uniform decrease in total health expenses approximately right after implementation across all specifications, with effects beginning to be sustainably pronounced and statistically significant after 3 years. This effect snowballs to become larger and more statistically significant with each passing year in the analysis. This effect is basically mirrored by the pattern seen in hospital care and physician & clinical services spendings.

[13] these estimates were obtained when the first 2 years after adoption were taken as transition years to avoid the bias and clutter that would be included if the transitory period were to be calculated into the fully post-treatment period.

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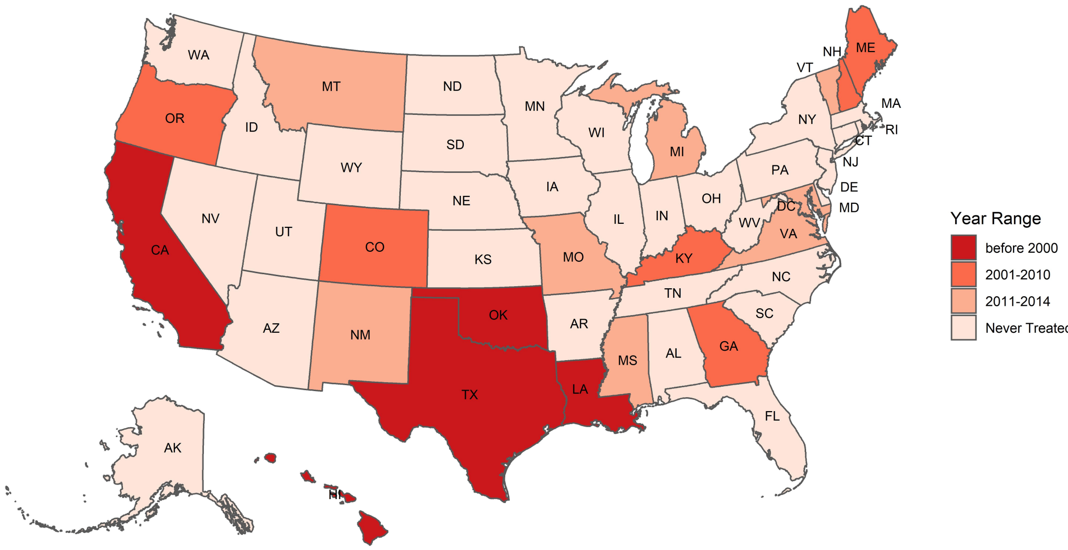
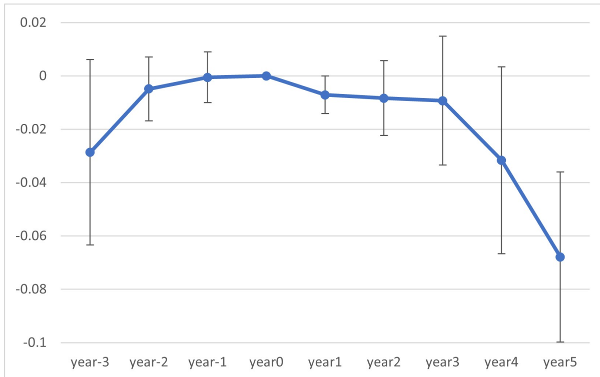
Figure 1: The Implementation of Telehealth Parity Laws Over Time



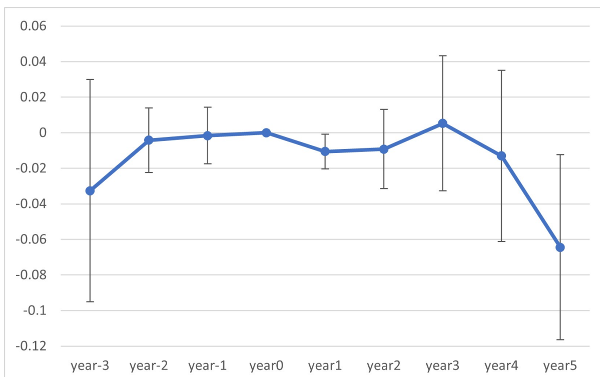
[1] This figure shows the timing of the implementation of telehealth parity laws across different states. Different colors indicate the time window of adoption, explained in the legend. During the study period, there are 5 states that passed the laws before 2000; 6 that passed the laws between 2001-2010, and 9 that passed the laws between 2011-2014. The 31 other states serve as control states, i.e. states without parity laws by 2014.

[2] According to the ATA State Telemedicine Toolkit (2017), there are 23 states that have implemented the telehealth parity laws on or before 2014. Among them, 3 states have been excluded from my treated sample since their laws became effective on 1/1/2015. In addition, the effective years of 9 other states have been revised according to each state's legislation.
The 3 excluded states are Arizona (eff. 1/1/2015, by Ariz. Laws 2013, c70,§ 4), New York (eff. 1/1/2015, by N.Y., S.B. 7852) and Tennessee (eff. 1/1/2015, by Tenn. Acts 2014, c. 675, § 1). The 9 states that have the effective year revised are California (from 1996 to 1997, by Stats 1996, c. 864, § 6), Hawaii (from 1999 to 1998, by Haw. Laws 1998, c 278, §2), Kentucky (from 2000 to 2001, by Ky. Acts 2000, c. 376, § 7), Colorado (from 2001 to 2002, by Colo. Laws 2001, c. 300, § 3), Georgia (from 2006 to 2005, by Ga. Laws 2005, c. 82, § 3), Oregon (from 2009 to 2010, by Or. Laws 2009, c. 384, § 2), Virginia (from 2010 to 2011, by Va. Acts 2010, c. 222), Missouri (from 2013 to 2014, by Mo. Laws 2013, S.B. 262), and Montana(from 2013 to 2014, by Mont. Laws 2013, c. 164, § 1). More details are available in Table A1.

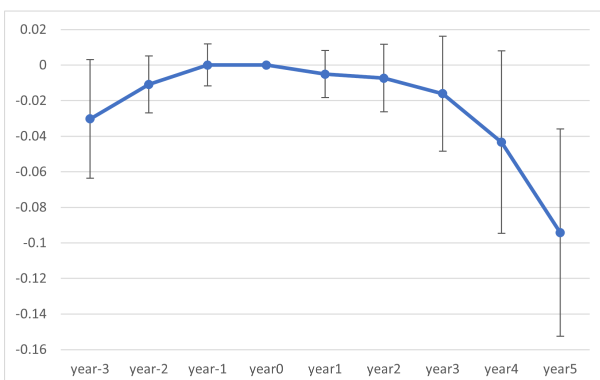
Figure 2: Event Study Analysis of Telehealth Parity Laws on Health Care Spendings (1991-2014)



(a) Total Cost



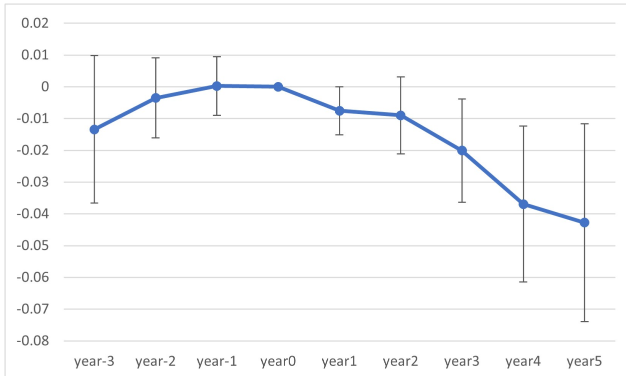
(b) Hospital Care



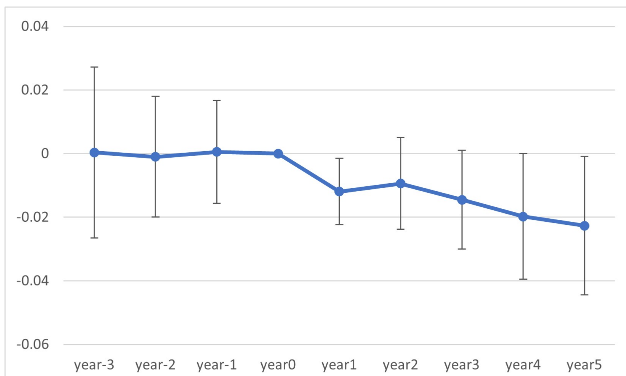
(c) Physician & Clinical Services

[1] Each figure presents the estimates from a separate regression, in which the outcome variable is total cost, hospital cost, and physician & clinical services cost, respectively. The health expenses data (1991-2014) are from Centers for Medicare & Medicaid Services (CMS).
[2] The treatment variable is a binary indicator capturing if the state ever adopted the telehealth parity laws.
[3] Regressions include year fixed effects and state fixed effects; standard errors are clustered at the state level. Event time relative to when a state adopts a telehealth parity laws is represented on the x-axis; coefficients are relative to the excluded period of the year prior to policy adoption. Error bars represent the 95% confidence intervals. Values have been reported in Table 3.

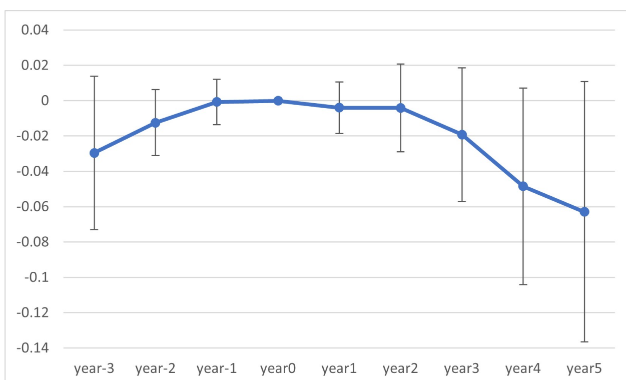
Figure 3: Event Study Analysis of Telehealth Parity Laws on Health Care Spendings, Controlled for State-specific Linear Trends (1991-2014)



(a) Total Cost



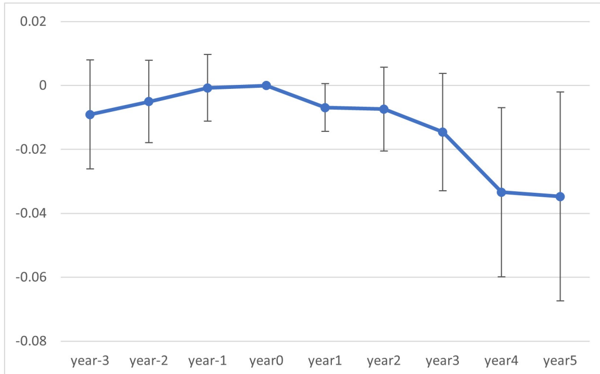
(b) Hospital Care



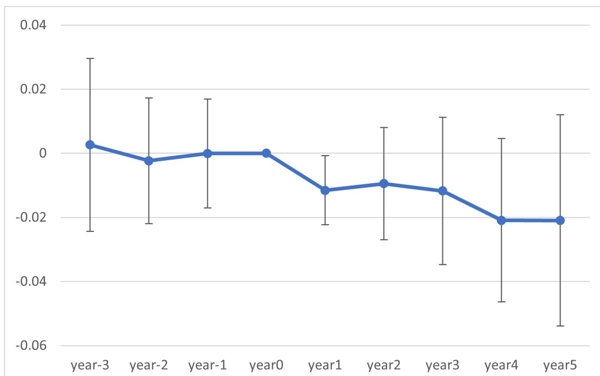
(c) Physician & Clinical Services

[1] Each figure presents the estimates from a separate regression, in which the outcome variable is total cost, hospital cost, and physician & Clinical services cost, respectively. The health expenses data (1991-2014) are from Centers for Medicare & Medicaid Services (CMS).
[2] The treatment variable is a binary indicator capturing if the state ever adopted the telehealth parity laws.
[3] Regressions include year fixed effects and state fixed effects; standard errors are clustered at the state level. Event time relative to when a state adopts a telehealth parity laws is represented on the x-axis; coefficients are relative to the excluded period of the year prior to policy adoption. Error bars represent the 95% confidence intervals. Values have been reported in Table A7.

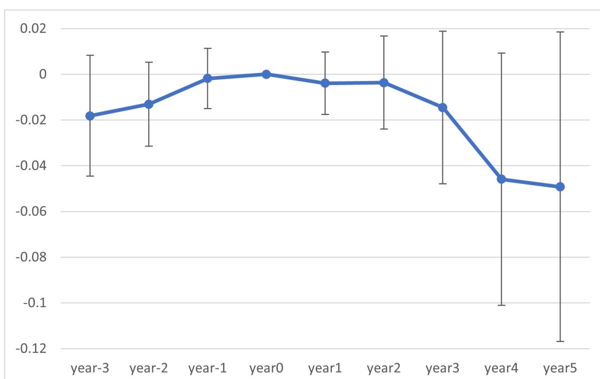
Figure 4: Event Study Analysis of Telehealth Parity Laws on Health Care Spendings by Stacked Clean Control Estimation (1991-2014)



(a) Total Cost



(b) Hospital Care

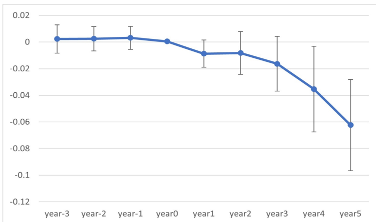


(c) Physician & Clinical Services

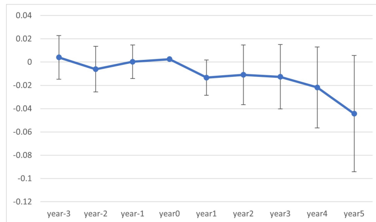
[1] Each figure presents the estimates from a separate regression, in which the outcome variable is total cost, hospital cost, and physician & clinical services cost, respectively. The health expenses data (1991-2014) are from Centers for Medicare & Medicaid Services (CMS).
[2] The treatment variable is a binary indicator capturing if the state ever adopted the telehealth parity laws.
[3] Regressions include year fixed effects and state fixed effects; standard errors are clustered at the state level. Event time relative to when a state adopts a telehealth parity laws is represented on the x-axis; coefficients are relative to the excluded period of the year prior to policy adoption. Error bars represent the 95% confidence intervals. Values have been reported in Table A8.

Figure 5: Event Study Analysis of Telehealth Parity Laws on Health Care Spendings by CS Estimation (1991-2014)

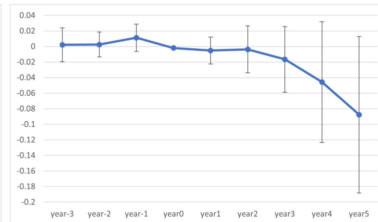
5.1 Control Group: Not Yet Treated



(a) Total Cost

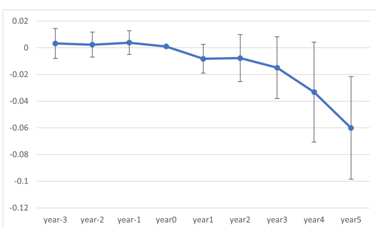


(b) Hospital Care

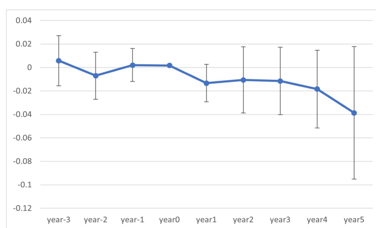


(c) Physician & Clinical Services

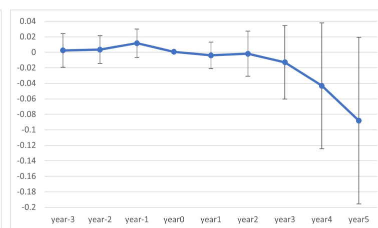
5.2 Control Group: Never Treated



(d) Total Cost



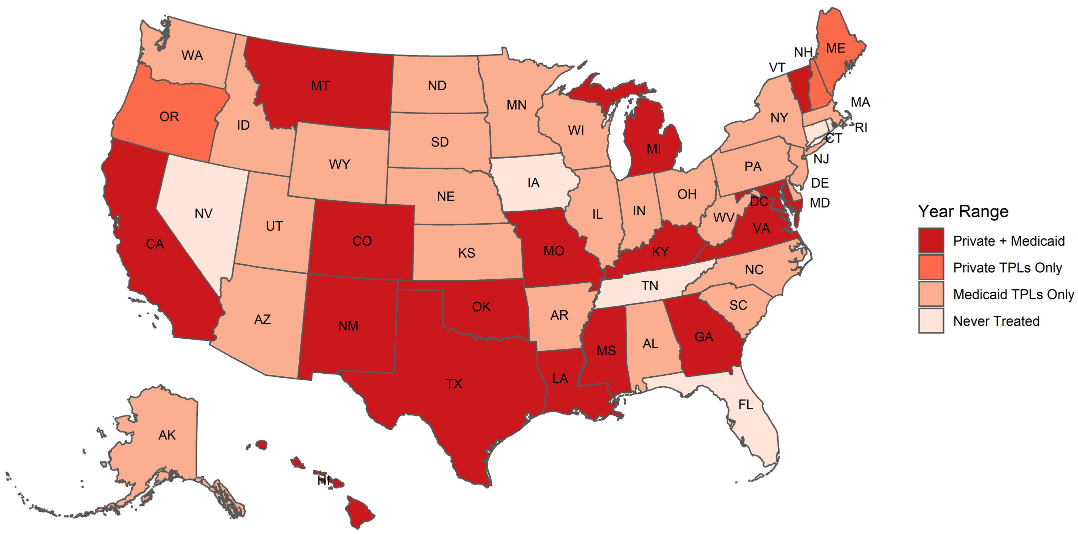
(e) Hospital Care



(f) Physician & Clinical Services

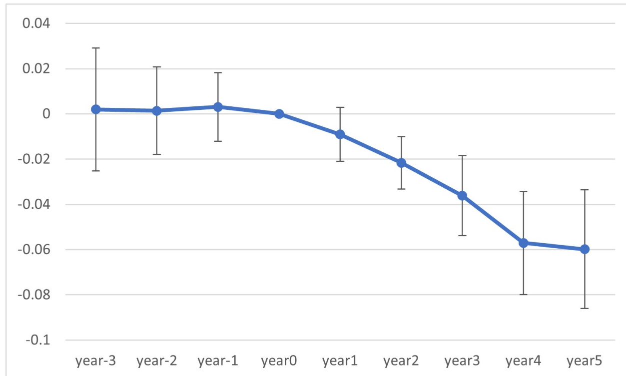
[1] Each figure presents the estimates from a separate regression, in which the outcome variable is as specified in the panel label. The health expenses data (1991-2014) are from Centers for Medicare & Medicaid Services (CMS).
[2] The treatment variable is a binary indicator capturing if the state ever adopted the telehealth parity laws.
[3] Values are estimated in R using the did Package by Callaway, Brantly and Pedro H.C. Sant'Anna (2020). Error bars represent the 95% conffidence intervals. The estimate for year5 is the averaged effect of year 4th to year 7th after adoption, and the estimate for year-3 is the averaged effect of year-4 to year-7 prior to adoption. Values have been reported in Table A9.

Figure 6: The Implementation of Telehealth Parity Laws and Medicaid coverage by 2014

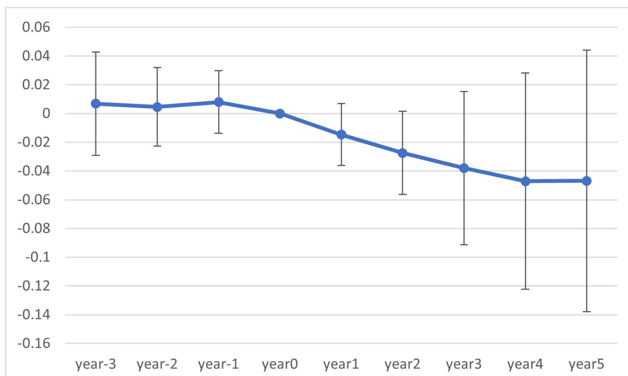


1 This figure shows the distribution of Medicaid TPLs compared to private TPLs by 2014, that 17 out of 51 states have required coverage in both private health plan and in Medicaid; 3 states have private TPLs only, 25 states have Medicaid telehealth coverage only, and 6 states have never been treated by any of these laws or policies. The detailed effective data of Medicaid TPLs is listed in Table A4.

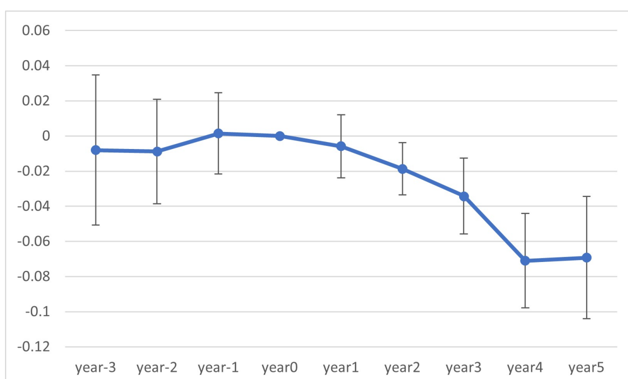
Figure 7: Event Study Analysis of Telehealth Parity Law on Health Care Spendings by Stacked Clean Control Estimation of early adopters (1991-2009)



(a) Total Cost



(b) Hospital Care



(c) Physician & Clinical Services

[1] Each figure presents the estimates from a separate regression, in which the outcome variable is total cost, hospital cost, and physician & clinical services cost, respectively. The health expenses data (1991-2014) are from Centers for Medicare & Medicaid Services (CMS).
[2] The treatment variable is a binary indicator capturing if the state ever adopted the telehealth parity laws.
[3] Regressions include year fixed effects and state fixed effects; standard errors are clustered at the state level. Event time relative to when a state adopts a telehealth parity laws is represented on the X-axis; coefficients are relative to the excluded period of the year prior to policy adoption. Error bars represent the 95% confidence intervals. Values have been reported in Table A10.

Table 1: Descriptive Statistics (1991-2014)

	(1) Full Sample		(2) Not-adopting States		(3) Adopting States		(4) p-Value
	1991	2014	1991	2014	1991	2014	1991
Total Health Expenses	2601.54	8336.81	2621.15	8445.31	2571.13	8168.62	.67
Hospital Care	1077.79	3331.72	1070.48	3339.18	1089.12	3320.15	.78
Physician & Clinical Services	649.35	1860.54	651.32	1890.01	646.28	1814.84	.88
Others	874.40	3144.55	899.35	3216.12	835.73	3033.63	.16
GDP per Capita	26500.26	53296.07	25989.38	52713.18	27292.11	54199.55	.65
Population-weighted Density	577.63	635.22	445.09	511.71	783.08	826.66	.42
Demographics							
Female (%)	51.10	50.61	51.08	50.53	51.13	50.74	.85
Native American or Inuit (%)	1.62	2.19	1.65	2.18	1.58	2.21	.94
Asian or Pac. Islander (%)	2.92	5.13	1.63	3.95	4.91	6.96	.20
African American (%)	10.85	12.31	8.91	10.88	13.84	14.52	.16
White (%)	84.61	80.37	87.80	82.99	79.67	76.31	.04
Hispanic or Latino (%)	5.54	11.35	4.51	10.73	7.14	12.29	.23
Age 0-4 (%)	7.50	6.24	7.46	6.29	7.56	6.16	.61
Age 5-19 (%)	21.57	19.40	21.60	19.60	21.53	19.09	.92
Age 20-34 (%)	24.24	20.83	23.96	20.64	24.67	21.11	.17
Age 35-54 (%)	25.86	25.87	25.61	25.74	26.25	26.08	.10
Age 55-64 (%)	8.29	12.90	8.40	12.85	8.12	12.98	.19
Age 65+ (%)	12.53	14.76	12.96	14.88	11.86	14.58	.07
High school or up (%)	76.22	88.54	76.61	88.88	75.62	88.02	.54
Bachelor's or up (%)	20.02	29.72	19.29	28.89	21.14	30.99	.12
# of States	51	51	31	31	20	20	51
# of Observations	969	255	589	155	380	100	51

[1] Shown are the differences in health expenses, income, and demographic characteristics among the full sample (50 states and D.C.), states adopting telehealth parity laws (19 states and D.C.), and states not adopting the TPLs (31 states) between 1991 and 2014. P-values from T-tests between non-adopting states and adopting states for each variable in 1991 are reported in column (4). Compared to other pre-treatment years, 1992-1994, the significance levels are similar.

[2] Per the method by Ottensmann (2018), the population-weighted density data is calculated by the author with census data from counties (`https://www.census.gov/library/publications/2012/dec/cph-2.html`). Since the census data is decennial, the values of 1991 and 2014 are represented by density data from 1990 and 2010, respectively.

[3] Education attainment data are of people aged 25 years and over. Due to data limitation, the values of 1991 are represented by education attainment data in 1990 from Digest of Educational Statistics 2000. The said values for 2014 are represented by education attainment data in 2014 from Digest of Educational Statistics 2005.

[4] Other data sources include: health expenses data from Centers for Medicare & Medicaid Services (CMS); the GDP data from the U.S. Bureau of Economic Analysis; the resident population data from the U.S. Bureau of Census; gender ratio, ethnic ratio, and age group breakdown from CDC's WONDER online database.

Table 2: Effects of Telehealth Parity Laws on Health Care Spendings (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Parity Laws	-0.0391**	-0.0296	-0.0593**
	(0.02)	(0.03)	(0.03)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	1224	1224	1224
R-squared	0.987	0.968	0.970

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

[2] Results are obtained from staggered DiD design, which takes the two-way fixed effect (TWFE) form. The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). The treatment variable is a dummy variable that equals one when it is two years or more after a state's telehealth parity laws became effective. As a control variable, GDP *per capita* was included in all models. Standard errors are clustered at the state level.

Table 3: Dynamic Effects of Telehealth Parity Laws on Health Care Spendings (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Year $t_s^* - 4^+$	-0.0287	-0.0326	-0.0302*
	(0.02)	(0.03)	(0.02)
Year $t_s^* - 3$	-0.0049	-0.0042	-0.0108
	(0.01)	(0.01)	(0.01)
Year $t_s^* - 2$	-0.0005	-0.0016	0.0001
	(0.00)	(0.01)	(0.01)
Year t_s^*	-0.0071**	-0.0106**	-0.0051
	(0.00)	(0.00)	(0.01)
Year $t_s^* + 1$	-0.0083	-0.0092	-0.0073
	(0.01)	(0.01)	(0.01)
Year $t_s^* + 2$	-0.0093	0.0053	-0.0161
	(0.01)	(0.02)	(0.02)
Year $t_s^* + 3$	-0.0316*	-0.0130	-0.0433*
	(0.02)	(0.02)	(0.03)
Year $t_s^* + 4^+$	-0.0679***	-0.0644**	-0.0942***
	(0.02)	(0.03)	(0.03)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	1224	1224	1224
R-squared	0.988	0.968	0.971

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

[2] The outcome variables are state level health expenses data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). As a control variable, GDP *per capita* was in all models. Standard errors are clustered at the state level.

Table 4: Effects of Telehealth Parity Laws on Health Care Spendings, Controlled for State-specific Linear Trends (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Parity Laws	-0.0275**	-0.0139*	-0.0370
	(0.01)	(0.01)	(0.02)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	1224	1224	1224
R-squared	0.997	0.994	0.987

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

[2] Results are obtained from staggered DiD design, which takes two-way fixed effect (TWFE) form. Furthermore, state specific linear trends have been controlled in all models, in line with the observed linearly increasing trends in the time before implementation in treatment states relative to controls in Table 3. The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). The treatment variable is a dummy variable that equals one when it is two or more years after a state's telehealth parity laws became effective. As a control variable, GDP *per capita* was included in all models. Standard errors are clustered at the state level.

Table 5: Robustness Check: Effects by CS estimation (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Control Group: Not yet Treated			
Parity Laws	-0.0500***	-0.0600***	-0.0716***
	(0.010)	(0.022)	(0.024)
Control Group: Never Treated			
Parity Laws	-0.0486***	-0.0569***	-0.0712***
	(0.010)	(0.021)	(0.024)

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.
[2] Values are estimated in R using the did Package by Callaway, Brantly and Pedro H.C. Sant'Anna (2020). The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS).The treatment variable is a dummy variable that equals one when it is two or more years after a state's telehealth parity laws became effective. As a control variable, GDP *per capita* was included in all models. Standard errors are clustered at the state level.

Table 6: The Implementation of Telehealth Parity Laws

State	Coverage Parity	Payment Parity	Cost-shifting Protection
Louisiana	1995(LTD)	1995	×
California	1997	×	×
Oklahoma	1997	×	×
Texas	1997	×	1997
Hawaii	1998	2014	×
Kentucky	2001	×	2001
Colorado	2002(LTD)	×	×
Georgia	2005	×	×
Maine	2009	×	2009
New Hampshire	2009	×	×
Oregon	2010	×	×
Virginia	2011	2011	2011
Maryland	2012	×	×
Michigan	2012	×	×
Vermont	2012	×	2012
Mississippi	2013	×	2013
New Mexico	2013	×	×
District of Columbia	2013	×	2013
Missouri	2014	2014	2014
Montana	2014	×	×

[1] This table reports the year that specific parity laws were adopted by each state. The sample period is 1991-2014, during which 19 states and the District of Columbia have enacted coverage parity laws; 4 states have passed payment parity laws; and 7 states and the D.C. have released cost-shifting protection laws. The state of Virginia and Missouri are the only 2 states that have adopted all three laws.

[2] Coverage parity laws require health plans to cover a health care service delivered via telehealth if the insurer would cover the same service if it were provided during an in-person consultation. Some states use the language prohibiting private health plans from excluding a medical service solely because the service is provided through telehealth/ telemedicine. The others require health insurance plans to provide coverage for telemedicine services to the same extent that the service would be covered if they were provided through in-person consultation.

[3] Payment parity laws govern the situation in which a state law expressly addresses payment and reimbursement rates for telehealth services compared to in-person health care. For some states, the language used is “at the same reimbursement rate”. For other states, the language pertaining to reimbursement sets a ceiling, or floor.

[4] Cost-shifting protection refers to the situation in which the state law prohibits a health plan from a charging any greater deductible, copayment, or coinsurance amount than would be applicable if the same health care was provided through face-to-face diagnosis, consultation, or treatment. The language used by each states varies. Details are provided in Table A1, Table A3, and Table A4.

Table 7: Robustness Check: Effects by Refined Treatment Dummies (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Coverage parity	-0.0551**	-0.0394	-0.0849**
	(0.02)	(0.03)	(0.04)
Payment parity	-0.0156	-0.0797**	0.0457
	(0.03)	(0.04)	(0.03)
Cost-shifting	0.0588*	0.0622	0.0676**
	(0.03)	(0.05)	(0.03)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	1224	1224	1224
R-squared	0.988	0.968	0.971

[1] Standard errors are reported in parentheses. Significance levels are indicated by * < .1, ** < .05, *** < .01.

[2] Results are obtained from staggered DiD design, which takes two-way fixed effect (TWFE) form. The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). The treatment variables are three dummy variables that equal one when it is two or more years after a state's coverage parity laws, payment parity laws, or cost-shifting protection became effective, respectively. As a control variable, *GDP per capita* has been included in all models. Standard errors are clustered at the state level.

Table 8: Robustness Check: Effects on Health Care Spendings with Contemporary Policies under Control (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Panel A: Adding Medicaid			
Coverage parity	-0.0370*	-0.0235	-0.0564**
	(0.02)	(0.03)	(0.03)
Medicaid	-0.0057	-0.0170	-0.0078
	(0.01)	(0.02)	(0.02)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	1224	1224	1224
R-squared	0.987	0.968	0.970
Panel B: Earlier Adopters			
Coverage parity	-0.0558***	-0.0493**	-0.0745**
by 2012	(0.02)	(0.02)	(0.03)
N	1122	1122	1122
R-squared	0.987	0.966	0.969
Coverage parity	-0.0616***	-0.0579**	-0.0783**
by 2011	(0.02)	(0.02)	(0.03)
N	1071	1071	1071
R-squared	0.987	0.965	0.968
Coverage parity	-0.0677***	-0.0680***	-0.0822**
by 2010	(0.02)	(0.02)	(0.03)
N	1020	1020	1020
R-squared	0.987	0.964	0.966
State FE	Y	Y	Y
Year FE	Y	Y	Y

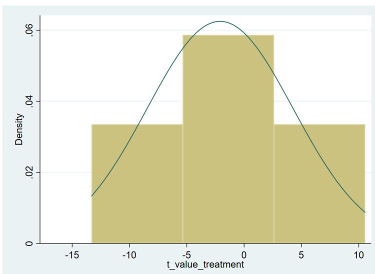
[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

[2] Results are obtained from staggered DiD design, which takes two-way fixed effect (TWFE) form. The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). The treatment variables are two dummy variables that equal one when it is two or more years after a state's private parity laws or Medicaid parity laws became effective, respectively. As a control variable, GDP *per capita* has been included in all models. Standard errors are clustered at the state level.

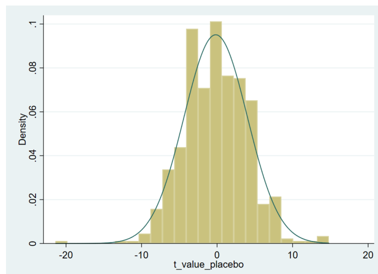
Appendices

Figure A1: Synthetic Control Analysis of Telehealth Parity Law on Total Health Care Spending (1991-2014)

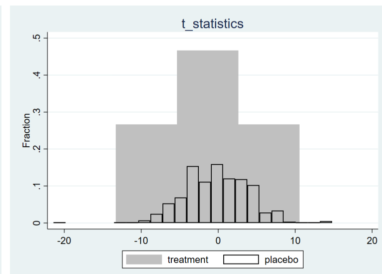
5.1 Without Lagging Effect



(a) t-values of Treated States

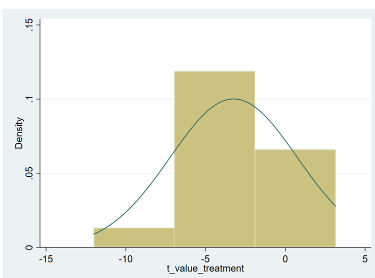


(b) t-values of Placebo States

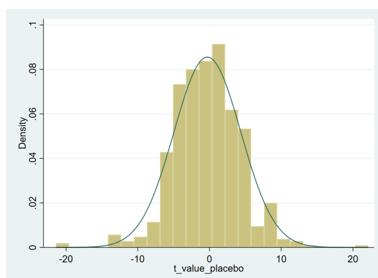


(c) Comparison of t-values Between Treated and Placebo States

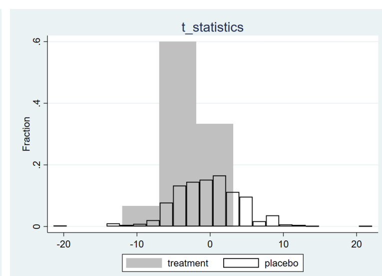
5.2 One Year Lag



(d) t-values of Treated States

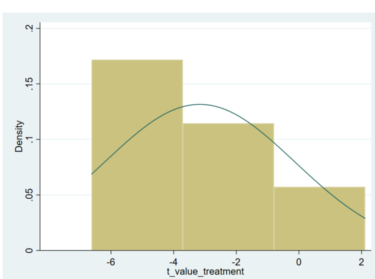


(e) t-values of Placebo States

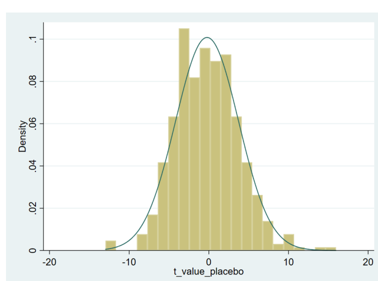


(f) Comparison of t-values Between Treated and Placebo States

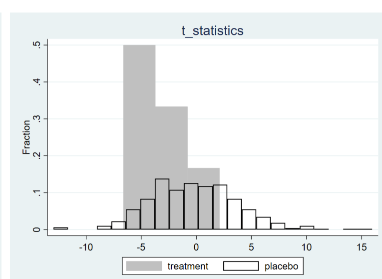
5.3 Two Years Lag



(g) t-values of Treated States



(h) t-values of Placebo States



(i) Comparison of t-values Between Treated and Placebo States

[1] The health expenses data (1991-2014) are from Centers for Medicare & Medicaid Services (CMS).

Table A1: Coverage Parity Laws of Each State

State	Statutes, codes, and regulations (source)
Louisiana (LTD)	Notwithstanding any provision of any policy or contract of insurance or health benefits issued, whenever such policy provides for payment, benefit, or reimbursement for any health care service, including but not limited to diagnostic testing, treatment, referral, or consultation, and such health care service is performed via transmitted electronic imaging or telemedicine, such a payment, benefit, or reimbursement under such policy or contract shall not be denied to a licensed physician conducting or participating in the transmission at the originating health care facility or terminus who is physically present with the individual who is the subject of such electronic imaging transmission and is contemporaneously communicating and interacting with a licensed physician at the receiving terminus of the transmission (La. Stat. tit. 22 § 1821, added by La. Acts 1995, No. 391, §1 (Unavaible online, see La. Acts 1997, Act 1313, §3 (H.B. 785)) for reference).
California	No health care service plan contract that is issued, amended, or renewed shall require face-to-face contact between a health care provider and a patient for services appropriately provided through telemedicine, subject to all terms and conditions of the contract agreed upon between the enrollee or subscriber and the plan (Cal. Health and Saf. Code § 1374.13, added by Stats 1996, c. 864, § 6 (S.B. 1665), eff. 1/1/1997).
Oklahoma	For services that a health care practitioner determines to be appropriately provided by means of telemedicine, health care service plans, disability insurer programs, or state Medicaid managed care program contracts issued, amended, or renewed on or after January 1, 1998, shall not require person-to-person contact between a health care practitioner and a patient (Okla. Stat. tit. 36, § 6803, added by Okla. Laws 1997, c. 209, § 3 (S.B. 48), eff. 7/1/1997).
Texas	It is prohibited that certain health benefit plans exclude a medical service solely because the service is provided through telemedicine. Telemedicine services may be subject to deductible, copayment, or coinsurance requirements not to exceed requirements for the same face-to-face services (Tex. Ins. Code § 1455.004, added by Tex. Acts 1997, 75th Leg., c. 1 (H.B. 2033), eff. 9/1/1997).
Hawaii	No health maintenance organization plan that is issued, amended, or renewed shall require face-to-face contact between a health care provider and a patient as a prerequisite for payment for services appropriately provided through telehealth in accordance with generally accepted health care practices and standards prevailing in the applicable professional community at the time the services were provided. (Haw. Rev. Stat. § 431:10A-116.3, added by Haw. Laws 1998, c 278, § 2 (H.B. 2852), eff. 7/1/1998).
Kentucky	A health benefit plan shall not exclude a service from coverage solely because the service is provided through telehealth and not provided through a face-to-face consultation if the consultation is provided through the telehealth network established (Ky. Rev. Stat. § 304.17A-138, added by Ky. Acts 2000, c. 376, § 7 (H.B. 177), eff. 7/15/2001).

Table A1 Continued: Coverage Parity Laws of Each State

State	Statutes, codes, and regulations (source)
Colorado (LTD)	No health benefit plan that is issued, amended, or renewed for a person residing in a county with one hundred fifty thousand or fewer residents may require face-to-face contact between a provider and a covered person for services appropriately provided through telemedicine (Colo. Rev. Stat. § 10-16-123, added by Colo. Laws 2001, c. 300, § 3 (S.B. 01-224), eff. 1/1/2002).
Georgia	No health benefit policy that is issued, amended, or renewed shall require face-to-face contact between a health care provider and a patient as a prerequisite for payment for services appropriately provided through telemedicine in accordance with generally accepted health care practices and standards prevailing in the applicable professional community at the time the services were provided (Ga. Code § 33-24-56.4, added by Ga. Laws 2005, c. 82, § 3 (H.B. 310), eff. 7/1/2005).
Maine	A carrier offering a health plan in this State may not deny coverage on the basis that the coverage is provided through telemedicine if the health care service would be covered were it provided through in-person consultation between the covered person and a health care provider. Coverage for health care services provided through telemedicine must be determined in a manner consistent with coverage for health care services provided through in-person consultation (Me. Stat. tit. 24-A §4316, added by Me. Laws 2009, c. 169, § 1 (NEW, HP0740), eff. 9/12/2009).
New Hampshire	An insurer offering a health plan in this state may not deny coverage on the sole basis that the coverage is provided through telemedicine if the health care service would be covered if it were provided through in-person consultation between the covered person and a health care provider (N.H. Rev. Stat. § 415-J:3, added by N.H. Acts 2009, c. 259:1 (S.B. 138FN), eff. 10/14/2009).
Oregon	A health benefit plan must provide coverage of a telemedical health service if the plan provides coverage of the health service when provided in person by the health professional (Or. Rev. Stat. § 743A.058, added by Or. Laws 2009, c. 384, § 2 (S.B. 24), eff. 1/1/2010).
Virginia	An insurer, corporation, or health maintenance organization shall not exclude a service for coverage solely because the service is provided through telemedicine services and is not provided through face-to-face consultation or contact between a health care provider and a patient for services appropriately provided through telemedicine services (Va. Code § 38.2-3418.16, added by Va. Acts 2010, c. 222 (S.B. 575), eff. 1/1/2011).
Maryland	An entity subject to this section may not exclude from coverage a health care service solely because it is provided through telemedicine and is not provided through an in-person consultation or contact between a health care provider and a patient (Md. Code, Ins. § 15-139, added by Md. Laws 2012, c. 579 (S.B. 718), eff. 10/1/2012).
Michigan	An expense-incurred hospital, medical, or surgical group or individual policy or certificate delivered, issued for delivery, or renewed in this state and a health maintenance organization group or individual contract shall not require face-to-face contact between a health care professional and a patient for services appropriately provided through telemedicine, as determined by the insurer or health maintenance organization (Mich. Comp. Laws § 500.3476, added by Mich. Acts 2012, Act 215 (H.B. 5421), eff. 6/28/2012).

Table A1 Continued: Coverage Parity Laws of Each State

State	Statutes, codes, and regulations (source)
Vermont	All health insurance plans in this state shall provide coverage for telemedicine services delivered to a patient in a health care facility to the same extent that the services would be covered if they were provided through in-person consultation (Vt. Stat. tit. 8 § 4100k, added by Vt. Acts 2012, No. 107, § 1 (H.B. 37), eff. 10/1/2012).
Mississippi	All health insurance plans in this state must provide coverage for telemedicine services to the same extent that the services would be covered if they were provided through in-person consultation (Miss. Code § 83-9-351, added by Miss. Laws 2013, c. 478 (H.B. 904), eff. 7/1/2013).
New Mexico	An individual or group health insurance policy, health care plan or certificate of health insurance that is delivered, issued for delivery or renewed in this state shall allow covered benefits to be provided through telemedicine services. Coverage for health care services provided through telemedicine shall be determined in a manner consistent with coverage for health care services provided through in-person consultation (N.M. Stat. § 59A-22-49.3, added by N.M. Laws 2013, c. 105, § 2 (H.B. 171), eff. 6/14/2013).
District of Columbia	A health insurer offering a health benefits plan in the District may not deny coverage for a healthcare servi ce on the basis that the service is provided through telehealth if the same service would be covered when delivered in person (D.C. Code § 31-3862, added by D.C. Law 20-26, § 3, 60 DCR 11117, eff. 10/17/2013).
Missouri	Under this act, health carriers shall not deny coverage for a health care service on the basis that the service was provided through telehealth if the same service would be covered when delivered in person. A health carrier may not exclude an otherwise covered health care service from coverage solely because the service is provided through telehealth rather than face-to-face consultation or contact between a health care provider and a patient (Mo. Rev. Stat. § 376.1900, added by Mo. Laws 2013, S.B. 262, eff. 1/1/2014).
Montana	Each group or individual policy, certificate of disability insurance, subscriber contract, membership contract, or health care services agreement that provides coverage for health care services must provide coverage for health care services provided by a health care provider or health care facility by means of telemedicine if the services are otherwise covered by the policy, certificate, contract, or agreement. Coverage under this section must be equivalent to the coverage for services that are provided in person by a health care provider or health care facility. (Mont. Code § 33-22-138, added by Mont. Laws 2013, c. 164, § 1, eff. 1/1/2014).

Table A2: Coverage for Telehealth by State Medicaid Programs

State	Source	Effective data
Alabama	Title XIX State Plan Amendment,09-008	2/1/2010
Alaska	Alaska Admin.Code §110.620	2/1/2010
Arizona	Telemedicine and E-health Law (2004)	2004
Arkansas	Telemedicine and E-health Law (2004)	2004
California	Stats 1996, c. 864, § 6 (S.B. 1665)	1/1/1997
Colorado	Colo. Rev. Stat. §25.5-5-320	1/1/2006
Connecticut	CT Public Act No. 16-198	7/1/2016
Delaware	Delaware Health and Social Services News	7/1/2012
D.C.	D.C. Code § 31-3863	10/17/2013
Florida	Fla. Admin. Code R. 59G-1.057	6/20/16
Georgia	Telemedicine and E-health Law (2004)	2004
Hawaii	Haw. Code R. § 17-1737-51.1	2/7/05
Idaho	Medicaid Basic Plan Benefits	5/8/2009
Illinois	Telemedicine and E-health Law (2004)	2004
Indiana	Ind. Code § 12-15-5-11	7/1/2013
Iowa	IA Senate File 505 (2015)	2015
Kansas	Telemedicine and E-health Law (2004)	2004
Kentucky	Ky. Rev. Stat. § 205.559	7/15/2001
Louisiana	Telemedicine and E-health Law (2004)	2004
Maine	MaineCare Benefits Manual, Telehealth	4/15/2016
Maryland	Medical Assistant Program, Telemedicine	10/1/2013
Massachusetts	S.B. 534	03/2009
Michigan	Medicaid Policy Bulletin MSA 06-22	5/1/2006
Minnesota	Minn. L. 1999, c 245, art 4, s 37	7/1/2001
Mississippi	Miss. Code § 83-9-351	7/1/2013
Missouri	Mo.L.2007, S.B. 577	2007
Montana	Telemedicine and E-health Law (2004)	2004
Nebraska	Laws 1999, LB 559, § 6	7/1/2000
Nevada	Nev. Rev. Stat. § 422.2721	7/1/2015
New Hampshire	N.H. Rev. Stat. § 167:4-d	7/6/2015
New Jersey	NJ Department of Human Services Division of Medical Assistance & Health Services, December 2013 Newsletter	12/2013
New Mexico	N.M. Code R. § 8.310.2.12	1/1/14
New York	N.Y. Dept. of Health, Medicaid Update	9/1/2006

Table A2 Continued: Coverage for Telehealth by State Medicaid Programs

State	Source	Effective data
North Carolina	NC Div. of Medical Assistance, Medicaid and Health Choice Manual, Clinical Coverage Policy No: 1H, Telemedicine and Telepsychiatry	8/1/1999
North Dakota	Telemedicine and E-health Law (2004)	2004
Ohio	Ohio Rev. Code § 5164.95	5/20/2014
Oklahoma	Okla. L. 1997, c. 209, § 3	7/1/1997
Oregon	DMAP 32-2015, f. 6-24-15	6/26/15
Pennsylvania	Dept. of Public Welfare, Notices, 37 Pa.B. 6237	11/24/2007
Rhode Island	Rhode Island Medicaid Fee Schedule	2017
South Carolina	SC Health and Human Services Dept. Physicians Provider Manual, s 2	10/1/11
South Dakota	Telemedicine and E-health Law (2004)	2004
Tennessee	Tenn. Code § 56-7-1002	1/1/2015
Texas	75th Legislature H.B. 2386, 75th Legislature	9/1/1997
Utah	Telemedicine and E-health Law (2004)	2004
Vermont	Vt. Acts 2012, No. 107, § 1 (H.B. 37)	10/1/2012
Virginia	Telemedicine and E-health Law. (2004)	2004
Washington	WAC 182-531-0100	9/28/13
West Virginia	Telemedicine and E-health Law. (2004)	2004
Wisconsin	Wis. Acts 2013, ch, 20,s 1043s	7/2/2013
Wyoming	Wyoming Medicaid 2016 Access Monitoring Review Plan	2007

Table A3: Payment Parity Law of Each State

State	Statutes, codes, and regulations (source)
Louisiana	The payment, benefit, or reimbursement to such a licensed physician at the originating facility or terminus shall not be less than seventy-five percent of the reasonable and customary amount of payment, benefit, or reimbursement which that licensed physician receives for an intermediate office visit (La. Stat. tit. 22 § 1821, added by La. Acts 1995, No. 391, §1 (Unavailable online), eff. 6/16/1995)
California	×
Oklahoma	×
Texas	×
Hawaii	Require equivalent insurance reimbursement for services, including behavioral health services, provided by a health care provider to a patient regardless of whether the service is provided through telehealth or via face-to-face contact between health care provider and patient; (Haw. Rev. Stat. § 431:10A-116.3, added by Haw. Law 2014, c 159,§ 3 (S.B.2469), eff. 6/30/2014).
Kentucky	×
Colorado	×
Georgia	×
Maine	×
New Hampshire	×
Oregon	×
Virginia	An insurer, corporation, or health maintenance organization shall not be required to reimburse the treating provider or the consulting provider for technical fees or costs for the provision of telemedicine services; however, such insurer, corporation, or health maintenance organization shall reimburse the treating provider or the consulting provider for the diagnosis, consultation, or treatment of the insured delivered through telemedicine services on the same basis that the insurer, corporation, or health maintenance organization is responsible for coverage for the provision of the same service through face-to-face consultation or contact (Va. Code § 38.2-3418.16, added by Va. Acts 2010, c. 222 (S.B. 575), eff. 1/1/2011).
Maryland	×
Michigan	×
Vermont	×
Mississippi	×
New Mexico	×
District of Columbia	×
Missouri	A health carrier must reimburse a telehealth provider for the diagnosis, consultation, or treatment of an insured delivered through telehealth on the same basis that the health carrier covers the service when it is delivered in person (Mo. Rev. Stat. § 376.1900, added by Mo. Laws 2013 (S.B. 262), eff. 1/1/2014).
Montana	×

Table A4: Cost-shifting Protection of Each State

State	Statutes, codes, and regulations (source)
Louisiana	×
California	×
Oklahoma	×
Texas	A deductible, copayment, or coinsurance applicable to a particular service provided through telemedicine may not exceed the deductible, copayment, or coinsurance required by the health benefit plan for the same service provided through a face-to-face consultation (Tex. Ins. Code § 1455.004, added by Tex. Acts 1997, 75th Leg., c. 1 (H.B. 2033), eff. 9/1/1997)..
Hawaii	×
Kentucky	A deductible, copayment, or coinsurance applicable to a particular service provided through telehealth shall not exceed the deductible, copayment, or coinsurance required by the health benefit plan for the same service provided through a face-to-face consultation (Ky. Rev. Stat. § 304.17A-138, added by Ky. Acts 2000, c. 376, § 7 (H.B. 177), eff. 7/15/2001).
Colorado	×
Georgia	×
Maine	A carrier may offer a health plan containing a provision for a deductible, copayment or coinsurance requirement for a health care service provided through telemedicine as long as the deductible, copayment or coinsurance does not exceed the deductible, copayment or coinsurance applicable to an in-person consultation (Me. Stat. tit. 24-A §4316, added by Me. Laws 2009, c. 169, § 1 (NEW, HP0740), eff. 9/12/2009).
New Hampshire	×
Oregon	×
Virginia	An insurer, corporation, or health maintenance organization may offer a health plan containing a deductible, copayment, or coinsurance requirement for a health care service provided through telemedicine services, provided that the deductible, copayment, or coinsurance does not exceed the deductible, copayment, or coinsurance applicable if the same services were provided through face-to-face diagnosis, consultation, or treatment (Va. Code § 38.2-3418.16, added by Va. Acts 2010, c. 222 (S.B. 575), eff. 1/1/2011).
Maryland	×
Michigan	×
Vermont	A health insurance plan may charge a deductible, co-payment, or coinsurance for a health care service provided through telemedicine so long as it does not exceed the deductible, co-payment, or coinsurance applicable to an in-person consultation (Vt. Stat. tit. 8 § 4100k, added by Vt. Acts 2012, No. 107, § 1 (H.B. 37), eff. 10/1/2012).
Mississippi	A health insurance plan may charge a deductible, co-payment, or coinsurance for a health care service provided through telemedicine so long as it does not exceed the deductible, co-payment, or coinsurance applicable to an in-person consultation (Miss. Code § 83-9-351, added by Miss. Laws 2013, c. 478 (H.B. 904), eff. 7/1/2013).
New Mexico	×

Table A4 Continued: Cost-shifting Protection of Each State

State	Statutes, codes, and regulations (source)
D.C.	A health insurer may require a deductible, copayment, or coinsurance amount for a healthcare service delivered through teleheath; provided, that the deductible, copayment, or coinsurance amount may not exceed the amount applicable to the same service when it is delivered in person (D.C. Code § 31-3862, added by D.C. Law 20-26, § 3, 60 DCR 11117, eff. 10/17/2013).
Missouri	A health care service provided through telehealth services shall not be subject to any greater deductible, copayment, or coinsurance amount than would be applicable if the same health care service was provided through face-to-face diagnosis, consultation, or treatment (Mo. Rev. Stat. § 376.1900, added by Mo. Laws 2013 (S.B. 262), eff. 1/1/2014).
Montana	×

Table A5: Probit Regression of State Characteristics on TPLs Adoption (1991)

	Coefficient	P> $\lvert z \rvert$
Total Health Expenses	-0.058	.31
Hospital Care	0.0099	.21
Others	-0.0061	.34
GDP per Capita	-0.0002	.25
Population-Weighted Density	0.0008	.32
Demographics		
Female (%)	6.1963	.02
Native American (%)	-0.0234	.93
African American (%)	-0.5188	.14
White (%)	-0.4685	.16
Hispanic or Latino (%)	0.1654	.09
Age 5-19 (%)	1.0864	.61
Age 20-34 (%)	1.0165	.65
Age 35-54 (%)	2.9339	.14
Age 55-64 (%)	-5.1012	.08
Age 65+ (%)	1.5012	.43
High school or up (%)	0.1883	.32
Bachelor's or up (%)	-0.2631	.36
# of States	51	

[1] The outcome variable is a binary indicating the adoption of TPLs at state level. Standard errors are clustered at the state level.
[2] Per the method by Ottensmann (2018), the population-weighted density data is calculated by the author with census data from counties (https://www.census.gov/library/publications/2012/dec/cph-2.html). Since the census data is decennial, the values of 1991 is represented by density data from 1990.
[3] Education attainment data are of people aged 25 years and over. Due to data limitation, the values of 1991 are represented by education attainment data in 1990 from Digest of Educational Statistics 2000.
[4] Other data sources include: health expenses data from Centers for Medicare & Medicaid Services (CMS); the GDP data from the U.S. Bureau of Economic Analysis; the resident population data from the U.S. Bureau of Census; gender ratio, ethnic ratio, and age group breakdown from CDC's WONDER online database.

Table A6: Effects on Health Care Spendings in the Immediate Years After Implementation (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Panel A: Without Lagging Effect			
Parity Laws	-0.0168	-0.0103	-0.0276
	(0.02)	(0.03)	(0.02)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	1224	1224	1224
R-squared	0.987	0.967	0.969
Panel B: One Year Lag			
Parity Laws	-0.0276	-0.0193	-0.0430*
	(0.02)	(0.03)	(0.03)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	1224	1224	1224
R-squared	0.987	0.967	0.970

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

[2] Results are obtained from staggered DiD design, which takes two-way fixed effect (TWFE) form. The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). In Panel A, the treatment variable is a dummy variable that equals one after a state's telehealth parity laws became effective. In Panel B, the dummy treatment variable equals one when it is one or more years after a state's telehealth parity laws became effective. As a control variable, GDP *per capita* has been included in all models. Standard errors are clustered at the state level.

Table A7: Dynamic Effects of Telehealth Parity Laws on Health Care Spendings, Controlled for State-specific Linear Trends (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Year $t_s^* - 4^+$	-0.0134	0.0004	-0.0296
	(0.01)	(0.01)	(0.02)
Year $t_s^* - 3$	-0.0035	-0.0010	-0.0125
	(0.01)	(0.01)	(0.01)
Year $t_s^* - 2$	0.0003	0.0005	-0.0007
	(0.00)	(0.01)	(0.01)
Year t_s^*	-0.0076**	-0.0119**	-0.0039
	(0.00)	(0.01)	(0.01)
Year $t_s^* + 1$	-0.0090	-0.0094	-0.0041
	(0.01)	(0.01)	(0.01)
Year $t_s^* + 2$	-0.0201**	-0.0145*	-0.0192
	(0.01)	(0.01)	(0.02)
Year $t_s^* + 3$	-0.0369***	-0.0198**	-0.0485*
	(0.01)	(0.01)	(0.03)
Year $t_s^* + 4^+$	-0.0428***	-0.0227**	-0.0629*
	(0.02)	(0.01)	(0.04)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	1224	1224	1224
R-squared	0.998	0.995	0.989

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, ** < .05, *** < .01.
[2] State-specific linear trends were controlled in all models, in line with the observed linearly increasing trends in the time before implementation in treatment states relative to controls in Table 3. The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). As a control variable, GDP *per capita* has been included in all models. Standard errors are clustered at the state level.

Table A8: Dynamic Effects by Stacked Clean Control Estimation (1991-2014)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Year $t_s^* - 4$	-0.0091	0.0026	-0.0182
	(0.01)	(0.01)	(0.01)
Year $t_s^* - 3$	-0.0051	-0.0024	-0.0131
	(0.01)	(0.01)	(0.01)
Year $t_s^* - 2$	-0.0007	-0.0000	-0.0018
	(0.01)	(0.01)	(0.01)
Year t_s^*	-0.0069*	-0.0115**	-0.0039
	(0.00)	(0.01)	(0.01)
Year $t_s^* + 1$	-0.0074	-0.0095	-0.0036
	(0.01)	(0.01)	(0.01)
Year $t_s^* + 2$	-0.0146	-0.0117	-0.0145
	(0.01)	(0.01)	(0.02)
Year $t_s^* + 3$	-0.0334**	-0.0209	-0.0459
	(0.01)	(0.01)	(0.03)
Year $t_s^* + 4$	-0.0348**	-0.0209	-0.0492
	(0.02)	(0.02)	(0.03)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	4992	4992	4992
R-squared	0.998	0.994	0.992

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.
[2] The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). As a control variable, GDP *per capita* was in all models. Standard errors are clustered at the state level.

Table A9: Dynamic Effects by CS Estimation (1991-2014)

	Control Group: Not yet Treated			**Control Group: Never Treated**		
	Total Health Expense	Hospital Care	Phys & CLIN Services	Total Health Expense	Hospital Care	Phys & CLIN Services
Year $t_s^* - 7$	-0.0023	0.0008	-0.0037	-0.0014	0.003	-0.004
	(0.005)	(0.010)	(0.011)	(0.006)	(0.010)	(0.011)
Year $t_s^* - 6$	0.0037	0.0075	0.0014	0.006*	0.0114*	0.0031
	(0.004)	(0.008)	(0.005)	(0.004)	(0.009)	(0.006)
Year $t_s^* - 5$	0.0039	0.0072	0.0018	0.0044	0.0071	0.0028
	(0.003)	(0.007)	(0.007)	(0.004)	(0.007)	(0.008)
Year $t_s^* - 4$	0.0041	0.0007	0.009	0.0042	0.002	0.0081
	(0.003)	(0.004)	(0.009)	(0.003)	(0.005)	(0.009)
Year $t_s^* - 3$	0.0025	-0.0061	0.0025	0.0024	-0.007	0.0034
	(0.003)	(0.007)	(0.006)	(0.004)	(0.007)	(0.007)
Year $t_s^* - 2$	0.0032	0.0003	0.0112	0.0039	0.0021	0.0117**
	(0.003)	(0.005)	(0.006)	(0.003)	(0.005)	(0.006)
Year $t_s^* - 1$	0.0005	0.0025	-0.0019	0.001	0.0017	0.0006
	(0.005)	(0.007)	(0.006)	(0.005)	(0.008)	(0.007)
Year t_s^*	-0.0087***	-0.0133**	-0.0052	-0.0082***	-0.0133**	-0.0039
	(0.004)	(0.006)	(0.007)	(0.003)	(0.006)	(0.006)
Year $t_s^* + 1$	-0.0082*	-0.0109	-0.0037	-0.0077	-0.0106	-0.0018
	(0.005)	(0.01)	(0.011)	(0.007)	(0.01)	(0.011)
Year $t_s^* + 2$	-0.0163**	-0.0126	-0.0166	-0.0149**	-0.0115	-0.0129
	(0.008)	(0.01)	(0.015)	(0.009)	(0.011)	(0.0169)
Year $t_s^* + 3$	-0.0353***	-0.0218**	-0.0457*	-0.0332***	-0.0184*	-0.0432*
	(0.012)	(0.013)	(0.028)	(0.013)	(0.012)	(0.030)
Year $t_s^* + 4$	-0.0367***	-0.022*	-0.0481*	-0.0355**	-0.0189	-0.0482*
	(0.016)	(0.016)	(0.035)	(0.017)	(0.018)	(0.037)
Year $t_s^* + 5$	-0.0556***	-0.0399**	-0.0687**	-0.0543***	-0.0369**	-0.069*
	(0.013)	(0.018)	(0.036)	(0.015)	0.02)	(0.042)
Year $t_s^* + 6$	-0.0756***	-0.055***	-0.112***	-0.0729***	-0.0476**	-0.1125***
	(0.01)	(0.022)	(0.041)	(0.013)	(0.026)	(0.043)
Year $t_s^* + 7$	-0.0814***	-0.0603***	-0.1218***	-0.0777***	-0.0513***	-0.1232***
	(0.009)	(0.018)	(0.036)	(0.011)	(0.022)	(0.038)

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.
[2] The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). As a control variable, GDP *per capita* has been included in all models. Values are estimated in R using the did Package by Callaway, Brantly and Pedro H.C. Sant'Anna (2020).

Table A10: Dynamic Effects of Early Adopters by Stacked Clean Control Estimation (1991-2009)

	(1) Total Health Expense	(2) Hospital Care	(3) Physician & Clinical Services
Year $t_s^* - 4$	0.0020	0.0068	-0.0081
	(0.01)	(0.02)	(0.02)
Year $t_s^* - 3$	0.0014	0.0046	-0.0088
	(0.01)	(0.01)	(0.01)
Year $t_s^* - 2$	0.0031	0.0080	0.0015
	(0.01)	(0.01)	(0.01)
Year t_s^*	-0.0091	-0.0146	-0.0059
	(0.01)	(0.01)	(0.01)
Year $t_s^* + 1$	-0.0216***	-0.0275***	-0.0187
	(0.01)	(0.01)	(0.01)
Year $t_s^* + 2$	-0.0362***	-0.0380***	-0.0342
	(0.01)	(0.01)	(0.03)
Year $t_s^* + 3$	-0.0570***	-0.0471***	-0.0710*
	(0.01)	(0.01)	(0.04)
Year $t_s^* + 4$	-0.0598***	-0.0468***	-0.0693
	(0.01)	(0.02)	(0.05)
State FE	Y	Y	Y
Year FE	Y	Y	Y
N	3444	3444	3444
R-squared	0.995	0.988	0.983

[1] Standard errors are reported in parentheses. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.
[2] The outcome variables are state level health expense data (1991-2014) from Centers for Medicare & Medicaid Services (CMS). As a control variable, GDP *per capita* was in all models. Standard errors are clustered at the state level.