Virtual Competition and Cost of Capital: Evidence from Telehealth*

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Abstract

We exploit the staggered implementation of telehealth parity laws to provide causal evidence that virtual competition adversely affects rural U.S. hospitals' financing costs. Using pre-pandemic data, we find that the competition from urban hospitals adopting telehealth services negatively affects rural hospitals' credit ratings, offer yields, and trade prices in the municipal bond market. We identify the channel for these negative effects with hospital financial reports and medical claim data: telehealth services redistribute revenues from rural to urban hospitals, which decrease rural hospital profitability and increase financial distress. Overall, we conclude that virtual competition creates financial distress for rural hospitals.

JEL codes: G12, G31, H74, H75, I11, I14, L31
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With cashflows representing nearly one third of the $4.1 trillion U.S. healthcare expenditures in 2020 (CMS, 2020), hospitals are essential to the healthcare system and the U.S. economy. In addition to preventive and urgent medical treatment, hospitals provide community benefits such as employment and wellness programs. However, these benefits are endangered by the fragile financial state of many hospitals nationwide. In the decade preceding the COVID pandemic, 120 rural hospitals closed (Chartis Center for Rural Health, 2020); the pandemic then resulted in an estimated $323 billion revenue loss for U.S. hospitals and 19 additional rural hospital closures in 2020 (AHA, 2020). One pre-pandemic factor affecting hospital viability is government intervention in insurance markets which affected hospital cost of capital (e.g. Gao, Lee, and Murphy, 2021; Koijen, Philipson, and Uhlig, 2016).

In this paper, we document additional uncertainty in the hospital credit market due to technology shocks. With a vibrant R&D sector in the pharmaceutical and medical device industry, hospital operations are challenged by the frequent adoption of new technologies and products. We examine the impact of telehealth technologies on hospital municipal bonds. In a manner similar to the technology disruption in other industries such as Fintech effects on traditional banking (Goldstein, Jiang, and Karolyi, 2019; Kim, 2021), Airbnb effects on local hotels (Zervas, Proserpio, and Byers, 2017), Uber effects on labor markets (Fos, Hamdi, Kalda, and Nickerson, 2019), and Craigslist effects on local newspapers (Gurun and Butler, 2012; Seamans and Zhu, 2014; Gurun, Matvos, and Seru, 2016; Gao, Lee, and Murphy, 2020), we find that the virtual competition from urban hospitals adopting telehealth services negatively affects rural hospitals' credit ratings, offer yields, and trade prices in the municipal bond market. We identify the channel for these effects using hospital financial statement data and granular medical claim information linked to telehealth visits. We document consistent evidence that telehealth adoption redistributes hospital revenues from rural providers to their urban competitors. Lastly, we examine the real effects on rural hospital bankruptcies and investment decisions.

While COVID accelerated the use of telehealth, the telehealth market was non-trivial in the pre-COVID era. Our medical claim data indicate that total payments for telehealth services nearly doubled every year leading up to the pandemic; we estimate $340 million in reimbursed telehealth revenues in 2019. Focusing on the pre-2020 period allows us to mitigate confounding negative pandemic effects on hospital financial conditions.

Establishing causal effects of telehealth adoption is a challenge, given potential confounding factors affecting hospitals' investment in new technology (supply) and variation in the utilization of the new telehealth technology (demand). Our identification strategy exploits a state-level quasi-natural experiment: staggered implementation of telehealth parity laws that require equivalent reimbursement of remote and in-person healthcare services (by Medicaid programs and commercial insurance providers). A large-sample survey of healthcare organizations indicates that the lack of reimbursement (prior to the passage of telehealth parity laws) is the key limitation to providing remote services, suggesting that these parity laws materially affect supply of such services.[1] After states adopt parity laws, revenue streams from remote services are secured, motivating their wider provision. To alleviate the concern that states endogenously implement telehealth parity, we include granular fixed effects at the state and year-month interaction level to control for time-varying state-level confounding factors and force comparison within each state.[2]

Our primary tests examine the differential impact of telehealth parity laws on urban-versus-rural hospitals' access to capital markets.[3] With secondary market trading data from 2000 to 2019, we find that following the adoption of telehealth parity laws, yields on affected rural hospital bonds increase by a significant 17 bps relative to bonds issued by urban hospitals in the same state, translating to $1.85 million additional interest payment every year. Estimates are consistent for credit spread over maturity-matched after-tax Treasury

[1] "KLAS-Chime Study: Healthcare Industry Moving Ahead with Telehealth Despite Concerns," the College of Healthcare Information Management Executives, 2017. See also Lee et al. (2020).

[2] We refer to year-month as month hereafter and denote these fixed effects as $State \times Month$ *FEs*. We are not simply controlling for seasonality since we have different fixed effects for each calendar year and month.

[3] Rurality is defined by USDA data and explained in Section 2.1.2.

rates (16.2 bps) and even larger when we control for regional healthcare conditions (25.2 bps). Given our pre-pandemic sample period for hospital data, our results cannot be explained by the effects of COVID-19.

Cross-sectional analyses provide additional tests of the hypothesized virtual competition channel. First, if the observed impact on rural hospital yields is driven by competition from urban hospitals, then the yield change should be greater for rural hospital bonds with higher *ex ante* default risk as these bonds are more sensitive to reduced cash flows. This is what we find. Changes in yields (or spreads) are significantly greater for revenue bonds than for general obligation (GO) bonds, for bonds with credit ratings below the sample median (prior to the shock), and for hospitals without a supporting internal capital market from a healthcare system. Second, if the observed changes in secondary market yields reflect the hypothesized virtual competition channel between hospitals, then we should not observe similar changes to rural versus urban bonds outside the healthcare sector. We offer a placebo test replicating our estimation with non-hospital municipal bond transaction data in the same period and find insignificant coefficients.

Given heavy retail investor participation in municipal markets and the opacity of hospital financials (relative to corporations with federal disclosure standards), we examine next the effect of these parity laws on the credit ratings of outstanding bonds issued by affected hospitals. We find that credit rating agencies (CRAs) increase the average downgrade frequency for rural hospitals by 1.3% – 1.5% every month after the shock, comparable to the unconditional average downgrading propensity. Affected rural hospital bonds end up rated an average of 0.9 – 2.0 notches lower as a result.

We then examine the impact of telehealth parity laws in primary markets to generate a direct estimate of new issuance cost, conditional on a hospital offering bonds. This analysis complements the secondary market analysis since municipal bond markets are illiquid and price discovery may be slow. Controlling for credit ratings and other bond characteristics, we find that offer yields of new bonds issued by affected rural hospitals increase by 20 bps relative to those issued by urban hospitals in the same state. The magnitude of this effect is comparable to the effects of Medicaid expansion, opioid abuse, marijuana liberalization, credit rating changes, and climate change on municipal bond prices.[4]

This increase in offer yields following the adoption of telehealth parity laws translates to an additional $2 million dollar interest cost to the average affected rural hospital. To the extent that the adverse effects on cash flows make new issues cost-prohibitive for affected rural hospitals, our estimates represent a lower bound on primary market effects. However, we find no evidence that the increased cost of borrowing reduces new issuance. Rural hospitals increase their yearly issuance frequency by approximately 4% following telehealth parity laws. Together, the results suggest negative feedback effects. The reduction in internal cash flow generation leads rural hospitals to rely more heavily on external debt financing at a higher cost of borrowing, which in turn exacerbates the deterioration in rural hospital financial conditions.

We explain the negative effects on rural hospital cost of capital through a virtual competition channel. Using medical claim data, we find evidence that telehealth adoption redistributes revenues geographically from rural to urban hospital via two ways – initial telehealth visits and in-person follow-up visits. This redistribution of revenues is accompanied by a decrease in rural hospitals' profitability: the average rural hospital loses profits to its urban counterpart in the same state at a magnitude of $1 million annually (representing 14% of the sample average). The results are also robust to using only patient service profits or profit margins as the outcome variable.

These adverse effects result in higher leverage and bankruptcy risk among rural hospitals. Leverage of affected rural hospitals increases 3% – 4%. Cox proportional hazard models show that affected rural hospitals are significantly more likely to close, following the adoption of

[4] Gao et al. (2021) report a 25 bps effect of Medicaid expansion on rural hospital bond yields; Cornaggia et al. (2021) report a 17 bps effect of opioid abuse on GO bond offer yields; Cheng et al. (2020) report a 7–11 bps increase in secondary market spread following the passage of medical marijuana laws; Cornaggia et al. (2018) report 19–33 bps decrease in spreads for upgraded municipal bonds. Painter (2020) estimates a 23 bps increase in yields in response to a 1% increase in flood risk; see also Goldsmith-Pinkham et al. (2021).

telehealth parity laws. Overall, the results suggest that telehealth adoption encouraged by parity laws exacerbate regional healthcare inequality. These results compliment a parallel literature documenting regional inequality in access to the financial sector as rural communities lose bank branch and mortgage markets access (FRB, 2019; Critchfield, Dey, Mota, and Patrabansh, 2019).

Our results have policy implications, though the welfare effects of telehealth services are not immediately obvious. Rural patients benefit from remote access to potentially better specialists in urban areas. However, they may then suffer due to local hospital closure and insufficient in-person care. To test whether improved access to urban healthcare services improve real healthcare outcomes among residents of rural counties, we obtain uncensored mortality data licensed from the CDC. We test whether access to urban healthcare services reduce the number of deaths (per 100,000 residents) due to heart failure, chronic kidney disease, diabetes, chronic obstructive pulmonary disease, or Alzheimer's. We find no reduction in rural mortality rates resulting from the ease of access to urban healthcare services.

Together, our results suggest policy intervention to maintain rural healthcare providers' financial solvency. States might invest directly in rural hospital infrastructure or provide tax subsidies or grants to rural providers as a substitution for debt. Creating urban-rural alliances may integrate the telehealth consulting process with local in-person treatment, which can increase revenue for hospitals in both areas.

Our paper contributes to a broad literature examining determinants of public financing costs and, more specifically, a recent strand of literature examining healthcare factors affecting municipal borrowing costs. We also contribute to the literature examining the capital structure and investment decisions of tax-exempt hospitals, and to prior work related to healthcare inequality. We review related papers in the next section.

1 Related Literature and Background

1.1 Literature

Our paper contributes to prior literature examining healthcare factors affecting municipal borrowing costs including opioid abuse (Cornaggia, Hund, Nguyen, and Ye, 2021), marijuana liberalization (Cheng, De Franco, and Lin, 2020), and Medicaid expansion (Gao et al., 2021). To our knowledge, this is the first paper to study the impact of telehealth technology, which is increasingly relevant since the COVID pandemic. We study regulatory changes (adoption of telehealth parity laws) with adverse effects on rural hospital bond yields where Gao, Lee, and Murphy (2021) study regulatory changes (Medicaid expansion) with advantageous effects on hospital bond yields.[5] Also related is work from Koijen et al. (2016) providing theory and evidence that government intervention adversely affects investment in medical research and development through a government-induced profit risk premium in equity returns of firms in the health care sector.

More broadly, we contribute to the literature documenting determinants of public financing costs such as tax policy (Ang, Bhansali, and Xing, 2010; Longstaff, 2011; Schultz, 2012; Garrett, Ordin, Roberts, and Serrato, 2017; Babina, Jotikasthira, Lundblad, and Ramadorai, 2021), liquidity and default risk (e.g., Ang, Bhansali, and Xing, 2014; Schwert, 2017), credit rating standards (Cornaggia, Cornaggia, and Israelsen, 2018), political connection (Butler, Fauver, and Mortal, 2009), racial bias (Dougal, Gao, Mayew, and Parsons, 2019), climate change (Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2021; Painter, 2020), information environment (Gao, Lee, and Murphy, 2020; Cuny, 2018), underwriting process (Cestau, Green, Hollifield, and Schürhoff, 2018; Cestau, 2019; Garrett, 2020), and state bankruptcy policies (Gao, Lee, and Murphy, 2019).

Our work is also related to the capital structure and investment decision of tax-exempt hospitals. Because non-profit organizations do not pay corporate income taxes, they receive

[5]Results from Gao et al. (2021) are broadly consistent with Duggan et al. (2022) and Lindrooth et al. (2018) that the Affordable Care Act (ACA) increases hospital revenues and reduces the likelihood of closures.

no debt tax shields benefits. However, there exists an indirect tax arbitrage because hospitals could, in theory, issue tax-exempt bonds and invest the proceeds in higher-yielding taxable securities. In this case, the difference in returns on hospital assets and liabilities presents tax-free profit. To prevent such arbitrage, the tax code requires that hospital bond proceeds must be directly invested. This requirement directly links hospital investment decisions to external financing costs; see Wedig et al. (1996) for a theoretical framework of optimal capital structure in this case. Empirically, hospitals increase capital expenditures with more endowment (Gentry, 2002) and positive cash flow shocks (Adelino, Lewellen, and Sundaram, 2015). See Adelino, Lewellen, and McCartney (2022), Gupta, Howell, Yannelis, and Gupta (2021), and Aghamolla, Karaca-Mandic, Li, and Thakor (2020) for how financial shocks affect quality of care.

Our paper also contributes to prior literature examining healthcare inequality (e.g. Culyer and Wagstaff, 1993) and focuses on the rural shortage. The geographical disparity includes provider shortages, uneven distribution, deficient quality, access limitations and inefficient utilization (for a complete review, see Weinhold and Gurtner, 2014). Recent trends in rural hospital closures raises further concerns over healthcare inequality (Kaufman, Thomas, Randolph, Perry, Thompson, Holmes, and Pink, 2016). Our contribution is empirical evidence that telehealth technology negatively affects rural hospital financing costs and thus real investment. The possibility of virtual competition to rural hospitals from urban hospitals providing telehealth services is first discussed theoretically in Rajan, Seidmann, and Dorsey (2013) who predict that telehealth adopters will take market share from in-person providers and thus more likely become monopolists following policy shocks increasing telehealth insurance coverage. Our results support their predictions.

Finally, related work from Zhou, Li, and Burtch (2021) examines cross-state telehealth services after policy changes facilitating treatment of remote patients across state lines. They find that urban physicians respond to the policy change, receive most of the revenue benefits, and reduce rural in-person visits. They also find that rural patients benefit from better quality of care, measured by subjective satisfaction and mortality. Different from our paper, they do not study whether these revenue changes are priced in the capital market, affect hospital bankruptcy risk, or hospital investment policy.

1.2 Telehealth Parity Law

In this paper, we focus on the predominant telehealth modality, also known as telemedicine, which is the use of technology to connect patients with physicians located at distant sites for clinical care. Prior to the COVID-19 pandemic, videoconferencing is the most common telehealth service. In this case, a patient presents physically at a local healthcare facility, such as a clinic or hospital. These facilities are defined as "originating sites."[6] A physician then joins the live video meeting from a distant location for patient examination and medication prescription. The remote physician receives the service fee, and the originating site charges a facilitating fee. Less frequent are (1) store-and-forward services, where patients submit offline medical data to remote physicians without synchronous meetings, and (2) remote monitoring, where physicians monitor discharged patients to reduce rehospitalization.

Telehealth market growth gained momentum during the COVID-19 pandemic, as lockdown orders eliminated many in-person healthcare visits. However, the adoption of telehealth parity laws, discussed below, fueled a rapid expansion of this virtual market well before the pandemic. Figure 1 exhibits the annual aggregate telehealth payments between 2012 and 2019 using Marketscan claim data, which consists of a representative sample of 14% of the insured U.S. population. The telehealth market grew exponentially in the years preceding the COVID pandemic, with total annual revenue nearly doubling every year since 2015. Because the sample is representative (Aizcorbe et al., 2012), we estimate the total *reimbursed* telehealth payments in the U.S. is over $340 million ($48.22 million/14%) in 2019.

[Figure 1 Here]

Besides technology breakthroughs, telehealth reimbursement policy is the key facilitator

[6] Most insurance policies restrict the scope of originating sites. For example, patient residences are not valid originating sites in Medicare.

of the rapid growth seen in Figure 1. Without uniform regulation of reimbursement for either private insurers or government programs, hospitals previously faced uncertain reimbursement for remote service.[7] This reimbursement risk disincentivized telehealth adoption.

Medicare, which is regulated at the federal level, only reimburses live videoconferencing services with originating sites in rural areas. Medicaid programs and private insurers are regulated at the state level with significant variation in reimbursement policies. In the years preceding the COVID-19 pandemic, 36 states and the District of Columbia enacted *telehealth parity laws* to promote telehealth services. Though details vary across states, these parity laws all require Medicaid and private insurance to reimburse telehealth services at the same rate as in-person services.

We use state-level variation in telehealth parity law implementation as a quasi-random natural experiment to study the effects of telehealth adoption. The treatment group is comprised of the 36 states (and D.C.) that adopt the telehealth parity laws in a staggered manner, as shown in Figure 2. Telehealth pioneers such as California and Texas first required reimbursement parity in the late 1990s. Most states (30 out of 37) in the treatment group implemented between 2010 - 2020. This variation in timing enables us to investigate effects with a long sample period and reduces concerns that a particular macroeconomic shock confounds our results.

[Figure 2 Here]

In the Appendix, we provide a case study for the legal details of parity laws using Washington, Minnesota, Oregon, Colorado, and New York as sample states. Parity laws vary in detail, and some are more restrictive. For example, while all treated states mandate full reimbursement for live video treatment, only 17 states and the District of Columbia require full reimbursement for store-and-forward services. States also vary on the coverage of patient residences as originating sites, necessary for the reimbursement of remote patient monitoring

[7] Practitioners cite the uncertain reimbursement system as "one of the most serious obstacles to telemedicine's more complete integration into healthcare practice"; see "Telemedicine Reimbursement: A National Scan of Current Policies and Emerging Initiatives," California Telemedicine and eHealth Center.

services. We focus on reimbursement for live video treatment for inclusion in the treatment group, rather than analyzing variation in the "intensity" of parity laws for two reasons.[8] First, live video treatment is the predominant modality, and it is unclear how large the profit impacts are generated by other restrictions.[9] Second, state policies may be liberal in one dimension but more restrictive in another. For example, Minnesota reimburses the store-and-forward services but does not allow the remote provider and the originating site to be in the same community. It is thus difficult to define whether Minnesota has a more- or less-restrictive parity law relative to an average treated state.

1.3 Impact on Revenues and Services

Telehealth adoption redistributes healthcare revenues from rural to urban providers. This shift in revenues reflects differences in the demand for and supply of telehealth services. On the demand side, telehealth services improve rural populations' limited access to specialized healthcare by connecting rural patients to urban specialists without travel costs. In a 2017 study, the U.S. Government Accountability Office interviewed a selected sample of state Medicaid officials and found that the percentage of rural population and the proximity to specialists are key contributing factors to telehealth benefits.[10] On the supply side, rural hospitals generally lack adequate facilities to provide high-quality telehealth services. Many rural hospitals were constructed following the passage of the Hill-Burton Act of 1947, and fail to renovate their facilities and services to better align with advanced healthcare. Regarding human capital, fewer than 10 percent of U.S. physicians practice in rural communities; this

[8] This requirement eliminates Alabama in the treatment group, which only has parities for mental health services.

[9] The 2016 survey of 3500 physicians by the American Medical Association indicates that 82% of telehealth adopters use videoconferencing as their modal telehealth delivery; see Kane and Gillis (2018). Videoconferencing is the dominant format reported among emergency medicine physicians, psychiatrists, and pathologists. Remote patient monitoring, by contrast, was utilized by fewer than 10% of physicians in every broad specialty other than internal medicine (10.9%).

[10] For example, Montana officials said "the state does not have any medical schools and has limited access to specialists. As such, telehealth services are important to providing patients with access to specialty care." 44% of the Montana population are in rural areas. See "Telehealth and Remote Patient Monitoring Use in Medicare and Selected Federal Programs," GAO-17-365, Apr 14, 2017.

shortage is even larger for specialists.[11]

[Table 1 Here]

Telehealth adoption leads to the redistribution of revenues through two channels. First, rural patients switch from local in-person services to remote services offered by urban hospitals. As shown in Table 1 Panel A, 81.60% of the rural patients (and nearly 100% of urban patients) choose urban telehealth providers and the majority of telehealth revenues are thus received by urban providers. Second, even for procedures that cannot be performed virtually, such as surgeries, telehealth adoption still increases a rural patient's propensity of being served by an urban provider because telehealth services reduce the transaction costs of initial consultancy and recovery monitoring for these services. In Table 1 Panel B, we calculate patients' cumulative probability of receiving an in-person treatment from the same provider after their first telehealth meeting. 36.6% of rural patients follow up with physically visiting their telehealth providers and the majority of these in-person visits occur within 180 days of the telehealth appointment. This is in line with the prior literature that shows telehealth services have the gateway effects to increase hospital admissions afterward (Ayabakan et al., 2020). In both cases, rural providers lose revenues due to virtual competition, and urban providers benefit from the influx of patients. In our empirical results, we exhibit the consequences of this virtual competition channel by examining the financial conditions at the hospital level. We also provide direct evidence of the above two channels using the granular claim-level data.

1.4 Hospital Bonds

Until the early 1970s, U.S. hospitals were heavily funded by philanthropic contributions and federal grants from the Hill-Burton Act. The percentage of capital funds obtained through borrowing rose sharply, from 17.5% in 1962 to over 70% after 1975 where it then stabilized (Wilson et al., 1982). The largest component of hospital debt is tax-exempt revenue bonds, which finance the construction of new facilities or upgrade existing hospitals. As the name

[11] For more statistics, see "Rural Report 2019", American Hospital Association.

suggests, revenue bonds are backed by cash flows generated from the project financed and therefore exhibit higher default risk than GO bonds backed by the issuing municipality and ultimately by the tax base.

[Table 2 Here]

Table 2 Panel A shows that 88% of sample hospital bonds are revenue bonds (i.e., 12% are GO bonds) compared to only 36% of non-hospital municipal bonds (64% GO bonds). A distinguishing feature of hospital bond markets is the unpredictable nature of hospital revenue. A significant portion of hospital revenue comes from reimbursements from commercial insurers and government-backed health insurance programs such as Medicare and Medicaid. As a result, hospital revenues are sensitive to policy shocks in the healthcare market (Koijen et al., 2016), such as Medicaid expansions (Gao et al., 2021). Moreover, hospital competitions affect the bargaining process with insurers (e.g. Gowrisankaran et al., 2015). Together, these factors result in a relatively high default rate among hospital bonds compared to other municipal bonds (Gao et al., 2019), which is the key factor for municipal bond yield spread (Schwert, 2017). It is therefore unsurprising to find in Table 2 Panel A that the average offer yield of hospital bonds is a significant 58 basis points (bps) higher compared to non-hospital municipal bonds.

Rural hospitals face have more troubles in accessing the municipal bond market as they face higher-than-average default risks. First, rural hospitals have lower patient volumes due to low population density in rural areas, so they lack economies of scale to cover fixed costs. Second, rural hospitals are more likely to serve patients with Medicare and Medicaid, which are known for underpayment problems; hospitals receive an estimated 87 cents from every dollar spent by Medicare and Medicaid patients.[12] These features significantly constrain rural issuers external financing abilities. Panel B shows that the average rural bond yield in the second market is almost 20 bps higher, even though their average bond size is roughly a half of the urban counterparts. The underlying financial discrepancies are apparent from Table

[12] "Underpayment by Medicare and Medicaid Fact Sheet," American Hospital Association, January 2019.

2 Panel C, which summarizes hospital profitability measures. A typical urban hospital's net income is over eleven times larger than its rural counterpart. The difference in total revenue is more than $800 million. Urban hospitals are on average five times larger in total assets than rural ones, measured by total assets, and accept almost 9,600 more patients annually.

2 Data and Empirical Method

2.1 Data

We analyze multiple sets of data. First, we collect data on municipal bonds and county socioeconomic fundamentals to test whether the effects of revenue redistribution after telehealth parity laws feed through to hospital cost of capital. Second, we collect hospital financial and operational data to test our hypothesis that increased virtual competition from urban hospitals following telehealth parity laws negatively impacts rural hospital financial conditions. Lastly, we utilize a proprietary database covering the medical claim information of a representative sample of privately insured individuals to show the direct evidence of telehealth adoption.

2.1.1 Municipal bond data and county characteristics

We construct a US municipal bond sample from two data sources – primary market issuance data and bond characteristics are obtained from the Mergent Municipal Fixed Income database (Mergent) and secondary market transaction data from the Municipal Securities Rulemaking Board (MSRB). We restrict the sample to bonds that have a positive offering amount and coupon rate, represent new borrowing (i.e., not for refunding purposes) and are offered via conventional channels. We exclude issues by US territories other than Puerto Rico. We identify 42,048 healthcare municipal bonds issued between 2000 and 2019 based on the indicated use of proceeds.[13] For these bonds, we collect secondary market transaction data from 2000 to 2019. We calculate secondary market yields at the bond-month level using the size-weighted average yield across all transactions for each bond in each month.

[13]We include bonds with proceeds used for hospitals, hospital equipment, and other healthcare purposes.

We estimate credit spreads for each bond in two ways: spread to maturity-matched Treasury bond and spread to maturity-matched yield on the tax-exempt Municipal Market Advisors AAA-rated curve (MMA curve) available from Bloomberg since 2001. To calculate the after-tax Treasury yield, we instrument marginal tax rates with estimates of top state rates by the NBER Taxism model available from 1977 to 2018.[14]

We use the credit rating history of each individual bond to identify credit rating at the time of issuance for primary market analysis and credit rating at the time of transaction for secondary market analysis.[15] When rating information is available from multiple rating agencies, we employ the harshest rating.

We geolocate each bond to a county using the first six digits of the bond's CUSIP, which uniquely identifies the issuer. Using information from Bloomberg, we link issuers' 6-digit CUSIPs to each county. We then match bond data to county-level characteristics using the Federal Information Processing Standard (FIPS) codes for issuer. We collect county-level control variables over the 1999-2018 period from two sources. County population, employment, and income data are from the Bureau of Economic Analysis (BEA). Labor force statistics are from the Bureau of Labor Statistics (BLS).

2.1.2 Hospital data

We construct a sample of Medicare-certified hospitals, which are required to provide annual cost reports to the Centers for Medicare & Medicaid Services (CMS). These cost reports are analogous to annual reports for public corporations, disclosing financial variables such as total assets, total patient revenues, operating expenses, net income, cash holdings, and total liabilities.[16] Unique in the hospital setting, they also disclose details on operational

[14] For the state rates information, see `http://users.nber.org/~taxsim/state-rates/maxrate.html`. For details of the Taxism model, see `http://users.nber.org/~taxsim/state-rates/`.

[15] We supplement Mergent data with rating histories provided by Ryan Israelsen and Marc Joffe.

[16] Hospital accounting differs significantly from standard FASB reporting requirements for corporations. Total revenue is calculated based on total service charges for patients, analogous to total sales in the standard accounting rule. There is no Cost of Goods Sold (COGS) item for hospitals, so patient revenue is defined as net patient revenue minus operating expenses (e.g., salaries and supplies). The difference between total and net patient revenues reflects the fact that insurers do not fully reimburse charges (according to contractual adjustments) and because patients cannot afford deductibles and coinsurance (defined as allowances and bad debt). Most hospitals do not pay income taxes due to their non-profit status.

information unique to hospitals such as patients discharged, available beds, ICU units, and employees in all treatment units. Because disclosure requirements changed significantly in 2009, we collect data from 2009 to 2018 (which is the most recent year for which most hospitals submit complete cost reports to CMS as of January 2021). We restrict our primary sample to 4,281 acute care hospitals and confirm that our results are robust to including other types of providers.[17] Because cost reports are filed with CMS annually, our panel has 40,492 hospital-year observations.

Of these 4,281 sample hospitals, 2,001 operate in areas classified as *Rural*. To measure county-level rurality, we collect from the USDA the urban-rural commuting area (RUCA) codes which classify ZIP code areas ranging from the largest metro areas (1) to the most rural areas (10).[18] We classify an area as *Rural* if its RUCA code is strictly greater than three and as *Urban* otherwise. The cutoff follows the Census Bureau's definition of an urbanized area, which means an urban nucleus of 50,000 or more people. This cutoff also relates to the geographical restrictions in some states' parity laws. For example, Oklahoma's Medicaid program limits the coverage for telemedicine services to members in rural areas, defined as counties with a population of less than 50,000 people.[19]

2.1.3 Medical Claim data

We collect patient level telehealth claim data using the IBM Marketscan database, which contains de-identified healthcare reimbursement information. The data provider sources claim information for employees, retirees, and dependents from over 260 medium and large employers and 40 health plans. The database covers over 43 million privately-insured individuals with employment-based health plans, which represent roughly 14% of all insured and 20% of all privately insured U.S. population. Marketscan is representative of the U.S. insured

[17] An acute care hospital provides general inpatient medical care and other related services for surgery, acute medical conditions or injuries. Hospitals outside these types care for only a particular type of patients, such as cancer center, psychiatric hospital, and rehabilitation center. 82% of initial sample hospitals are acute care hospitals.

[18] For detail, see `https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes.aspx`.

[19] Oklahoma Administrative Code §317:30-3-27(c), 2016 Edition.

population (Aizcorbe et al., 2012) and is widely used in the health economics literature (e.g. Ho, 2009; Clemens and Gottlieb, 2017; Deschenes et al., 2017).

Each observation in the Marketscan database represents a claim, documenting patient ID and provider ID (both de-identified), diagnosis codes, procedure codes, payments, revenue codes, place of service, patient location, and service date. Telehealth service is defined as the claims satisfying at least one of the following criteria: (1) revenue code is 0780 (Telemedicine - general classification) or 0789 (Telemedicine - telemedicine); (2) procedure modifier is G0 (Telehealth services furnished for purposes of diagnosis, evaluation, or treatment of symptoms of an acute stroke), GT (Service via interactive audio and video telecommunications systems), 95 (An alternative to GT after 2017), or GQ (Asynchronous services); (3) procedure group is 113 (Physician telephone/online visits); (4) place of service is 2 (Telehealth).

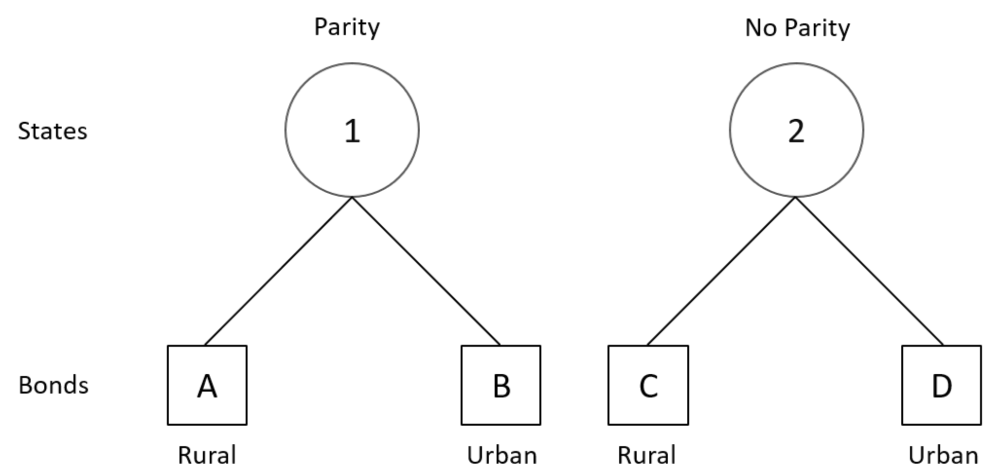
Our sample covers 2.18 million telehealth services used by 1.05 million unique patients and provided by 16,328 unique providers from 2012 to 2019. For each patient-provider pair that has a telehealth service, we keep track of their in-person follow-up visits, i.e., non-telehealth visits that happen after the initial telehealth service date. For the full sample of urban and rural patients, 31.12% of the 433,462 patient-provider pairs have in-person follow-up visits within a year, and about 35% of them ever do so in the sample; this number increases slightly to 36.6% for rural patients, indicating that rural patients are at least as likely to follow up in person after the first telehealth visit.

Since the provider's information in Marketscan is de-identified, we cannot link physicians to affiliated hospitals to generate hospital-level revenues associated with telehealth. Because we focus on the revenue impacts on the supply side, we aggregate each provider's total payments across both telehealth and follow-up visits claims in a year. If a provider has no telehealth or follow-up services following her first appearance in the sample, we code her telehealth and gateway revenues as zero.

2.2 Identification Strategy

Our main research question is whether the telehealth parity laws affect urban-versus-rural hospitals' access to capital markets by widening differences in urban versus rural hospital bonds' yields and credit spreads. Telehealth parity laws are adopted at the state level over several years; see Figure 2. Treated states adopt parity laws and control states do not. Treated hospital bonds are those issued in the treated states. The following figure illustrates our identification strategy. State 1 represents all treated states (adopt parity laws) and State 2 represents all control states (do not adopt parity laws). Within each state, there exists a rural-urban bond pair, A-B and C-D. The quasi-natural experiment is the adoption of the telehealth parity law by State 1. We hypothesize that the difference in yields between bonds A and B (treated bonds) will increase relative to the difference in yields between bonds C and D (control bonds).

Figure: Identification Strategy



We express the experiment as Equation (1). In our focal tests of hospital cost of capital, the outcome variable represents either the yield or spread (to Treasury or MMA) of bond i at time t.

$$Y_{i,j,k,t} = \beta Rural_i \times Parity_{j,t} + \gamma Rural_i + \delta_t' X_{i,t} \times \mathbf{1}_t + \eta' Z_{k,t-1} + State \times Month\, FEs + \varepsilon_{i,j,k,t} \quad (1)$$

$Rural_i$ indicates whether bond i is issued in a rural area (defined in Section 2.1 above) and $Parity_{j,t}$ equals one if the bond is issued in a state j that enacted a telehealth parity law in month t and zero otherwise. The focal regressor $Rural_i \times Parity_{j,t}$ thus equals one only for a bond issued by a rural hospital in the treatment state (Bond A in the identification figure above) and equals zero for other bonds (Bonds B, C, and D in the figure). We also include an indicator for whether the bond is issued by a hospital located in a rural area, $Rural_i$. We include control variables at both bond and county levels shown previously to affect municipal bond yields. Following Gao et al. (2021), we include a vector of bond level controls $X_{i,t}$ and interact them with time indicators at the yearly frequency. These characteristics include (1) credit rating at the time of transaction, (2) log maturity, (3) log size, indicator variables for whether the bond is (4) general obligation, (5) callable, (6) insured, (7) reoffered or (8) negotiated.[20] Following Gao et al. (2020), we include a vector of lagged county characteristics ($Z_{k,t-1}$) including: (1) population level, (2) per capita income, (3) one-year population growth, (4) one-year employment growth, and (5) labor force participation. The inclusion of $State \times Month$ fixed effects forces within-state comparison (A-B vs. C-D in the identification figure). This specification is close to a staggered triple-difference regression where an additional variable $Parity_{j,t}$ is required. However, this variable is absorbed by the granular fixed effects in our specification.

The inclusion of $State \times Month$ fixed effects addresses concerns that treated states may endogenously choose to enact telehealth parity laws. Any unobserved state-level time-varying heterogeneity is absorbed by the $State \times Month$ fixed effects, and our identification comes from within-state differences between rural and urban hospitals. This identification thus is valid provided that the decision to enact a telehealth parity law is not dependent on the pre-adoption difference in yields for bonds issued by rural versus urban hospitals. We take several steps to verify this condition. First, Table A.2 of the Online Appendix shows that state-level hospital characteristics (e.g., state-level average hospital income, revenue or patient volume in urban and rural areas), population size, economic conditions, share of older people, and

[20]We exclude credit rating from bond controls when rating and downgrade are the outcome variables and instead control for initial rating fixed effects.

political preference do not predict the timing of parity law adoption under a Cox hazard model. The results alleviate the potential concern that urban hospitals strategically lobby for the parity laws in states with vulnerable rural hospitals. Second, we search for anecdotal details to understand what prevents the fourteen control states from adopting the parity laws and we find no evidence suggesting that state legislators were concerned about the potential financial distress for rural hospitals. For example, North Carolina lawmakers introduced the telehealth parity law in 2015 but were denied during the public hearing, as stakeholders raised concerns over informed consent, standards of care, and control over abortion drugs. Florida lawmakers instead believe that the comprehensive coverage of telehealth must be voluntary between the insurer and provider.[21] These anecdotes provide suggestive evidence that the increased financial distress for rural hospitals after the parity laws is an unintended consequence that is not intentionally preempted by the control states. Lastly, we supplement previous results with parallel trends in rural versus urban hospital bond yields, as well as those in rural and urban hospital financial conditions.

We test for capital market effects of telehealth parity laws first with analysis of secondary market transactions for outstanding bonds issued by affected hospitals. For the treatment group, we restrict our sample to bonds issued prior to the date the treated state adopts a parity law. We apply this restriction to address the concerns that (1) issuing hospitals could endogenously change new bonds' features after the shock and (2) a selected sample of issuers could potentially respond to the policy shock.[22] Focusing on bonds outstanding prior to the adoption of the parity law circumvents these concerns. Since state law adoption is staggered, the analogous issue-date restriction for the control group is less obvious. We restrict our sample of control bonds to those issued in control states prior to 2014 for two reasons: (1) to avoid confounding effects from Medicaid expansion and (2) the majority

[21] See "Telehealth Bill Gets Hung Up at Legislature," North Carolina Health News, June 2018, and 2019 Florida Legislature House Bill 23.

[22] For example, if high-quality urban issuers and low-quality rural issuers endogenously participate in the primary market bond issuance, we would observe, following the shock, an increase in the difference in yields for urban hospital bonds versus rural hospital bonds.

of telehealth parity laws are implemented after 2015. We confirm that our results are not sensitive to this 2014 cutoff; we obtain comparable estimates when we (1) include all bonds issued by hospitals in control states and (2) discard all bonds issued in control states (thus comparing only bonds A and B from the identification figure above).

We further test for capital market effects of telehealth parity laws with analysis of primary market issuance by aggregating issuing frequency at the county level, financial condition and investment at the hospital level, and telehealth revenues at the provider level. This specification follows Equation (1) except that the unit of observation and time frequency are adjusted for the corresponding data.

3 Empirical Results

3.1 Bond Yield in the Secondary Market

We begin by analyzing the impact of the telehealth parity law adoption on outstanding hospital bonds' secondary market pricing. We first estimate Equation (1) with $Yield_{i,t}$ as the dependent variable and report the results in Panel A of Table 3. The coefficient on the key explanatory variable $Rural_i \times Parity_{j,t}$ reported in Column (1) is 17 bps, indicating that the urban-rural yield difference in treated states increases significantly relative to bonds issued by hospitals in control states. This increase is almost equivalent to the additional cost of capital (19.59 bps) for rural providers in the sample. In dollar terms, these basis points translate approximately to \$1.85 million in interest expense for a typical affected rural hospital.[23] The economic magnitude is large, given the annual net income for hospitals is also approximately \$7 million.

Because U.S. healthcare markets differ geographically, variation in local market concentration may affect the findings in column (1). We thus add fixed effects to the specification in column (2) generated by the interaction between Hospital Referral Regions (HRRs) and

[23] The calculation is 17 bp $\times$ \$97.57 million $\times$ 11.16 years, where we use the average issue amount and maturity for hospital bonds.

year–month.[24] We obtain stronger results (25.16 bps impact) in column (2) after controlling for these variations.

[Table 3 here]

In Section 3, we explain the reasons for truncating the control group to bonds issued before 2014, after restricting the treatment group to bonds issued before each state adopts telehealth parity laws. Columns (3) and (4) of Table 3 show that results do not depend on the specific calendar threshold. By dropping the control states, i.e. those without parity laws, we essentially estimate a simple DID model in column (4) where rural hospital bonds in treated states are "treated" and urban hospital bonds issued in the same state serve as the control group. Given the robustness of these results, we employ the bonds issued in control states prior to 2014 throughout our empirical analysis unless otherwise noted.

We observe an increase in the difference between urban and rural hospital bond yields could obtain either because rural hospital bonds in treated states have higher yields relative to urban hospital bonds issued in control states or because the urban bonds generally have lower yields. In column (5), we replace the *State-Month* fixed effects to obtain the coefficient of $Parity_{j,t}$.[25] This coefficient has a small magnitude (0.94 bps) and is statistically insignificant, suggesting that yields of urban hospital bonds issued in treated states are not affected. Given that municipal bonds carry low credit risk relative to other assets classes and offer limited upside potential, yield changes are more likely to be driven by investors' perception of downside risk. Thus, the marginal increase in profits and revenues are less likely to be reflected in the cost of capital for urban hospital issuers with high *ex ante* credit quality. On the other hand, the coefficient of the interaction term is significantly positive and the net effect on treated rural hospital bonds remains highly positive. Therefore, the within-state inequality on costs of capital is mostly a result of rural hospital's distress.

[24] HRRs define regional healthcare markets. The Dartmouth Atlas of Health Care develops HRRs by grouping communities based on referral patterns for tertiary care for Medicare beneficiaries, focused on referrals for major cardiovascular surgical procedures and neurosurgery. HRRs often combine communities across state borders so their fixed effects will not be absorbed by those of states.

[25] We add granular issuer fixed effects and month fixed effects. The former absorbs the rurality of issuing location.

Panel B of Table 3 replicates results from Panel A using alternative measures of bond prices: *Spread* (to maturity matched Treasury) and *SpreadMMA* (to maturity matched yield on the MMA curve). Column (1) estimates Equation (1) with $Spread_{i,t}$ as the dependent variable. The coefficient on the interaction term indicates an effect of 17.55 bps. In dollar terms, these bps translate to $\sim$ \$1.9 million in interest payments for an affected rural hospital.

Our identification strategy relies on a parallel trend assumption that there exists no significant difference in trend in the outcome variables prior to the shock (the adoption of telehealth parity law). To test this assumption in a staggered treatment framework, we estimate the following equation and report the results in Figure 3.

$$Y_{i,j,k,t} = \sum_{n\in[-3,0)\cup(0,6]} \beta^n Rural_i \times Parity^n_{j,t} + \gamma Rural_i + \delta'_t X_{i,t} \times \mathbf{1}_t + \eta' Z_{k,t-1} + State \times Month\, FEs + \varepsilon_{i,j,k,t}. \quad (2)$$

Equation (2) separates treatment effects into calendar groups relative to the time when a state adopts a telehealth parity law, indexed by an integer n. $Parity^n_{j,t}$ equals one if the bond's state j adopted a parity law for n years in calendar time t and zero otherwise.[26] Negative values denote pre-treatment periods. We plot on a ten-year window around the shock for the treatment group, including three years before the shock and six years afterward. To avoid perfect collinearity, we drop $Parity^0_{j,t}$ so all estimates are relative to the treatment effects in the year when the state adopts the parity law. Across all three outcome variables, we observe that the coefficient estimates are close to zero in the periods leading to the treatment (with negative n values).

[Figure 3 here]

Figure 3-(a) shows that, for the treatment group, the rural-urban yield differences are insignificantly different from zero before the shock. Recent econometrics literature, such as Goodman-Bacon (2021) and Sun and Abraham (2021), argues that with staggered events, our estimated coefficient β^n is a weighted average of all treatment effects across event dates. Moreover, a late-treated group may be included as the "control group" for the early-shocked

[26] Mathematically, we denote the month when the state enacted the parity law by τ. We verify whether $\lfloor (t-\tau)/12 \rfloor$ is n where $\lfloor \cdot \rfloor$ is the floor function.

groups, which can make the estimated coefficients in Equation (2) inconsistent by including treatment effects from other events. We address this concern in different ways. First, in Figure 3-(b), we replicate the analysis by only including observations in the parity states and use urban hospital bonds in these states as the control group. The plot is very similar to Figure 3-(a), suggesting that the coefficients are not affected by including observation from non-parity states. Second, we alternatively use the interaction weighted (IW) estimator from Sun and Abraham (2021) and make the bonds in non-parity states (i.e., the never-treated units) as the control group in Figure 3-(c). Lastly, we only keep observations of rural bonds in parity states and use the last-treated group as the control group for the IW estimators of earlier events in Figure 3-(d). Sun and Abraham (2021) show that the IW estimator is consistent in both cases even under heterogeneous treatment effects across event dates. We also confirm that the plots are robust if we use spreads as the outcome variable.

These figures further indicate that the effects of telehealth parity laws take roughly one to two years to emerge significantly and persist forward. There exist several explanations for the delayed reaction. First, the illiquidity of the municipal bond market mutes price discovery. (We therefore examine primary market effects in the next section.) Second, the adoption of telehealth parity laws spans a long sample period. We thus split the treatment groups into early-adopting (before Jan 2015) and late-adopting (after Jan 2015) states and present the dynamic effects in Figure A.1 of the Online Appendix. Treatment effects in late-adopting states are immediate and significant, likely reflecting the fact that telehealth usage was limited in early years and that investors learn to price these effects in late-adopting states. To further support the parallel trend assumption, we visualize the treatment effects of parity laws on urban and rural regions separately in Figure A.2 where we estimate and plot the coefficients of $Parity^n_{j,t}$ in the urban and rural treatment groups. This figure confirms our result in column (5) of Table 3 Panel A that hospital cost of capital stays unchanged in urban areas and drifts upward in rural ones.

We report the results from cross-sectional analysis in Table 4. If our hypothesized virtual competition channel explains the results in Table 3, then we should observe that the effects are stronger among hospital bonds with higher *ex ante* default risk. We first bifurcate the sample into GO versus revenue bonds, since revenue bonds exhibit greater default risk, on average (e.g. Cornaggia et al., 2022). Indeed, all coefficients of $Rural \times Parity$ in the GO subsample are negative from -11.19 bps to -14.12 bps, whereas those in the revenue sample are close to the baseline results in Table 3. Because the fraction of hospital bonds that are GO is highly unbalanced in the secondary sample, we interpret these results with caution. Second, we bifurcate the sample above and below the median credit rating at the time of issuance (single A, $HighRating_i = 1$ if above), which makes the bifurcation more balanced by design. The coefficients on $Parity_{j,t} \times Rural_i$ in columns (1) – (3) suggest that highly-rated rural hospital bonds are not affected by the parity law shock. The changes in bond costs concentrate in the below A at issuance group, with jumps between 34.3 bps and 35.6 bps.

[Table 4 Here]

Some rural hospitals belong to a large hospital system that operates across states and has urban branches as well. For affected bonds issued by such hospitals, the impact of telehealth adoption will be much smaller for two reasons. First, the existence of an internal capital market by the profitable system significantly reduces the default risk. Second, a hospital system provides an alliance potential such that remote delivery of urban consultancies can be complemented by in-person examination and treatment by physicians at local rural hospitals. In this case, rural providers may even financially benefit from the telehealth adoption through collaboration. In Panel C, we identify whether the issuer belongs to a large system and confirm that the results concentrate in those stand-alone and small system affiliated rural hospitals.

We evaluate next the effect on the credit ratings of outstanding bonds issued by affected rural hospitals. Credit ratings are especially important in municipal markets due to heavy retail investor participation and hospital financials are more opaque than typical corporations with federal disclosure standards. We employ Equation (1) with two modifications.[27] First, the dependent variables measure hospital bond credit conditions: $Rating_{i,t}$ is the numeric value of bond i's credit rating in month t with the potential range of 0 (D) to 21 (AAA). The hospital bonds ratings in our sample range from 12 (*BBB-*, 1^{st} percentile) to 21 (AAA, 99^{th} percentile); see Online Appendix Table A.3 for a complete distribution. $Downgrade_{i,t}$ is an indicator variable that takes value of one if bond i is downgraded in month t, and zero otherwise. Unconditionally, hospital bonds have a 1.76% monthly likelihood of downgrade. Our second modification to Equation (1) is to drop credit ratings at the time of transaction from the vector of bond-level controls (since they serve as dependent variables here). Instead, we include the initial credit rating at issuance fixed effects in columns (3) and (6) to alleviate the concern that rating scale is constrained (such that bonds rated *BBB-* have less room for downgrade than bonds rated AAA).

[Table 5 here]

Overall, we observe from Table 5 that outstanding bonds issued by rural affected hospitals are more likely to be downgraded, leading ratings to be 0.9 – 2.0 notches lower (columns 1 to 3). This magnitude of rating change is large compared to prior analysis of credit rating changes in the municipal bond market (e.g Cornaggia et al., 2020). This difference is likely due to the fact that most hospital bonds are revenue bonds (rather than general obligations backed by tax dollars) and their ratings are sensitive to project cashflows. Downgrade frequency increases significantly by 1.3% – 1.5% for treated rural providers (columns 4 to 6). The economic magnitude is comparable to $Downgrade_{i,t}$'s unconditional average.

3.2 Robustness Check of the Secondary Market Results

We perform a few robustness checks using secondary market transaction data. First, we interpret the preceding results through a virtual competition channel where telehealth services redistribute revenues from rural to urban hospitals within treated states, leading to higher

[27] Please see Section 2.2 for details on the construction of treatment and control groups. We employ monthly observations at the bond level in the secondary market as indicated there.

cost of capital for rural hospitals. An alternative explanation is that the concurrent rural population outflows in states with parity laws exceed the rural to urban population shift in control states without parity laws. This concern is alleviated to some extent by the explicit controls of the level and growth rate of local population in Equation (1).

If differential rural-to-urban population transfers is the underlying mechanism, then the reduced local tax base in rural areas should affect the yields for non-hospital municipal bonds as well. Thus, we replicate the tests in Table 3 on the non-hospital bond sample described in Panel A of Table 2. The results of this exercise are tabulated in Table A.4 of the Online Appendix. Consistent with our expectation, we observe insignificant coefficients on the interaction variable, despite a sample of more than 7 million observations. Also, the R^2 is nearly zero for this placebo test, compared to the R^2 of 0.55 to 0.70 in our baseline regressions in Table 3. These insignificant results in the placebo test in Table A.4 lend further support to our interpretation of results in Table 3.

We then perform another placebo test by randomly selecting a set of 37 states into a pseudo treatment group and randomly assigning months between 2010-01 and 2018-12 as pseudo event dates. We then replicate the tests from Table 3 with these placebo shocks, and report the results in Table A.5 of the Online Appendix. Here, we find insignificant results, suggesting that the urban-rural differences in hospital cost of capital are not affected by a random group of shocks in the same sample period.

We also exploit county-level data on broadband internet access, a necessary condition for the utilization of telehealth service, to strengthen our identification. Rural hospitals in counties with limited broadband access and outdated internet infrastructure should be less affected by virtual competition. Thus, we do not expect the cost of capital to change for such hospitals after their states pass parity laws. Granular broadband accessibility data became publicly available in June 2016, when the Federal Communications Commission (FCC) began biannual reporting at the county level.[28] Both fixed and mobile providers are

[28] According to the FCC, the definition of broadband internet is a minimum of 25 Mbps download and 3 Mbps upload speeds. See https://broadbandmap.fcc.gov/#/data-download for the data.

required to file Form 477 to FCC by listing the locations where they offer internet services at certain speeds. Based on these locations, FCC then report the percentage of population without high-speed providers nearby as a proxy for internet infrastructure. Using these data, we separately sort rural and urban counties into tertiles based on the percentage of the population without broadband access in 2016.[29] In the rural quartile with the worst internet coverage, more than 45% residents have no broadband access (shown in Panel A of Table 6). As predicted, parity law adoption does not affect rural hospital bond yields in this tertile (Panel B column 1 reports an insignificant coefficient). In the medium rural tertile, 79% of residents have broadband internet access. The coefficient on the key variable $Rural_i \times Parity_{j,t}$ indicates an effect of 22.57 bps on rural hospital bond yields in this group, which is marginally statistically insignificant. Lastly, we obtain the strongest effects in the rural tertile with best broadband access, where only 9.7% of the rural population have no access to broadband services.

[Table 6 here]

In addition, we replace the credit rating at the time of transaction, a control variable for secondary yields analysis in Equation (1), with either initial rating or lagged rating in the previous trading month.[30] We conduct this robustness test to alleviate the potential concern that the rating at transaction already reflects the deteriorated financial condition of affected rural hospitals (as indicated Table 5) and thus confounds our estimation of the effect on yields. We report the results in Table A.6 of the Online Appendix. We also acknowledge that the coefficients of *Rural* in Table 3 are close to zero and statistically insignificant, which seems inconsistent with rural issuers being more risk. These results are driven by the granular rating controls that absorb broad default risks in the rural area. Once we drop any rating measures in the control variables, the coefficients become positively significant in Panel C. For all the three panels, our estimates of parity law impacts remain consistent and

[29] We use the coverage ratio in 2016 since it is close to the time of most parity law adoptions. Our results are robust when we use the average percentage of population without broadband from 2016 to 2020.

[30] Initial rating is the first available rating for each bond in the secondary trading sample.

significant.

3.3 Bond Issuance in the Primary Market

We examine next the impact of telehealth parity laws on hospital bond yields in primary markets. The primary market analysis in this section complements the secondary market analysis in Section 3.1 in important ways. Because municipal bonds are thinly traded, price discovery could be incomplete in secondary market trading. Also, dollar estimates of increased interest expense in Section 3.1 are hypothetical since the coupons on outstanding bonds are fixed. Primary market analysis offers estimated real effects of telehealth parity laws on hospital cost of capital (in basis points and dollar terms). We believe the secondary market analysis is equally important since the primary market analysis is subject to selection issues: the composition of new issuers may endogenously change after the telehealth parity law is in place. For example, if adversely affected rural hospitals choose not to issue in the post-shock period due to the negative impact on their borrowing costs, these effects would not be observable. The results in this section provide a direct estimate of new issuance cost, conditional on a hospital's willingness to offer bonds, given the prices they face.

We estimate Equation (1) with primary market offer yields and spreads as dependent variables and report the results in Table 7. We add bond characteristics as control variables to mitigate the selection issue noted, and control for either initial rating or initial rating by time fixed effects. Columns (2), (4) and (6) have the closest specification to the secondary market results, and we observe that the difference in issuance costs between urban and rural hospitals issuers increases by 16 bps – 21 bps after the shock. For example, column (2) implies a 19.5 bps increase in issuing yield, translating into a 2.1 million in new issuance cost.

[Table 7 Here]

Although we add bond characteristics as control variables in Table 7, a given bond characteristic may contribute to hospital financing costs differently before and after the shock. To test whether this is the case, we examine several bond characteristics that correlate with credit risk, including credit ratings, issue size, and the propensity for insurance and for GO versus Revenue bond issuance to learn whether issuers change these characteristics following the adoption of telehealth parity laws. The results from this exercise are reported in Table A.7 of the Online Appendix. Here we find no significant differences between urban and rural hospitals following the adoption of parity laws in terms of credit rating (measured either as an ordinal ranking or above/below median level), issue size, or GO issuance likelihood. However, we do find that new issuance by rural hospitals becomes 25% less likely to be insured, which is significant at the 5% level. This loss of insurance may explain in part the higher *ex post* yields faced by rural hospitals in Table 7, given the increased default risk shown in Section 4 above.

Given the concern over potential selection effects mentioned above (e.g., adversely affected rural hospitals may be less likely to issue in the post-shock period due to higher borrowing costs), we test whether telehealth parity law adoption differently impacts issue frequency. For this test, we create a panel of yearly data at the county level.[31] We estimate Equation (1) with a new dependent variable $Issue_{k,t}$ that takes the value of one if at least one hospital bond is issued in county k in year t, and zero otherwise. We include lagged county characteristics (vector $Z_{k,t-1}$ in Equation 1) as control variables along with *County* fixed effects. Results from this exercise are reported in Table 8.

[Table 8 Here]

We infer from Table 8 that hospitals in urban counties reduce new issuance frequency by a significant 3% following the state adoption of a telehealth parity law. However, the urban-rural difference in issuance frequency widens by 3.8%–4.4%, approximately 40% of the unconditional average probability (10.6%) of hospital bond issuance in rural areas. The net effect implies that hospitals in rural counties issue more frequently even though the shock increases their borrowing costs. We interpret these results as a substitution effect between internal cash flow generation and external financing, consistent with the pecking order of

[31] We require a county to have at least one hospital bond issued since 2000 for inclusion into this test.

Myers and Majluf (1984): urban hospitals generate higher internal cashflows and reduce new debt issuance; rural hospitals do the opposite.

In column (4) of Table 8 we test whether adoption of telehealth parity laws affects the amount of capital raised, conditional on a new bond issuance. Because hospitals are required to fully invest the proceeds of tax-exempt bond issues, we predict that this dollar measure of issuance size should be insensitive to the shock, conditional on issuance.[32]

To summarize our primary market results, we find that rural hospitals become more reliant on external financing (increased issuance frequency) following the adoption of telehealth parity laws even though they face higher borrowing costs. These primary market effects are larger in magnitude than the secondary market price effects documented in Section 3.1. The secondary market tests are useful for gauging price impact on current investors. The primary market tests assess the real effects of virtual competition on affected municipal hospitals. Together, these analyses lead us to conclude that telehealth parity laws adversely affect rural hospitals' cost of capital relative to urban hospitals operating in the same state.

4 The Virtual Competition Channel

We explain the preceding results of an increase in rural hospital bond yields through a virtual competition channel where the telehealth parity laws redirect revenues from rural to urban hospitals. In this section, we evaluate whether telehealth parity law adoption adversely affects the profitability of rural hospitals and thus increases their likelihood of financial distress, by estimating the following equation at the hospital level.

$$Y_{m,t} = \beta Rural_m \times Parity_{j,t} + \gamma' Controls_{m,t} + State \times Yr\, FEs + Hospital\, FEs + \varepsilon_{m,t}. \quad (3)$$

In contrast to Equation (1), where dependent variables are bond yields, the outcome variables $Y_{m,t}$ in Equation (3) are business fundamentals from hospital m's financial statements in year t. Accordingly, we replace the bond-level controls (vector $X_{i,t}$) and county-level con-

[32]This requirement does not necessarily imply new investment in physical assets; the definition of charitable investment has a broad scope including charitable patient care and other community benefits; for details, see "Charitable Hospitals - General Requirements for Tax-Exemption Under Section 501(c)(3)", IRS.

trols (vector $Z_{k,t-1}$) with lagged values for the log of total income, log of total assets, bed counts, and the log of total liabilities (indicated by $Controls_{m,t}$). We control for hospital fixed effects, *Hospital* FEs, adjusting for unobserved differences at the provider level and absorbing the coefficient of $Rural_m$ since a hospital's rurality is constant over time. We include state-by-year fixed effects, $State \times Yr$ FEs, rather than $State \times Month$ FEs, since the hospital financial statements are reported at annual frequency.

Table 9 reports the results of these regressions. From column (1), we observe that a typical rural provider loses net income to its urban counterparts in the treated states at a magnitude of 1.6% of total assets. In dollar terms, this translates to a \$1.01 million loss for an average affected rural hospital.[33]

[Table 9 here]

In column (2), we replace the *State-Year* fixed effects with *Year* fixed effects to separate the within-state changes.[34] Here we observe that urban treated hospitals see a profit increase equivalent to 1.2% of their total assets, indicated by the coefficient of $Parity_{j,t}$. This translates to an average of \$4.6 million in profit gains to urban hospitals.[35] The net effect on rural hospitals is calculated by adding the coefficients of $Rural_i \times Parity_{j,t}$ (-1.7%) and $Parity_{j,t}$ (1.3%), generating a loss of 0.6% of total assets. So urban and rural hospital profits move in opposite directions following the shock; the urban hospitals benefit at the loss of rural hospitals in the treated state. Additional results suggest that this policy change redirects patients flow from rural to urban hospitals in the treated state, rather than increasing either the customer base or the frequency of more expensive services for the healthcare industry as a whole.[36]

One concern of using net income as an outcome variable is that this measure is the residual profit after taking off other non-operating expenses, which possibly include the

[33] \$1.01 million = 1.6%×\$63.3 million, which is the average rural sample total assets.

[34] Hospital fixed effects will absorb the state fixed effects, since a hospital's location does not change.

[35] \$4.6 million = 1.2%×\$384.7 million, which is the average urban sample total assets.

[36] Table A.8 in the Online Appendix shows that the average treatment effect of telehealth parity laws on hospital revenues is close to zero with an insignificant coefficient estimate of 0.4% or 1.3%.

increased bond costs. In this case, the net profit can mechanically decrease even without patient losses. To address this concern, we focus on the net profit from patient services in columns (3) and (4), defined as total patient revenues less contractual allowances and discounts, and total operating expenses. We document an even larger loss of 2.7% as a fraction of total assets. Similarly, hospital profitability, measured by the profit margin, also significantly decreases as shown in columns (5) and (6).

In columns (7) to (8), we examine the effects on hospital leverage. We observe a significant 2.7% – 3.8% increase in leverage, equivalent in magnitude to 5.4% – 7.6% of the unconditional average leverage among rural hospitals. Theoretically, these higher debt amounts endogenously increase rural hospitals' propensity for bankruptcy (e.g. Leland, 1994), which is also consistent with hospital closure results we show later in Table 11. These increased borrowing activities also echo our findings in Table 8. Consistent with the secondary market result, we similarly plot the parallel trend figures in Figure A.3 to confirm that there exist no significant changes before the shock.

In Section 1.3, we argue that telehealth adoption redistributes revenues geographically from rural to urban hospitals via two ways – telehealth visits and in-person follow-up visits. We exhibit the results on both in Table 10 by aggregating the claim information from Marketscan to provider-year level observations. In this table, the coefficients of $Parity_{p,t}$ measure the revenue growths in different categories for urban telehealth providers after their states pass the parity law. Column (1) focuses on the direct benefit from telehealth visits, and the coefficient estimate suggests a significant growth of 44% for urban hospitals. This result is consistent with the expectation that rural patients switch from local in-person services to remote services offered by urban hospitals, which tends to be outpatient services. In addition, even for inpatient treatments that cannot be performed virtually, affected rural patients also become more likely to choose urban providers, since telehealth provides access to consultancy and recovery. We proxy this channel by focusing on the revenues generated by follow-up visits in column (2), and find that urban telehealth adopters experience a 28%

revenue growth in this category. In column (3) we find consistent magnitudes when we combine the revenues from both categories.

The large negative coefficients of the interaction term indicate that rural providers lose their competitive edges in the telehealth market, as they suffer from an increasing number of high-quality entrants from urban areas. The results also imply that the revenue losses for rural hospitals are not limited to in-person services, but also extend to the virtual ones. The coefficient magnitudes are large, consistent with the fast-growing overall market sizes in Figure 1.

4.1 Real Effects

In this section, we consider the real effects of financial distress for rural hospitals. Given the negative effects of telehealth parity laws on affected rural hospitals' borrowing costs and net incomes, we predict that rural hospitals in treated states are more likely than other hospitals to close. To test this hypothesis, we identify 129 hospital closures from 2010 to 2020 from our 4,281 sample hospitals.[37] We then estimate a Cox proportional hazards model with hospital closure as the outcome variable and report results in Table 11.[38] Columns (1) and (2) show that affected rural hospitals are indeed significantly more likely to close. In the remaining columns of Table 11, we split the sample of hospitals by rurality and find that the implementation of parity laws significantly increases the propensity of closure only in the rural areas. To quantify the economic magnitude, we plot the estimated effects of $Rural_m \times Parity_{j,t}$ on the hospital survival probability over time in Figure 4. Over a 9-year horizon, an affected rural hospital is around 6% more likely to close compared to others. This difference is almost twice of the 3% cross-sectional closure likelihood (129 out of 4281). Because the closure probabilities of rural hospitals in non-parity states are almost the same

[37]We match 88 rural hospital closures from the public data by Cecil G. Sheps Center of UNC. For urban closures, we follow the convention of the Office of Inspector General that a closed hospital is "a facility that stopped providing general, short-term, acute inpatient care." We then manually search the news of each urban hospital with zero inpatient discharges to eliminate cases such as mergers, acquisitions, and name.

[38]We analyze hospital closure data rather than hospital bond default data because the default data from Mergent and Bloomberg appear incomplete (a smaller number of default events than hospital closures).

as those of urban hospitals, we conclude that the "Rural & Parity" results in Figure 4 is driven by the telehealth parity laws rather than worsening conditions in rural areas.

[Table 11 and Figure 4 Here]

In a corporate finance setting, employee downsizing and asset divestiture is a common response to financial distress (e.g. Denis and Denis, 1995; Kang and Shivdasani, 1997; Benmelech et al., 2021; Falato and Liang, 2016). So, even if affected rural hospitals are not bankrupt, they can divest physical assets or downsize their employee headcount following the adoption of telehealth parity laws. To test this hypothesis, we revisit the hospital sample and confirm that the number of ICU units, number of employees, and average physician salaries all significantly decrease among affected rural hospitals. We report the results in Table A.9.

5 Welfare and Policy

This paper documents significant unintended financial consequences of telehealth parity laws. A rigorous quantitative analysis of the net welfare effects of telehealth parity laws is outside the scope of this paper. We acknowledge this limitation and hope future research will contribute to this important line of inquiry. In this section, we provide suggestive evidence that telehealth parity laws do not improve healthcare outcomes and offer a qualitative discussion of tradeoffs to place our empirical results into context. We then conclude with policy recommendations.

We provide evidence that residents in rural areas switch their healthcare providers from local rural hospitals to urban hospitals after their states adopt telehealth parity laws. This revealed preference is *prima facie* evidence that urban hospitals' telehealth services add value to residents of rural areas. Reducing travel costs (time and cash) for patients in need of urban specialists should allow greater productivity and discretionary income to improve the local (rural) economy. To the extent that competition encourages innovation, expanding the choice set of healthcare providers should mitigate deleterious effects of monopolistic supply. Finally, redirecting some rural patients to urban telehealth may alleviate any capacity pressure in rural hospitals and thus result in more attentive care. Indeed, we analyze survey data and find slightly higher average patient satisfaction with in-patient care provided by rural hospitals following telehealth parity laws. We report the results in Table A.10 in the Internet Appendix.

However, analysis of mortality rates due to chronic disease does not indicate that telehealth parity laws improve real healthcare outcomes among residents of rural counties. Using uncensored mortality data licensed from the CDC, we test whether this improved access to urban healthcare services reduces the number of deaths (per 1,000 residents) due to heart failure, chronic kidney disease, diabetes, chronic obstructive pulmonary disease, or Alzheimer's. We find no significant reduction in rural mortality rates resulting from the ease of access to urban healthcare services. These results are reported in Table A.11 in the Internet Appendix.

The fact that we do not find significant changes in chronic disease mortality highlights the potential negative offsetting effects due to hospital divestment and closures, consistent with prior healthcare literature establishing negative consequences following rural hospital closure. In theory, new clinics and physician centers should enter the area later, in which case healthcare supply is maintained following a period of transition. In practice, however, this shift from hospitals to physicians' offices is observed only following urban hospital closures (Buchmueller et al., 2006). Rural areas do not attract these non-hospital substitutes (Rosenbach and Dayhoff, 1995), and rural patients seek next-nearest hospital-based emergency departments for urgent or even primary care (Wishner et al., 2016). Using the QCEW data from U.S. Bureau of Labor Statistics, we find that the number of government-sponsored ambulatory surgery centers (ASCs) slightly decreases in treated rural counties after 2010, and private ASCs do not fill the gap (Table A.12). Following rural hospital closure, transition time to the next-nearest provider increases significantly, and timely treatment is delayed particularly for emergency care (Miller et al., 2020; Wishner et al., 2016). Indeed, Troske and Davis (2019) show that ambulance transportation time increases by 76% in rural zip codes following hospital closures, but does not change for closures of urban counterparts. A related consideration is that if the closed rural hospitals provided poor healthcare services, then their closure would improve patient welfare by forcing them to seek (better) services further from home. However, Song and Saghafian (2019) document that with more patient inflows, replacement hospitals reduce service duration and speed up treatment, which ultimately decrease quality of care. Recent work by Carroll (2019) and Gujral and Basu (2019) supports this conclusion with evidence that rural hospital closures will increase local inpatient mortality, especially for time-sensitive health conditions.

The COVID pandemic of 2020 highlights the consequences of the physician shortage and ICU bed shortage and their joint contribution to human mortality, especially among senior citizens in rural areas.[39] Overall, our results commend policies to support basic and acute healthcare services in rural areas features with low-income elderly population with relatively low-rated hospitals. For example, there are federal and state funding opportunities for rural telehealth adoption such as the investment by the U.S. Department of Health and Human Services (HHS) to strengthen rural HIT infrastructure.[40] States that adopt telehealth parity laws may consider funding opportunities to sponsor rural healthcare development similar to the Telehealth Resource Center in California.[41]

Perhaps even more useful than short-term government grants are long-term alliances between rural and urban hospitals. Such alliances facilitate efficient remote delivery of urban consultancies complemented by in-person examination and treatment by physicians at local rural hospitals.[42] The current telehealth reimbursement policies do not facilitate such collaboration since the originating site is permitted only a small facilitation fee, but these

[39] "Millions Of Older Americans Live In Counties With No ICU Beds As Pandemic Intensifies," KHN 2020.

[40] "HHS Awards over $35 million to Increase Access to High Quality Health Care in Rural Communities," HHS 2020.

[41] For detailed operation of this center, see `https://www.caltrc.org/`.

[42] In recent years, many states, such as Oklahoma, Oregon, and South Carolina, have initiated government-funded inner-state telehealth alliance and network to connect rural hospitals with urban providers and academic medical centers. In addition, we find that rural hospitals affiliated with hospital systems suffer less in terms of revenue loss after the shock, suggesting potential benefits of such alliances in securing (rural) hospital revenue.

policies could be amended to foster collaboration. A shared system allowing specialist consultation with in-person follow-up treatments locally arguably allows for quality healthcare and sustains the local rural hospital to provide acute care. Finally, states may also consider clearing regulatory barriers to allow rural hospitals to form alliances with commercial telehealth platforms provided by CVS, Walgreens, and Walmart.

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Figures

Figure 1: Total Telehealth Payments Over Time

This figure plots the time series of total telehealth payments using the Marketscan data from 2012 to 2019. A detailed definition of telehealth claims is in Section 2.1.3. In recent years, this database covers over 43 million privately-insured individuals with employment-based health plans, which represent roughly 14% of all insured and 20% of all privately insured U.S. population.

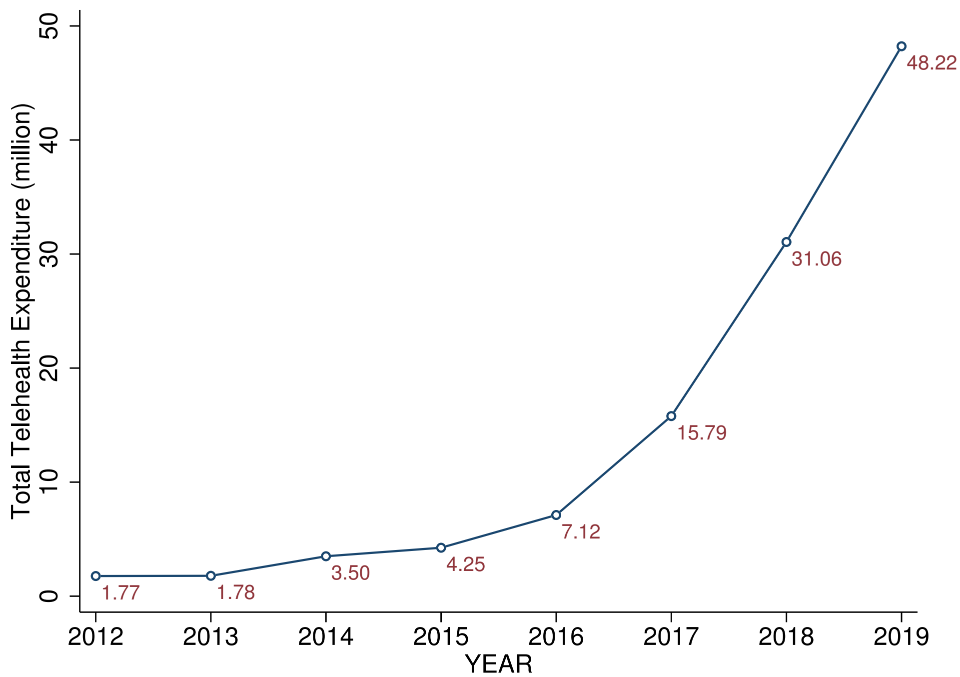


Figure 2: Telehealth Parity Law Implementation Over Time

This figure plots the timing of telehealth parity law implementation across different states. Different colors indicate the time window of adoption, explained in the legend. Gray states are the control states, i.e. states without parity laws.

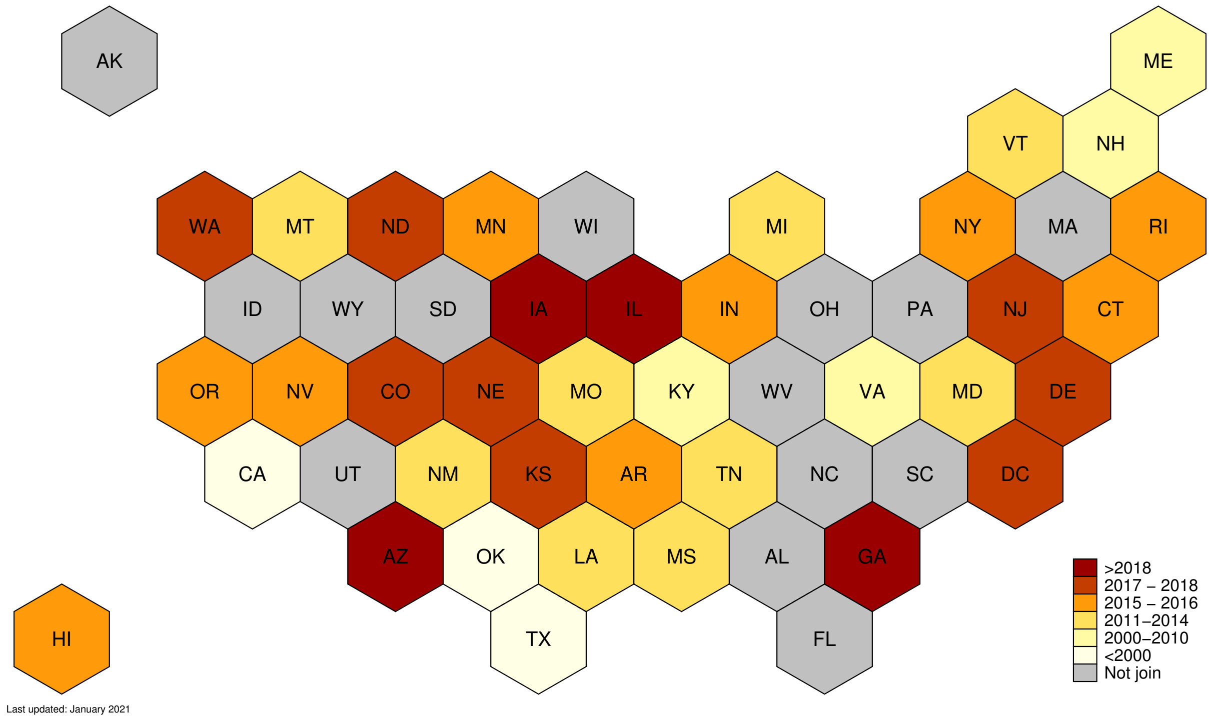


Figure 3: Dynamic Effects of Telehealth Adoption on Costs of Capital in the Secondary Market

This figure plots effects of telehealth adoption on costs of capital in six-month periods before and after the shock using Equation (2) and the the interaction weighted (IW) estimator from Sun and Abraham (2021). Circles represent the estimated coefficients β^n and dashed lines indicate the 95% confidence interval. In Figure (a), we use $Yield_{i,t}$ as the outcome variable to estimate Equation (2) in the full sample. In Figure (b), we replicate the analysis in the sample of parity states. We follow Sun and Abraham (2021) and plot the IW estimator in each event period using either non-parity states (Figure c) or the last treated rural hospitals (Figure d) as the control group. In the last two figures, we use $Spread_{i,t}$ (Figure e) and $SpreadMMA_{i,t}$ (Figure f) as the outcome variable for Equation (2).

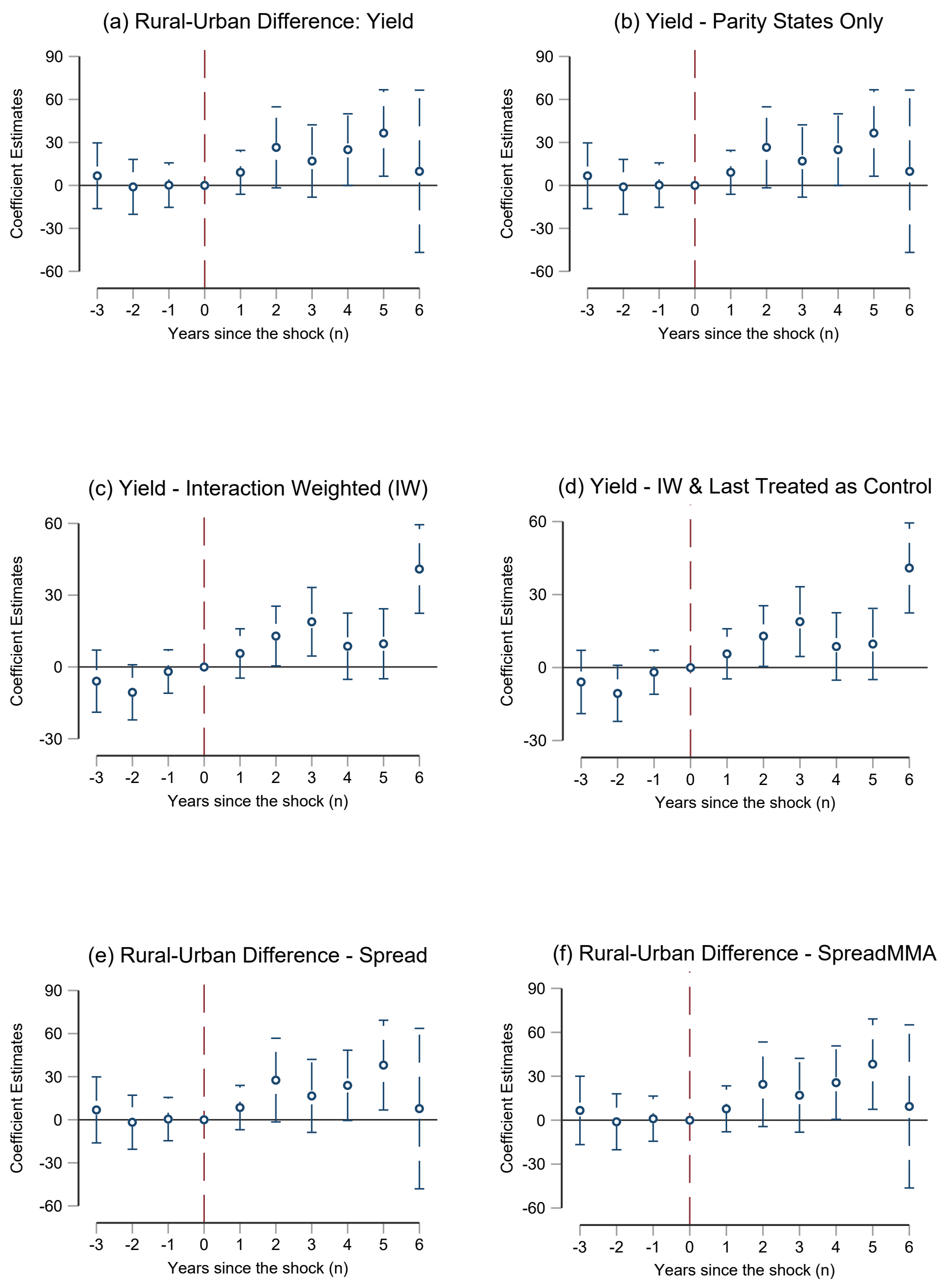
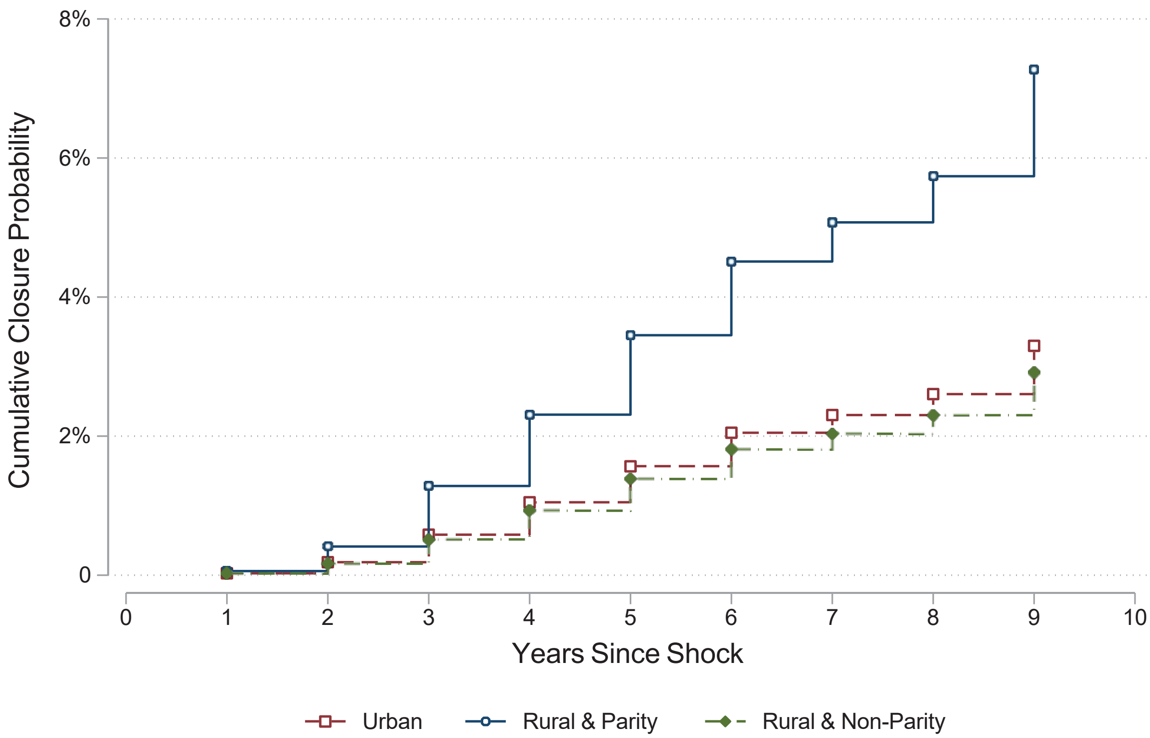


Figure 4: Effects of Telehealth Adoption on Hospital Closure

This figure plots effects of telehealth adoption on hospital closures, using the estimation from Table 11 column (1). The blue line plots the estimated cumulative closure probability with $Rural_m \times Parity_{j,t} = 1$, the green line plots with $Rural_m = 1$ and $Parity_{j,t} = 0$, and the red line plots the probability with $Rural_m = 0$. We use the mean values of other predictors for estimation.



Tables

Table 1: Distribution of Telehealth Providers and Probability of Follow-up Visits

This table reports the geographic distribution of telehealth providers (in Panel A) and the cumulative probability of in-person follow-up visits (in Panel B) using the Marketscan data from 2012 to 2019. In Panel A, we calculate the percentage of telehealth service claims by urban patients that are either provided by urban or rural telehealth providers in the first row. The second row follows a similar calculation, except that we focus on the telehealth service claims by rural patients. In Panel B, a follow-up visit is non-telehealth visit to the telehealth provider that happens strictly later than the first telehealth service date. The first three columns report the probability of having a follow-up visit within 180 days, one year, or two years after the first telehealth service date, respectively. The last column reports the probability of having a follow-up visit any time after the first telehealth service date.

Panel A: Geographic Distribution of Telehealth Providers

		Telehealth Provider Location		
		Urban	**Rural**	**Sum**
Patient	**Urban**	99.56%	0.44%	100.00%
Location	**Rural**	81.60%	18.40%	100.00%

Panel B: Cumulative Probability of In-person Follow-up Visits Over Time

Window	**<=180 Days**	**One year**	**Two Years**	**Ever**
Full Sample	25.74%	31.12%	34.00%	34.93%
Urban Patients	25.56%	30.94%	33.84%	34.79%
Rural Patients	27.80%	33.20%	35.78%	36.60%

Table 2: Sample Characteristics

This table reports the difference in bond characteristics between hospital bonds and non-hospital bonds issued in the period of 2000 to 2019 (Panel A), secondary-market bond characteristics between rural and urban hospital bonds (Panel B), and operational characteristics between rural hospitals and urban hospitals (Panel C). Detailed variable definitions are in Table A.1. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Bond Characteristics: Hospital v.s. Non-Hospital

	Non-Hospital	Hospital	Difference
Number of Bonds	1,651,031	42,048	
Bond Size (Million)	2.35	6.92	−4.57***
Offering Yield (bp)	307.49	365.44	−57.95***
Offering Spread (bp)	101.41	154.15	−52.75***
Offering Spread over MMA (bp)	23.6	71.54	−47.95***
Years to Maturity (year)	9.82	11.17	−1.35***
Above A Rating (percent)	0.71	0.45	0.26***
Insured (percent)	0.43	0.24	0.19***
General Obligation (percent)	0.64	0.12	0.52***
Metro Area (percent)	0.9	0.88	0.03

Panel B: Hospital Bond Characteristics: Rural v.s. Urban

	Rural	Urban	Difference
Number of Hospitals	32,447	510,980	
Bond Size (Million)	10.86	19.99	−9.13***
Offering Yield (bp)	432.25	412.66	19.59***
Offering Spread (bp)	241.36	229.72	11.64***
Offering Spread over MMA (bp)	146.84	137.49	9.35***
Years to Maturity (year)	13.07	13.31	−0.24***
Above A Rating (percent)	0.45	0.51	−0.06***
Insured (percent)	0.35	0.28	0.07***
General Obligation (percent)	0.07	0.02	0.05***

Panel C: Hospital Characteristics: Rural v.s. Urban

	Rural	Urban	Difference
Number of Hospitals	2,001	2,280	
Net Income (Million)	1.01	12.38	−11.38***
Margin	0.01	0.04	−0.02***
Total Revenue (Million)	124.21	949.69	−825.48***
Total Assets (Million)	63.33	384.72	−321.39***
Discharge	1,724.46	11,308.54	−9,584.08***
Debt/TA	0.51	0.59	−0.09***
ICU Units	8.71	30.36	−21.65***

Table 3: Telehealth Parity Adoption and Bond yield in the Secondary Market

This table reports the differential effect of telehealth parity adoption on rural hospital municipal bonds in the secondary transaction market using Equation (1). The sample period is 2000–2019 and the unit of data is a monthly bond observation. $Yield_{i,t}$ is the size-weighted transaction yield at bond-month level. $Spread_{i,t}$ is the spread to maturity-matched after-tax Treasury rates and $SpreadMMA_{i,t}$ is spread to maturity-matched yields from the Municipal Market Advisors AAA-rated curve. $Rural_i$ equals one when the bond is issued in a rural area, and $Parity_{j,t}$ equals one if bond i's state j has enacted the parity law in month t, and zero otherwise. *Controls* include bond characteristics interacted with trade year indicators and county fundamentals. Bond characteristics include credit rating at the time of transaction, log maturity, log size, indicator variables for whether the bond is general obligation, callable, insured, reoffered or negotiated. County fundamentals include population level, per capita income, population growth, employment growth, and labor participation. *State-Month FE* is the state by year-month fixed effect, which will absorb the direct effect of $Parity_{j,t}$. *HRR-Month FE* is the hospital referral regions by year-month fixed effect. *Issuer FE* is the issuer fixed effect. *Control Group* include the hospital bonds in states without the telehealth parity law. Standard errors are double clustered by county and trade year-month and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Yield

	(1) ***Yield***	(2) ***Yield***	(3) ***Yield***	(4) ***Yield***	(5) ***Yield***
Parity × Rural	16.984**	25.162**	17.888**	21.011**	11.455**
	(1.981)	(2.101)	(2.093)	(2.498)	(2.329)
Rural	2.981	−2.130	2.733	0.495	
	(0.735)	(-0.447)	(0.632)	(0.102)	
Parity					0.935
					(0.318)
Controls	Y	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y	N
Issuer FE	N	N	N	N	Y
Month FE	N	N	N	N	Y
HRR-Month FE	N	Y	N	N	N
Control Group	<2014	<2014	All	No	<2014
N	529,184	525,478	562,198	349,576	529,350
Adj. R^2	0.62	0.65	0.28	0.60	0.65

Panel B: Spread

	(1) ***Spread***	(2) ***Spread***	(3) ***SpreadMMA***	(4) ***SpreadMMA***
Parity × *Rural*	17.553**	25.314**	16.244*	23.768*
	(2.001)	(2.069)	(1.831)	(1.949)
Rural	3.358	−1.976	2.612	−2.570
	(0.849)	(−0.426)	(0.649)	(−0.536)
Controls	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y
*HRR-Month F*E	N	Y	N	Y
Control Group	<2014	<2014	<2014	<2014
N	529,184	525,478	528,185	524,497
Adj. R^2	0.50	0.54	0.44	0.49

Table 4: Heterogeneous Effects of Telehealth Parity Adoption

This table reports the heterogeneous effects of telehealth parity adoption on rural hospital municipal bonds in the secondary transaction market using Equation (1). The sample period is 2000–2019 and the unit of data is a monthly bond observation. $Yield_{i,t}$, $Spread_{i,t}$, $SpreadMMA_{i,t}$, $Rural_i$ and $Parity_{j,t}$ are defined in the same way as Table 3. Go_i is one if bond i is a general obligation bond, and zero otherwise. $HighRating_i$ is one if bond i has an issuance rating above the sample median (single A), and zero otherwise. $System_i$ is one if bond i is issued by a hospital belonging to a hospital system covering at least two states. *Controls* include bond characteristics interacted with trade year indicators and county fundamentals. Bond characteristics include credit rating at the time of transaction, log maturity, log size, indicator variables for whether the bond is general obligation, callable, insured, reoffered or negotiated. *State-Month FE* is the state by year-month fixed effect, which will absorb the direct effect of $Parity_{j,t}$. *Control Group* include the hospital bonds issued before 2014 in states without the telehealth parity law. Standard errors are double clustered by county and trade year-month and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: General Obligation

	$GO_i = 1$			$GO_i = 0$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Yield	***Spread***	***SpreadMMA***	***Yield***	***Spread***	***SpreadMMA***
$Parity \times Rural$	−11.189	−12.450	−14.121	16.710*	17.374*	16.132*
	(−0.586)	(−0.672)	(−0.835)	(1.889)	(1.918)	(1.763)
$Rural$	13.603**	13.449**	14.542***	4.320	4.734	3.846
	(2.311)	(2.061)	(2.698)	(0.985)	(1.108)	(0.886)
$Controls$	Y	Y	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y	Y	Y
N	11,173	11,173	11,157	516,979	516,979	515,999
Adj. R^2	0.68	0.62	0.58	0.62	0.50	0.44

Panel B: Credit Rating

	$HighRating_i = 1$			$HighRating_i = 0$		
	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***	(4) ***Yield***	(5) ***Spread***	(6) ***SpreadMMA***
Parity × *Rural*	−0.500	−0.680	−2.726	35.602**	35.544**	34.265**
	(−0.039)	(−0.053)	(−0.221)	(2.109)	(2.106)	(1.999)
Rural	−5.812	−5.811	−6.431	14.080	14.067	13.596*
	(−1.198)	(−1.193)	(−1.302)	(1.544)	(1.545)	(1.791)
Controls	Y	Y	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y	Y	Y
N	266,404	266,404	265,975	262,000	262,000	261,444
Adj. R^2	0.68	0.55	0.47	0.54	0.44	0.39

Panel C: Cross-State System

	$System_i = 1$			$System_i = 0$		
	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***	(4) ***Yield***	(5) ***Spread***	(6) ***SpreadMMA***
Parity × *Rural*	6.741	5.436	0.604	15.917*	16.474*	15.696*
	(0.382)	(0.322)	(0.034)	(1.722)	(1.761)	(1.666)
Rural	6.775	8.740	5.722	3.385	3.829	3.148
	(0.517)	(0.706)	(0.435)	(0.746)	(0.871)	(0.712)
Controls	Y	Y	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y	Y	Y
N	96,498	96,498	96,174	431,625	431,625	430,961
Adj. R^2	0.69	0.59	0.55	0.62	0.51	0.44

Table 5: Telehealth Parity Adoption and Bond Credit Ratings

This table reports the effects of telehealth parity adoption on rural hospital municipal bond credit ratings using Equation (1). The sample period is 2000–2019 and the unit of data is a monthly bond observation. $Rating_{i,t}$ is the numeric value of bond i's credit rating in month t with the potential range of 0 (D) to 21 (AAA). $Downgrade_{i,t}$ is an indicator variable that takes value of one if bond i is downgraded in month t, and zero otherwise. $Rural_i$ equals one when the bond is issued in a rural area, and $Parity_{j,t}$ equals one if bond i's state j has enacted the parity law in month t, and zero otherwise. *Controls* include bond characteristics interacted with trade year indicators and county fundamentals. Bond characteristics include log maturity, log size, indicator variables for whether the bond is general obligation, callable, insured, reoffered or negotiated. *State-Month FE* is the state by year-month fixed effect, which will absorb the direct effect of $Parity_{j,t}$. *IssueRating FE* is the bond initial rating upon issuance fixed effect. *Control Group* include the hospital bonds issued before 2014 in states without the telehealth parity law. Standard errors are double clustered by county and trade year-month and t-statistics are reported in parentheses. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Rating***	(2) ***Rating***	(3) ***Rating***	(4) ***Downgrade***	(5) ***Downgrade***	(6) ***Downgrade***
$Parity \times Rural$	−1.976**	−1.429*	−0.914*	0.013*	0.015**	0.014**
	(−2.175)	(−1.718)	(−1.914)	(1.927)	(2.335)	(2.113)
$Rural$	−0.784**	−0.961***	−0.026	0.002	−0.005	−0.004
	(−2.060)	(−3.395)	(−0.242)	(0.883)	(−1.570)	(−1.206)
$Controls$	N	Y	Y	N	Y	Y
State-Month FE	Y	Y	Y	Y	Y	Y
IssueRating FE	N	N	Y	N	N	Y
N	540,664	529,505	529,505	540,664	529,505	529,505
Adj. R^2	0.13	0.18	0.70	0.04	0.06	0.06

Table 6: Telehealth Parity Adoption and Accessibility to Fixed Broadband

This table shows how the effects on costs of capital depend on the accessibility of fixed broadband. We separately split rural and urban counties into tertiles based on their accessibility to fixed broadband data in 2016. In Panel A, we report the average percent of population without broadband access in each group and in both areas. In Panel B, we report the subsample analysis across different groups. $Yield_{i,t}$, $Spread_{i,t}$, $SpreadMMA_{i,t}$, $Rural_i$ and $Parity_{j,t}$ are defined in the same way as Table 3. *Controls* include bond characteristics interacted with trade year indicators and county fundamentals explained in Section 2.2. *State-Month FE* is the state by year-month fixed effect, which absorbs the direct effect of $Parity_{j,t}$. *Control Group* include the hospital bonds issued before 2014 in states without the telehealth parity law. Standard errors are double clustered by county and trade year-month and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Accessibility to Fixed Broadband by Groups

	Rurality	***Worst***	***Medium***	***Best***
Avg. Percent of Population Without Broadband in 2016	Rural	0.455	0.209	0.097
	Urban	0.096	0.026	0.008

Panel B: Effects on Costs of Capital by Accessibility

	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***	(4) ***Yield***	(5) ***Spread***	(6) ***SpreadMMA***
Parity × *Rural*	4.542	4.167	3.456	22.572	23.126	22.687
	(0.406)	(0.372)	(0.307)	(1.538)	(1.427)	(1.521)
Rural	6.860	8.260	7.051	9.320	8.429	7.586
	(1.111)	(1.383)	(1.146)	(0.693)	(0.668)	(0.562)
Accessibility	*Worst*	*Worst*	*Worst*	*Medium*	*Medium*	*Medium*
Controls	Y	Y	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y	Y	Y
N	184,143	184,143	183,838	172,730	172,730	172,291
Adj. R^2	0.62	0.47	0.39	0.72	0.58	0.48

	(7) ***Yield***	(8) ***Spread***	(9) ***SpreadMMA***
Parity × *Rural*	63.905**	65.604**	66.924***
	(2.416)	(2.436)	(2.633)
Rural	6.539	5.599	6.470
	(0.835)	(0.748)	(0.836)
Accessibility	*Best*	*Best*	*Best*
Controls	Y	Y	Y
State-Month FE	Y	Y	Y
N	170,851	170,851	170,611
Adj. R^2	0.70	0.58	0.51

Table 7: Telehealth Parity Adoption and offering yield in the Primary Market

This table reports the differential effect of telehealth parity adoption on rural hospital municipal bonds in the primary issuance market using Equation (1). The sample period is 2000–2019 and the unit of data is a bond upon issuance. The outcome variables $Yield_{i,t}$, $Spread_{i,t}$, and $SpreadMMA_{i,t}$ are defined in the same way as Table 3. $Rural_i$ equals one when the bond is issued in a rural area, and $Parity_{j,t}$ equals one if bond i's state j has enacted the parity law in month t, and zero otherwise. *Controls* include bond characteristics interacted with issuance year indicators and county fundamentals. Bond characteristics include log maturity, log size, indicator variables for whether the bond is general obligation, callable, insured, reoffered or negotiated. County fundamentals include population level, per capita income, population growth, employment growth, and labor participation. *State-Month FE* is the state by year-month fixed effect, which will absorb the direct effect of $Parity_{j,t}$. *IssueRating FE* is the bond initial rating upon issuance fixed effect. *IssueRating-Time FE* is the bond initial rating upon issuance by issuing year fixed effect. *Control Group* include the hospital bonds in states without the telehealth parity law. Standard errors are double clustered county and issuance year-month and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Yield	***Yield***	***Spread***	***Spread***	***SpreadMMA***	***SpreadMMA***
Parity × Rural	30.195***	19.586**	31.783***	20.844**	26.633**	16.097**
	(2.681)	(2.275)	(2.811)	(2.337)	(2.200)	(2.383)
Rural	−2.238	1.430	−3.352	0.431	−3.723	−0.504
	(−0.364)	(0.279)	(−0.573)	(0.085)	(−0.609)	(−0.093)
Controls	Y	Y	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y	Y	Y
IssueRating FE	Y	N	Y	N	Y	N
IssueRating-Time FE	N	Y	N	Y	N	Y
N	34,764	34,760	34,764	34,760	33,638	33,636
Adj. R^2	0.97	0.97	0.90	0.91	0.88	0.90

Table 8: Telehealth Parity Adoption and County-Level Issuance Frequency

This table reports the differential effect of telehealth parity adoption on rural hospital's access to capital by estiaming the following Equation:

$$Y_{k,t} = Rural_k \times Parity_{j,t} + Controls_{k,t} + County\,FEs + State \times Yr\,FEs + \varepsilon_{k,t}.$$

The sample period is 2000–2019 and the unit of data is a county (indexed by k) by year (indexed by t) observation. $Issue_{k,t}$ takes the value of one if at least one hospital bond is issued in county k in year t, and zero otherwise. $TotalAmt_{k,t}$ is the log amount of total issuance of hospital bonds in county k in year t. In column (4), we only include the county-year observations with bond issuance. $Rural_k$ equals one when county k is in a rural area, and $Parity_{j,t}$ equals one if the county's state j has enacted the parity law in year t, and zero otherwise. *Controls* are county fundamentals including population level, per capita income, population growth, employment growth, and labor participation. Standard errors are clustered by county and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Issue***	(2) ***Issue***	(3) ***Issue***	(4) ***TotalAmt***
$Parity \times Rural$	0.044***	0.038***	0.033**	88.106
	(3.291)	(2.871)	(2.308)	(1.314)
$Parity$	−0.028**	−0.030***		
	(−2.396)	(−2.589)		
$Controls$	N	Y	Y	Y
State-Yr FE	N	N	Y	Y
County FE	Y	Y	Y	Y
Yr FE	Y	Y	N	N
N	22,180	22,167	22,068	3,251
Adj. R^2	0.24	0.24	0.24	0.39

Table 9: Telehealth Parity Adoption and Hospital Financial Conditions

This table reports the effects of telehealth parity adoption on rural hospital financial conditions using Equation (3). The sample period is 2009—2018 and the unit of data is an annual hospital observation. $NetInc/TA_{m,t}$ is hospital m's net income to total asset ratio in year t, $PatInc/TA_{m,t}$ is hospital m's patient service income in year t, which is total patient revenues less contractual allowances and discounts, and total operating expenses. $Profitability_{m,t}$ is net income divided by total income (net patient revenues and total other income). $Debt/TA_{m,t}$ is hospital m's debt to total asset ratio in year t. $Rural_m$ equals one when hospital m is in a rural area, and $Parity_{j,t}$ equals one if the hospital's state j has enacted the parity law in year t, and zero otherwise. *Controls* include lagged variables of the logarithm of total income, the logarithm of total assets, bed counts, and the logarithm of total liabilities. *Hospital FE* is the hospital fixed effect and *State-Yr FE* is the state by year fixed effect. *Yr FE* is the year fixed effect. Standard errors are double clustered by county and year and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***NetInc/TA***	(2) ***NetInc/TA***	(3) ***PatInc/TA***	(4) ***PatInc/TA***	(5) ***Profitability***	(6) ***Profitability***	(7) ***Debt/TA***	(8) ***Debt/TA***
Parity × Rural	−0.016**	−0.018***	−0.027***	−0.027***	−0.007*	−0.008**	0.027*	0.038**
	(−2.489)	(−3.549)	(−3.449)	(−3.502)	(−1.975)	(−2.357)	(2.167)	(3.124)
Parity		0.012**		0.010		0.003		−0.033**
		(2.325)		(1.279)		(0.894)		(−2.873)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y	Y	Y
State-Yr FE	Y	N	Y	N	Y	N	Y	N
Yr FE	N	Y	N	Y	N	Y	N	Y
N	37,492	37,492	37,492	37,492	37,560	37,560	37,139	37,139
Adj. R^2	0.48	0.47	0.62	0.62	0.54	0.53	0.82	0.82

Table 10: Telehealth Parity Adoption and Revenue Redistribution

This table reports how telehealth parity adoption redistributes revenues among rural and urban providers using the claim data from Marketscan by estimating

$$Y_{p,t} = Rural_p \times Parity_{p,t} + Parity_{p,t} + Provider\,FEs + Yr\,FEs + \varepsilon_{p,t}.$$

The sample period is 2012–2019 and the unit of data is a provider (indexed by p) by year (indexed by t) observation. $Log(Tele)_{p,t}$ is the log amount of total telehealth payments received by provider p in year t. $Log(Follow)_{p,t}$ is the log amount of total in-person follow-up visit payments received by provider p in year t. $Log(Total)_{p,t}$ is the log amount of both telehealth and follow-up visit payments received by provider p in year t. $Rural_p$ equals one when provider p is in a rural area, and $Parity_{p,t}$ equals one if the provider's state j has enacted the parity law in year t, and zero otherwise. Provider fixed effects and year fixed effects are included. Standard errors are clustered by provider and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Log(Tele)***	(2) ***Log(Gate)***	(3) ***Log(Total)***
Parity $\times$ *Rural*	−1.166***	−0.723***	−0.590***
	(−7.964)	(−4.828)	(−3.990)
Parity	0.440***	0.283***	0.361***
	(4.209)	(2.643)	(3.409)
Provider FE	Y	Y	Y
Yr FE	Y	Y	Y
N	24,485	24,485	24,485
Adj. R^2	0.50	0.42	0.40

Table 11: Telehealth Parity Adoption and Hospital Closure

This table reports the effects of telehealth parity adoption on hospital closure from Cox proportional hazard regressions as follows

$$h_m(t) = h_0(t)\exp(\beta_1 Parity_{j,t} \times Rural_m + \beta_2 Parity_{j,t} + \beta_3 Rural_m + Controls_{m,t}).$$

$h_m(t)$ is the hazard function at time t with "failure" denoting hospital closure. The sample period starts from 2000 and the yearly hospital observations continue until a closure or the end of the sample period (2018). $Rural_m$ equals one when hospital m is in a rural area, and $Parity_{j,t}$ equals one if the hospital's state j has enacted the parity law in year t, and zero otherwise. We report the raw coefficients of Cox regressions instead of the hazard rates. Columns (3) and (4) only include the rural counties whereas columns (5) and (6) only include urban counties. *Controls* include lagged variables of the logarithm of total income, the logarithm of total assets, bed counts, and the logarithm of total liabilities. Standard errors are double clustered by county and year and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Closure***	(2) ***Closure***	(3) ***Closure***	(4) ***Closure***	(5) ***Closure***	(6) ***Closure***
Parity × *Rural*	1.130**	1.157**				
	(2.108)	(2.302)				
Parity	−0.376	−0.444	0.626***	0.486**	−0.257	−0.318
	(−0.938)	(−1.192)	(3.661)	(2.407)	(−0.622)	(−0.826)
Rural	−0.278	−1.040***				
	(−0.854)	(−3.485)				
Sample	Urban&Rural	Urban&Rural	Rural	Rural	Urban	Urban
Controls	N	Y	N	Y	N	Y
N	37,809	33,924	17,535	16,257	20,274	17,667

Online Appendix

Table of Contents

A.I Telehealth Parity Law Details

In this section, we provide a case study to summarize the details of telehealth parity laws using the legislation of Washington, Minnesota, Oregon, Colorado, and New York, which are the states passing the parity law in 2015. We select this group since their legislative details are representative of the parity laws in recent years. Below is the list of bills where we collect the information:

- Washington Substitute Senate Bill 5175 (WA SB5175) in 2015;
- Minnesota Senate Bill SF981 (MN SF981) in 2015;
- Oregon Senate Bill 144 (OR SB144) in 2015;
- Colorado House Bill 15-1029 (CO HB15-1029) in 2015;
- New York Bill A02552 (NY A02552) in 2015.

Unless otherwise specified, the quotes in this section are from the corresponding bills in the above states. We include additional details from other documents by state departments of health.

A.I.1 Purpose of Parity Laws

In the paper, we argue that a practical reason for states to adopt the parity law is to increase access of healthcare for under-served rural population through telehealth. We now provide supporting evidence from the legal details.

Most states do not explicitly state the practical purpose of parity laws in their bills. For example, WA SB5175 briefly writes "*it is the intent of the legislature to recognize the application of telemedicine as a reimbursable service by which an individual receives medical services from a health care provider without in-person contact with the provider. It is also the intent of the legislature to reduce the compliance requirements on hospitals when granting privileges or associations to telemedicine physicians.*" One exception is with Colorado where the state expects to achieve network adequacy through telehealth services (CO HB15-1029). Network adequacy is defined as "*a carrier providing a managed care plan shall maintain a network that is sufficient in numbers and types of providers to assure that all covered benefits to covered persons will be accessible without unreasonable delay.*" In particular, the bill emphasizes that "*the division of insurance, in cooperation with the chief medical officer for the state, shall evaluate a carrier's network adequacy plan concerning the use of telehealth for providers who are specialists and sub-specialists for rural areas. The division and chief medical officer shall conduct the review in a timely fashion so as not to delay access to health care services.*"

We supplement with other anecdotal details of practical purposes. The New York Department of Health summarizes the need of telehealth services for the following six aspects: "*growing population; provider shortage; increase of older, home-bound, physically-challenged individuals coping with chronic diseases; lack of access to medical services in rural and geographically isolated areas; explosion in computer-based technology; and consumer population at ease with computer-based/electronic transactions.*"[43] The Minnesota Hospital Association summarizes the rationales into the following: "*Telemedicine improves the quality of patient care; Telemedicine benefits residents, especially those in rural communities; Consumer interest and support of telemedicine is growing.*"[44]

A.I.2 Definition of Parity

In general, a parity law requires two aspects of parity: coverage and reimbursement. We use the wording in MN SF981 as example. For coverage, a common statement is as follows:

"*A health carrier shall not exclude a service for coverage solely because the service is provided via telemedicine and is not provided through in-person consultation or contact between a health care provider and a patient.*"

The regulation for reimbursement is stated as:

"*A health carrier shall reimburse the distant site health care provider for covered services delivered via telemedicine on the same basis and at the same rate as the health carrier would apply to those services if they had been delivered by the distant site provider in person.*"

A.I.3 Covered Services

Broadly speaking, telehealth "*means a mode of delivery health care services through telecommunications systems, including information, electronic, and communication technologies, to facilitate the assessment, diagnosis, consultation, treatment, education, care management, or self-management of a covered person's health care while the covered person is located at an originating site and the provider is located at a distant site*" (CO HB15-1029). In the paper, we discuss three types of major services, and state policies differ in which type of services can be covered by the parity law.

The most common service is synchronous live-conferencing, also know as "telemedicine." For example, NY A02552 defines it as "*the use of synchronous, two-way electronic audio visual communications to deliver clinical health care services.*" All states parity laws cover telemedicine services. However, most states do not reimburse audio-only or text-only services, even if they are synchronous. CO HB15-1029 explicitly writes telehealth "*does not include the delivery of health care services via telephone, facsimile machine, or electronic*

[43] See "New York State Telehealth Parity Law Update", Center for Health Care Policy and Resource Development, New York Department of Health.

[44] See "Fact sheet: Minnesota Telemedicine Act (SF 981/HF 1246)," Minnesota Hospital Association.

mail."

The second service is "store and forward," which is defined as "*the transmission of a patient's medical information from an originating site to a health care provider at a distant site without the patient being present, or the delivery of telemedicine that does not occur in real time via synchronous transmissions*" (MN SF981). OR SB144 does not cover this service. WA SB5175 requires that "*if the service is provided through store and forward technology there must be an associated office visit between the covered person and the referring health care provider,*" and "*if the health care service is medically necessary.*" NY A02552, MN SF981 and CO HB15-1029 cover this service without restrictions.

The last service is remote patient monitoring, which is defined as "*the use of synchronous or asynchronous electronic information and communication technologies to collect personal health information and medical data from a person at an originating site that is transmitted to a telehealth provider at a distant site for use in treatment and management of medical conditions that require frequent monitoring*" (NY A02552). Other than New York, all other states in this case study do not cover this service.

A.I.4 Originating Site

Originating site "*a site at which a patient is located at the time health care services are delivered to him or her by means of telehealth*" (NY A02552). Most states do not allow using the patient home as the originating site, except that New York allows doing so only if the service is remote patient monitoring. States typically list a set of facilities that can serve as the originating site, typically include

1. Hospital;
2. Rural health clinic;
3. Federal qualified health center;
4. Physician's or other health care provider's office;
5. Community mental health center;
6. Skilled nursing facility;
7. Renal dialysis center.

This list can be found in OR SB144 or WA SB5175. States also require that health carrier cannot refuse services based on the location of patients. For example, the following statement is commonly included "*a health carrier may not distinguish between originating sites that are rural and urban in providing the coverage required*" (WA SB5175).

Since the service fees are reimbursed to the distant healthcare provider, in order to provide incentives for facilities to serve as the originating site, most states include statements allowing a "facility fee." For example, MN SF 981 includes "*if a health care provider provides the facility used as the originating site for the delivery of telemedicine to a health carrier's insured or enrollee, the health carrier shall make a facility fee payment to the originating site health care provider.*" While the federal program Medicare fixes the facility fee at $25, state policies allow negotiation based carriers. For example, WA SB5175 states "*reimbursement must be subject to a negotiated agreement between the originating site and the health plan.*" Anecdotal evidence suggests that the facility fee varies between $50 and $350, depending on the insurance coverage.[45]

A.I.5 Other Contents

Other contents in the bills are standard and usually do not vary across states. These items include (i) the definition of healthcare providers and facilities, which in general follow the same definition of in person services; (ii) health plans and carriers (insurers) subject to the law, which include state-sponsored public plans and private insurers licensed to operate in the state; and (iii) the effective dates.

[45] See "'The Charges Seem Crazy': Hospitals Impose a 'Facility Fee' — For a Video Visit," Kaiser Health News, 2021.

A.II Tables

Table A.1: Variable Definition and Summary Statistics

Variable	Definition	N	Mean	Std	P25	Median	P75
Panel A: Bond Variables							
Offer Yield	Offering yield at issuance	41,949	365.64	130.41	281	381	455
Spread	Spread over maturity-matched after-tax Treasury rates	41,764	154.49	78.31	99.6	147.57	201.09
SpreadMMA	Spread to maturity-matched yields from the Municipal Market Advisors AAA-rated curve	40,618	71.68	61.96	27	62	107
Coupon	Coupon rate at issuance	41,949	4.43	1.01	4	5	5
Log_size	Log of bond issue size	41,949	14.51	1.54	13.48	14.48	15.49
Callable	Whether the bond is callable	41,949	0.47	0.5	0	0	1
Reoffer	Whether the bond is reoffered	41,949	0.29	0.45	0	0	1
Insured	Whether the bond is insured	41,949	0.24	0.43	0	0	0
Rating	Credit rating at issuance	41,949	16.01	2.21	14	16	21
Maturity	Years to maturity	41,949	11.16	7.33	6	10	15
Panel B: Hospital Variables							
Margin	Profit margin	39,618	0.025	0.131	-0.015	0.032	0.083
TA	Total assets (million)	39,437	232.760	598.082	18.396	64.897	227.649
Debt/TA	Total liabilities over total assets	39,389	0.551	0.503	0.248	0.450	0.694
Cash/TA	Cash holdings over total assets	38,596	0.093	0.132	0.010	0.051	0.128
Rev	Total patient revenues (million)	40,492	561	1,047	38	162	660
NetIncome	Total revenues minus operational expenses, contractual allowances, discounts and charity care (million)	40,492	7.022	77.093	-0.517	1.331	10.377
Discharge	Inpatient discharges	40,246	6,788.929	9,769.853	511.326	2,367.193	9,767.568
ICUUnits	ICU bed counts over total beds	24,661	23.276	27.855	8.000	14.000	28.984
RemoteService	Remote Service Score (0 – 3)	24,704	1.010	0.984	0.000	1.000	2.000
Employment	Number of employees in treatment units	40,081	994	3,875	141	393	1,159

Table A.2: Telehealth Parity Adoption Timing and Hospital Characteristics

This table shows that state-level hospital characteristics cannot predict the timing of telehealth parity law adoption from Cox proportional hazard regressions as follows

$$h_j(t) = h_0(t)\exp(\beta X_{j,t}).$$

$h_j(t)$ is the hazard function at time t with "failure" denoting a state adopting the parity law. The sample period starts from 2000, which is the earliest year for which we can extract hospital net income, total revenue and number of patient discharges. The yearly state observations continue until an adoption or the end of the sample period (2020). $X_{j,t}$ is a vector of state characteristics in year t, including the average net income (in millions) across all *rural* hospitals in state j at year t ($AvgRuralIncome_{j,t}$), the average total revenues (in millions) across all *rural* hospitals in state j at year t ($AvgRuralRev_{j,t}$), the average number of patient discharges (in thousands) across all *rural* hospitals in state j at year t ($AvgRuralDischarge_{n,t}$). $AvgUrbanIncome_{j,t}$, $AvgUrbanRev_{j,t}$ and $AvgUrbanDischarge_{j,t}$ are defined similarly, except that we take the average across all *urban* hospitals. $LogPopulation_{j,t}$ is the logarithm of total population. $LogPInc_{j,t}$ is the logarithm of personal income per capita. $Unemployment_{j,t}$ is the unemployment rate. $OldShare_{j,t}$ is the share of state population aging 65 and above from the Surveillance, Epidemiology, and End Results Program (SEER) of the National Cancer Institute (NIH). $DemRatio_{j,t}$ is the ratio between democratic voters over republican ones for elections of the U.S. presidency from the MIT Election Data and Science Lab. We report the raw coefficients of Cox regressions instead of the hazard rates. Standard errors are clustered at the state level and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Adoption***	(2) ***Adoption***
AvgRuralIncome	0.019	0.018
	(0.903)	(0.759)
AvgRuralRev	−0.004	−0.004
	(−0.657)	(−0.550)
AvgRuralDischarge	−0.233	−0.283
	(−1.025)	(−1.106)
AvgUrbanIncome	0.001	0.001
	(0.299)	(0.260)
AvgUrbanRev	−0.000	−0.000
	(−0.153)	(−0.090)
AvgUrbanDischage	0.059	0.022
	(0.418)	(0.142)
LogPopulation		0.171
		(0.929)
LogPInc		0.179
		(0.229)
Unemployment		−0.043
		(−0.365)
OldShare		0.869
		(0.058)
DemRatio		0.174
		(0.418)
N	713	711

Table A.3: Distribution of Hospital Bond Issuance Ratings

This table reports the distribution of hospital bond credit ratings at issuance ranked from the highest to the lowest. *Rating* is the numeric value assigned to each letter rating, shown in column (2) for Moody's and column (3) S&P respectively. Column (4) shows the frequency of occurrence and column (5) shows the percentage of each in our sample. Column (6) reports the cumulative percentages.

(1) *Rating*	(2) Moody's	(3) S&P	(4) Frequency	(5) Percent	(6) Cum.
21	Aaa	AAA	7,864	18.75	18.75
20	Aa1	AA+	1,379	3.29	22.03
19	Aa2	AA	3,855	9.19	31.22
18	Aa3	AA-	5,794	13.81	45.04
17	A1	A+	5,850	13.95	58.98
16	A2	A	5,415	12.91	71.89
15	A3	A-	4,542	10.83	82.72
14	Baa1	BBB+	2,978	7.1	89.82
13	Baa2	BBB	2,571	6.13	95.95
12	Baa3	BBB-	1,277	3.04	98.99
11	Ba1	BB+	221	0.53	99.52
10	Ba2	BB	146	0.35	99.86
9	Ba3	BB-	29	0.07	99.93
8	B1	B+	5	0.01	99.95
7	B2	B	11	0.03	99.97
6	B3	B-	12	0.03	100
5	Caa1	CCC+	0	0.00	100
4	Caa2	CCC	0	0.00	100
3	Caa3	CCC-	0	0.00	100
2	Ca	CC	0	0.00	100
1	C	C	0	0.00	100
0	D	D	0	0.00	100
Total			41,949	100	

Table A.4: Placebo Test: Non-hospital Bonds

This table replicates Table 3, except we use the sample of non-hospital bonds. The sample period is 2005–2019 and the unit of data is a monthly bond observation. $Yield_{i,t}$, $Spread_{i,t}$, $SpreadMMA_{i,t}$, $Rural_i$ and $Parity_{j,t}$ are defined in the same way as Table 3. *Controls* include bond characteristics and county fundamentals explained in Section 2.2. *State-Month FE* is the state by year-month fixed effect, which absorbs the direct effect of $Parity_{j,t}$. *Control Group* include the hospital bonds issued before 2014 in states without the telehealth parity law. Standard errors are clustered by state year-month and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***
Parity × *Rural*	24.591	27.548	24.864
	(0.395)	(0.381)	(0.400)
Controls	Y	Y	Y
State-Month FE	Y	Y	Y
N	7,633,135	7,321,641	7,633,135
Adj. R^2	0.00	0.00	0.00

Table A.5: Placebo Test: Random Shocks

This table replicates Table 3, except we use a sample of placebo shocks. These shocks are generated by randomly selecting 37 states and picking months from 2010-01 to 2018-12 as their event months. The sample period is 2000–2019 and the unit of data is a monthly bond observation. $Placebo_{j,t}$ is one if the bond's state j has been treated by the placebo shock by month t, and zero otherwise. $Yield_{i,t}$, $Spread_{i,t}$, $SpreadMMA_{i,t}$, and $Rural_i$ are defined in the same way as Table 3. *Controls* include bond characteristics interacted with trade year indicators and county fundamentals explained in Section 2.2. *State-Month FE* is the state by year-month fixed effect, which absorbs the direct effect of $Parity_{j,t}$. *Control Group* include the hospital bonds issued before 2014 in states without the telehealth parity law. Standard errors are double clustered by county and trade year-month and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***
$Placebo \times Rural$	0.061	−0.416	−0.300
	(0.003)	(−0.020)	(−0.015)
$Rural$	−4.736	−3.788	−4.752
	(−0.717)	(−0.577)	(−0.714)
$Controls$	Y	Y	Y
State-Month FE	Y	Y	Y
N	612,359	612,359	611,113
$Adj.\,R^2$	0.45	0.35	0.30

Table A.6: Rating Control Variables Robustness

This table reports effects of telehealth parity adoption on rural hospital municipal bonds in the secondary transaction market using Equation (1) by replacing the control variable current ratings with either initial rating (Panel A) or the lagged rating in the previous transaction (Panel B), or dropping the ratings completely (Panel C and Panel D). For the first three panels, the sample period is 2000–2019 and the unit of data is a monthly bond observation. $Yield_{i,t}$, $Spread_{i,t}$, $SpreadMMA_{i,t}$, $Rural_i$ and $Parity_{j,t}$ are defined in the same way as Table 3. *Controls* include bond characteristics interacted with trade year indicators and county fundamentals explained in Section 2.2, except that the current ratings are replaced. *State-Month FE* is the state by year-month fixed effect, which absorbs the direct effect of $Parity_{j,t}$. *Control Group* include the hospital bonds issued before 2014 in states without the telehealth parity law. For Panel D, the sample period is 2000–2019 and the unit of data is a bond upon issuance, and other details are the same as Table 7, except that the initial rating FEs are dropped . Standard errors are double clustered by county and trade year-month and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Controlling for Initial Ratings

	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***
Parity × Rural	29.523**	29.380**	28.705**
	(2.204)	(2.198)	(2.110)
Rural	4.808	4.837	5.007
	(0.964)	(0.970)	(1.008)
Controls	Y	Y	Y
State-Month FE	Y	Y	Y
N	528,912	528,912	527,913
Adj. R^2	0.60	0.48	0.42

Panel B: Controlling for Lagged Ratings

	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***
Parity × Rural	17.131**	16.987*	16.472*
	(1.976)	(1.965)	(1.848)
Rural	3.126	3.153	3.365
	(0.771)	(0.778)	(0.834)
Controls	Y	Y	Y
State-Month FE	Y	Y	Y
N	528,912	528,912	527,913
Adj. R^2	0.61	0.50	0.43

Panel C: Drop Rating Controls

	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***
Parity × *Rural*	29.938*	29.790*	28.894*
	(1.847)	(1.841)	(1.762)
Rural	19.589***	19.618***	19.758***
	(2.819)	(2.826)	(2.877)
Controls	Y	Y	Y
State-Month FE	Y	Y	Y
N	531,761	531,761	530,762
Adj. R^2	0.58	0.46	0.39

Panel D: Drop Rating Controls in the Primary Market

	(1) ***Yield***	(2) ***Spread***	(3) ***SpreadMMA***
Parity × *Rural*	27.840**	28.802**	23.754
	(2.001)	(2.073)	(1.586)
Rural	9.859	9.418	9.080
	(1.311)	(1.258)	(1.163)
Controls	Y	Y	Y
State-Month FE	Y	Y	Y
N	34,764	34,764	33,640
Adj. R^2	0.96	0.88	0.86

Table A.7: Telehealth Parity Adoption and Bond Characteristics in the Primary Market

This table replicates Table 7, except the dependent variables here are bond characteristics. The sample period is 2000–2019 and the unit of data is a bond upon issuance. *Rating* is the numeric value of bond rating from Table A.3. *HighRating* is an indicator variable that takes the value of one when the numeric rating is above the sample median (single A), and zero otherwise. *Log(Size)* is the logarithm of bond amount. *GO* is an indicator variable that takes the value of one when the bond is general obligation, and zero otherwise. *Insured* is one if the bond is insured, and zero otherwise. $Rural_i$ and $Parity_{j,t}$ are defined in the same way as in Section 2.2. *Controls* include bond characteristics interacted with issuance year indicators and county fundamentals. If a bond characteristic serves as the outcome variable, we drop them from the control variables. *State-Month FE* is the state by year-month fixed effect, which will absorb the direct effect of $Parity_{j,t}$. *IssueRating FE* is the initial rating upon issuance fixed effect and being included as indicated. *Control Group* include the hospital bonds in states without the telehealth parity law. Standard errors are double clustered by county and issuance year-month and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Rating***	(2) ***HighRating***	(3) ***Log(Size)***	(4) ***GO***	(5) ***Insured***
Parity × *Rural*	−0.317	0.057	0.008	0.191	−0.246**
	(−0.406)	(0.368)	(0.018)	(1.252)	(−2.460)
Controls	Y	Y	Y	Y	Y
State-Month FE	Y	Y	Y	Y	Y
IssueRating FE	N	N	Y	Y	Y
N	34,764	34,764	34,764	34,764	34,764
Adj. R^2	0.83	0.83	0.63	0.89	0.86

Table A.8: State-Wide Effects on Hospital Revenues

This table reports additional effects of telehealth parity adoption on rural hospital revenues using Equation (3). The sample period is 2009—2018 and the unit of data is an annual hospital observation. $NetInc/TA_{m,t}$, $PatInc/TA_{m,t}$, $Rural_m$ and $Parity_{j,t}$ are defined in the same way as Table 9. *Controls* include lagged variables of the logarithm of total income, the logarithm of total assets, bed counts, and the logarithm of total liabilities. *Hospital FE* is the hospital fixed effect and *Yr FE* is the year fixed effect. Standard errors are double clustered by county and year and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***NetInc/TA***	(2) ***PatInc/TA***
Parity	0.003	−0.004
	(0.689)	(−0.655)
Controls	Y	Y
Hospital FE	Y	Y
Yr FE	Y	Y
N	37,492	37,492
Adj. R^2	0.47	0.61

Table A.9: Telehealth Parity Adoption and Hospital Investments

This table reports the effects of telehealth parity adoption on rural hospital investment using Equation (3). The sample period is 2009–2018 and the unit of data is an annual hospital observation. $ICUUnits_{m,t}$ is the number of ICU beds for hospital m in year t, $Employment_{m,t}$ is the number of employees in treatment units, and $Salary_{m,t}$ is the average salary of employees. $Rural_m$ equals one when hospital m is in a rural area, and $Parity_{j,t}$ equals one if the hospital's state j has enacted the parity law in year t, and zero otherwise. *Controls* include lagged variables of the logarithm of total income, the logarithm of total assets, bed counts, and the logarithm of total liabilities. *Hospital FE* is the hospital fixed effect and *Yr FE* is the year fixed effect. Standard errors are double clustered by county and year and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***ICUUnits***	(2) ***ICUUnits***	(3) ***Employment***	(4) ***Employment***	(5) ***Salary***	(6) ***Salary***
Parity × Rural	−3.397***	−2.490**	−106.164**	−106.942***	−5481.463***	−5092.906***
	(−3.810)	(−2.855)	(−3.090)	(−3.256)	(−4.610)	(−4.726)
Parity		0.335		101.080*		3559.674***
		(0.478)		(2.195)		(4.883)
Controls	Y	Y	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y	Y	Y
State-Yr FE	Y	N	Y	N	Y	N
Yr FE	N	Y	N	Y	N	Y
N	23,111	23,111	37,415	37,415	37,415	37,415
Adj. R^2	0.82	0.82	0.18	0.18	0.93	0.93

Table A.10: Telehealth Parity Adoption and Hospital Patient Satisfaction

This table reports the effects of telehealth parity adoption on rural hospital patient satisfaction using Equation (3). The satisfaction survey is from CMS Hospital Consumer Assessment of Healthcare Providers and Systems. Notice that a patient can be surveyed only if he/she uses in-person services of the hospital. So the rural treatment effect only applies to those who still use local services after the parity law. The sample period is 2000–2018 and the unit of data is an annual hospital observation. $Overall_{m,t}$ is the percentage (ranging from 0 – 100) of patients who give the highest rating for hospital m's overall treatment in year t. $Recommend_{m,t}$ is the percentage of patients who would recommend hospital m to similar patients in year t. $PainCtrl_{m,t}$ is the percentage (ranging from 0 – 100) of patients who give the highest rating for hospital m's pain control in year t. $Info_{m,t}$ is the percentage of patients who believe physicians in hospital m give them clear information for recovery in year t. $Rural_m$ equals one when hospital m is in a rural area, and $Parity_{j,t}$ equals one if the hospital's state j has enacted the parity law in year t, and zero otherwise. *Controls* include lagged variables of the logarithm of total income, the logarithm of total assets, bed counts, and the logarithm of total liabilities. *Hospital FE* is the hospital fixed effect and *Yr FE* is the year fixed effect. Standard errors are double clustered by county and year and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Overall***	(2) ***Recommend***	(3) ***PainCtrl***	(4) ***Info***
$Parity \times Rural$	0.776*	1.261**	0.382	0.344
	(1.955)	(3.300)	(1.017)	(1.459)
Controls	Y	Y	Y	Y
Hospital FE	Y	Y	Y	Y
State-Yr FE	Y	Y	Y	Y
N	24,650	24,648	21,393	24,649
Adj. R^2	0.78	0.81	0.54	0.67

Table A.11: Telehealth Parity Adoption and County Chronic Disease Death

This table reports the effect of telehealth parity adoption on rural county chronic disease death. The sample period is 2000–2019 and the unit of data is an annual county observation. $HFdeath_{k,t}$, $CKDdeath_{k,t}$, $Alzdeath_{k,t}$, $COPDdeath_{k,t}$, and $Diabetedeath_{k,t}$ are the number of deaths per thousand population due to heart failures, chronic kidney disease, Alzheimer's disease, chronic obstructive pulmonary disease, and diabetes in county k in year t. The deaths data are from CDC Wonder database. $Rural_k$ equals one when county k is in a rural area, and $Parity_{j,t}$ equals one if the county's state j has enacted the parity law in year t, and zero otherwise. *Controls* are county fundamentals including population level, per capita income, population growth, employment growth, and labor participation. *State-Yr FE* is the state by year fixed effect and *County FE* is the county fixed effect. Standard errors are clustered by county and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***HFdeath***	(2) ***CKDdeath***	(3) ***Alzdeath***	(4) ***COPDdeath***	(5) ***Diabetedeath***
Parity × Rural	−0.013	−0.005	−0.010	−0.002	−0.001
	(−1.330)	(−0.724)	(−0.862)	(−0.157)	(−0.253)
Controls	Y	Y	Y	Y	Y
State-Yr FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
N	60,397	60,397	60,397	60,397	60,397
Adj. R^2	0.47	0.36	0.51	0.52	0.28

Table A.12: Telehealth Parity Adoption and Ambulance Surgery Centers in Rural Counties

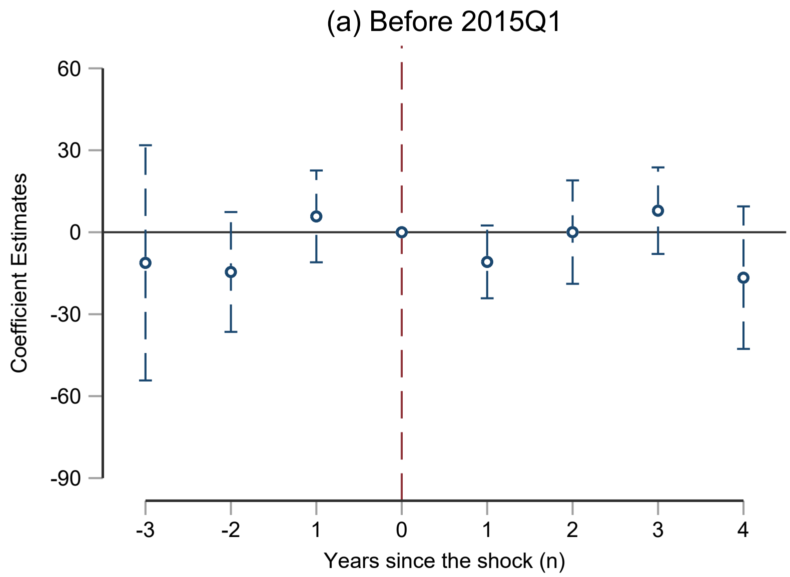
This table reports the effect of telehealth parity adoption on rural county ambulance surgery centers (ASCs). The sample period is 2010–2019 and the unit of data is an annual county observation. $Log(ASC)_{k,t}$, $Log(GovtASC)_{k,t}$, and $Log(PrivASC)_{k,t}$ are the log amount of one plus establishment number of ASCs, government sponsored ASCs, and private ASCs in county k and year t. The ASC establishment data are from QCEW database by U.S. Bureau of Labor Statistics. $Rural_k$ equals one when county k is in a rural area, and $Parity_{j,t}$ equals one if the county's state j has enacted the parity law in year t, and zero otherwise. *Controls* are county fundamentals including population level, per capita income, population growth, employment growth, and labor participation. *State-Yr FE* is the state by year fixed effect and *County FE* is the county fixed effect. Standard errors are clustered by county and t-statistics are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) ***Log(ASC)***	(2) ***Log(GovtASC)***	(3) ***Log(PrivASC)***
$Parity \times Rural$	−0.012	−0.012*	−0.004
	(−0.709)	(−1.678)	(−0.230)
Controls	Y	Y	Y
State-Yr FE	Y	Y	Y
County FE	Y	Y	Y
N	19,214	19,214	19,214
Adj. R^2	0.96	0.95	0.96

A.III Figures

Figure A.1: Robustness Check: Early- v.s. Late-Adopting States

This figure plots a robust check of the dynamic effects of telehealth adoption by splitting the treatment group into early-adopting and late-adopting states, using the median of adopting time (2015Q1). We follow the method in Figure 3 and use spread as the outcome variable to account for the differences of risk-free rates over time.



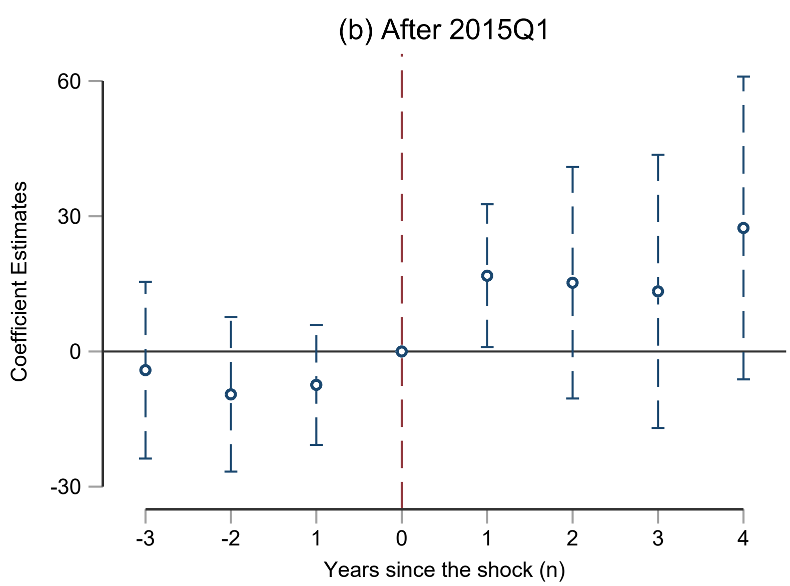


Figure A.2: Robustness Check: Urban and Rural Treatment Effects

This figure plots a robust check of the dynamic effects of telehealth adoption by splitting the treatment group into urban and rural bonds and estimating the raw effects before and after the shock. We follow the method in Figure 3, except that we separately estimate the coefficients in the rural treatment group (blue) and urban treatment group (red), and we can include issuer fixed effects along with the state month fixed effects.

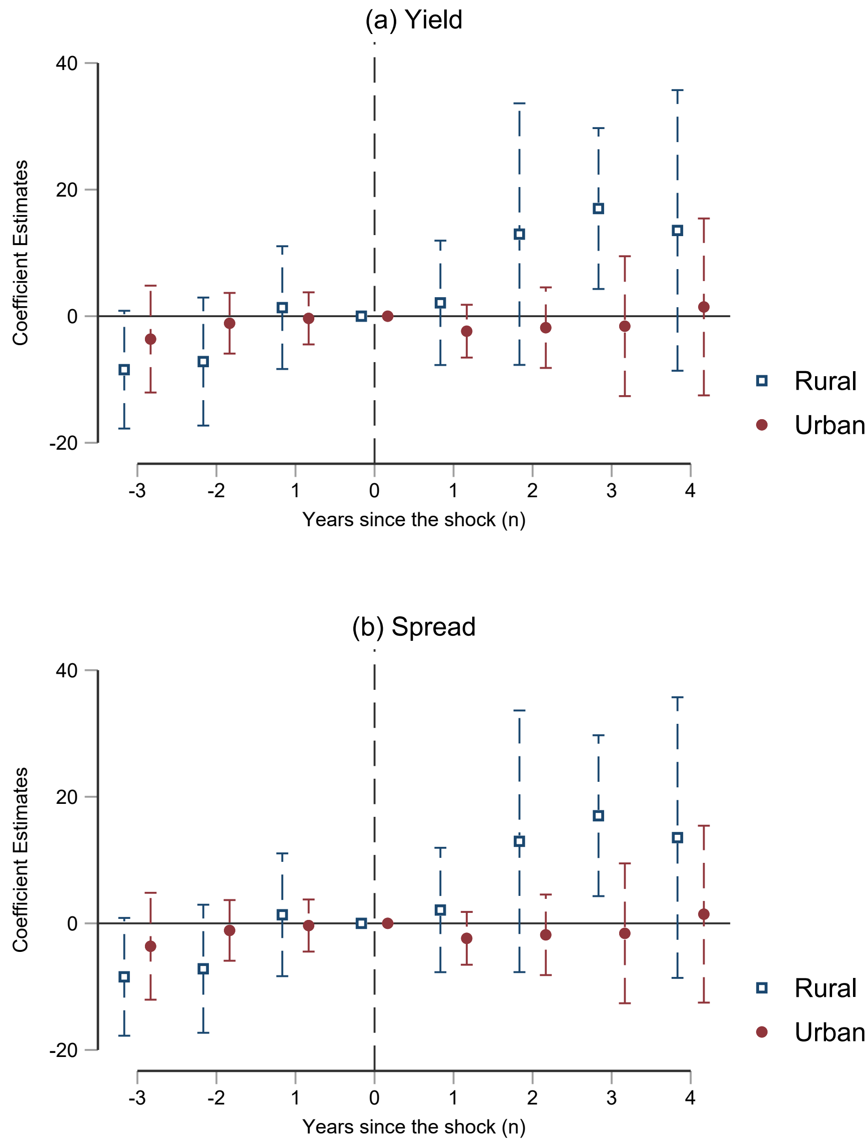


Figure A.3: Parallel Trend of Hospital Financial Conditions

This figure plots the dynamic effects of telehealth adoption on financial conditions. We follow the method in Figure 3, except that we estimate the effects on the yearly hospital sample.