Price Regulation, Technology and Provider Redistribution

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In the presence of price regulation, providers and consumers often communicate value through non-price attributes, such as service quality. This paper studies how Price and Cost Controls generated by state-level variations in the framing of telehealth parity laws, combined with broadband internet, affect provider distribution at the macro level. The effects differ between metro and non-metro areas, depend on the difference between pre- and post-regulation price levels, and cannot be explained by conventional models of price regulation. The paper provides suggestive evidence for non-price competition and technology-induced quality adjustments as key mechanisms for equilibrium quantity shifts signified by provider redistribution.

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I INTRODUCTION

Conventional economic theory posits that price controls, such as price ceilings or price floors, lead to market inefficiencies. Price ceilings typically result in shortages as they cause suppliers to reduce quantity supplied, while price floors can lead to surpluses as they encourage higher than equilibrium quantity supplied. However, these models often fall short in contexts where non-price factors significantly influence market behavior. In all conventional studies, price—defined as the amount received by the provider—is usually conflated with cost—defined as the amount paid by the consumer. However, in healthcare, what providers receive and what consumers pay are distinct; "price" implies physician reimbursements, whereas "cost" entails deductibles, co-pays, and insurance paid by consumers. Moreover, there is a tripartite relationship, involving a third-party insurer, instead of the biparty "provider-consumer" relationship in conventional theories. Thus, price and cost, otherwise conflated in conventional market models, become differentiated. While conventional models focus mostly on the supply side effects arising out of price controls only, Telehealth Parity Laws and the availability of a rich panel data provide a unique opportunity to study Cost Controls along with Price Controls, while highlighting the non-price factors at play. Since broadband internet is crucial for telehealth, it's presence as a technological mediator affects the input supply elasticities and opportunity cost of time, substantially altering the regulation policy outcomes.

With the onset of the global pandemic and social distancing norms, healthcare rapidly shifted towards telehealth. The surge in telehealth usage led to the swift adoption of Telehealth Parity Laws (henceforth TPLs) across various states.[1] This shift was facilitated by the already increasing use of the internet for health-related purposes.[2] Adopted in a staggered manner by various states since 1995, TPLs seek to establish parity between "reimbursements" received by physicians for telehealth services (Price Controls) and the "deductibles, co-pays, and insurance" paid by consumers for telehealth services (Cost Controls), with those for in-person services. Distinct "framing" of laws resulted in varied combinations of a type of Price Control—such as Price Ceiling, Price Floor, or Price Parity—with a type of Cost Control—such as Cost Ceiling or Cost Parity—across states.

This study addresses two major aspects. First, it builds upon conventional price regulation theory, supply chain theory and theory of non-monetary factors of demand, to predict shifts in health-

[1] Telehealth visits increases by 154% from March 2019 to March 2020 (Koonin et al., 2020). Telehealth usage grew by 60% from 2012 to 2013, with 40-50% rise in institutional adoption by 2016. Usage varied by demographics, socioeconomic status, and geography (Lucas and Villarroel, 2022).

[2] *Figure A.I, Online Appendix*, shows the increase in health-related internet usage from 2012 to 2018.

care service equilibrium quantity by examining the role of non-price or quality competition in a regulated market. The distortion of input mix causing production inefficiency and the change in consumption mix causing consumption inefficiency, provide the microfoundations for the allocative inefficiency of the healthcare services at the macro level as signified by physician redistribution. Second, the theoretically predicted shifts in equilibrium service quantities are empirically investigated by considering the unique combinations of types of Price Control with types of Cost Control as treatment types. Heterogeneous impacts are captured by estimating the Average Treatment Effects on the Treated (ATT) for each treatment type, where the physician count serves as a proxy for healthcare service quantity. A rich panel dataset that comprises of state-wise Price and Cost Control types, county-level physician counts, and residential broadband connections, allow to estimate these treatment effects, which quantify the theoretically predicted equilibrium service quantity shifts.

Contrary to previous studies that treat TPLs as a uniform treatment (Restrepo (2018); Cornaggia, Li and Ye (2023)), this study takes into account the impact of diversity in the framing of these laws across states. For example, a higher physician reimbursement rate for telehealth (owing to a Price Floor, for instance) in one state may encourage telehealth investment, while a restrictive Cost Control (such as Cost Parity) in another may deter telehealth utilization.

This study contributes to the literature on price regulations in the healthcare sector by addressing limitations of conventional models, some of which predict reduced expenditure and trading quantities under a Price Ceiling, and guaranteed trade levels under a Price Floor. Some other studies suggest that regulations can reduce consumer surplus in specific demand structures, leading to misallocation and increased rent-seeking (Lee and Saez (2012); Bulow and Klemperer (2012)). Furthermore, other studies suggest that regulations allow only high-value buyers to receive goods without affecting supply or demand curves, inherently reducing traded quantities and exacerbating shortages with demand shifts (Acemoglu, Laibson and List, 2021). Additionally, some other studies posit that highly elastic supply with Price Ceiling can eliminate all trade, despite potential gains from trade (Krugman and Wells, 2020). However, these models are inadequate to capture the full breadth of market behaviors beyond price adjustments.

Models which incorporate the non-price factors like quality, queueing, and search costs become significant when price mechanisms are restrained (Deacon and Sonstelie, 1985). Markets engage in non-price competition through quality adjustments as a regulatory compliance strategy, shaping supply and demand (Cheung (1974); Murphy (1980); Leffler (1982); Raymon (1983); Ippolito (2003)). The regulated healthcare market could exhibit adaptations such as scheduling strategies aimed at preserving revenue streams, longer wait times for in-person care resulting from provider consolidations (Comanor and Frech, 1985), or more frequent visits for single health episodes, partitioning services like drug administrations across multiple appointments (Frech, 2001). Price regulations might deter prospective professionals from entering the field, while established physicians adjust their services to balance clinical consultations and more lucrative procedures.

The supply chain approach challenges the conventional belief that Price Controls always lead to shortages and inefficiencies, by analyzing how the price-regulated markets distort input mixes away from cost minimization towards regulatory compliance (Mulligan, 2024). A binding Price Ceiling reduces marginal costs and increases quantity, while a Price Floor does the opposite. Under a Price Ceiling, this manifests into consumers accepting lower-quality products requiring more personal effort. Conversely, a Price Floor shifts inputs away from consumers. Nevertheless, this study diverges from Mulligan's assertion that Price Ceilings and Price Floors inherently have effects opposite to each other, while specifying the conditions under which this assertion holds true. These conditions are validated by the empirical results. Moreover, the supply chain approach focuses on rotations of the supply curve induced by Price Controls as the sole determinant of the regulated equilibrium quantity along a static demand curve. This study overcomes this limitation by modeling the rotations in both supply and demand curves as determinants of regulated equilibrium quantity.

The conventional and supply chain models have Price Ceiling above and Price Floor below the market equilibrium, while focusing only on binding regulations. Typically, a Floor correlates with excess supply and a Ceiling with excess demand (Acemoglu, Laibson and List, 2021). However, TPLs introduce unique scenarios where the Market Equilibrium Reimbursement Rate for In-person services (MERR-I) can function as either a Price Ceiling or a Price Floor, while the Market Equilibrium Cost Rate for In-Person Services (MECR-I) could function as a Cost Ceiling or Cost Parity, based on each state's policy. Prior to TPLs, telehealth services were generally priced below MERR-I, making the Price Ceiling non-binding in a conventional sense. This led to advocacy for TPLs to address the undervaluation of telehealth versus in-person services (Yamamoto (2014); Mahar, Rosencrance and Rasmussen (2018)). This study, therefore, assesses the effects of non-binding regulations as well as binding ones, substantially diverging from the conventional or supply chain frameworks mentioned above.

The study evaluates Cost Controls in conjunction with Price Controls, building upon Acton (1975)'s insights on non-monetary demand factors. Wage rates, opportunity costs of time, and technological infrastructure differ substantially between metro and non-metro areas. This leads to distinct behavioral changes among physicians and consumers, causing shifts in equilibrium quantities. The study explores how the effects of TPLs differ for metro and non-metro areas. If input supply elasticities are accounted for, the effects of these regulations vary based on degree of urbanization and local technological infrastructure. This highlights the inadequacy of a "one-size-fits-all" approach in canonical models and emphasizes the importance of regional differences in evaluating the policy impacts of regulations.

Importantly, this study recognizes unique features of the healthcare market, such as third-party insurers and their rate schedules, which could potentially misalign with the regulated prices owing to the equal reimbursement mandates. The economic surplus held by insurers could be redistributed to providers through such mandates. The co-payments, deductibles, and insurer-defined reimbursement rates, add layers of indirect Price Control beyond conventional supply and demand forces. The study accounts for these factors and their influence on market outcomes.

Remote healthcare delivery and access to health information are significantly enhanced by internet connectivity. Broadband rollout has been linked to economic benefits (Canzian, Poy and Schüller (2019); Chen, Ma and Orazem (2023); Haller and Lyons (2018)) and health benefits (Van Parys and Brown (2023); Tomer et al. (2020)). However, the number of internet providers or broadband infrastructure have been used as proxies for broadband access or penetration. This study refines this metric by using granular county-level residential connection data. This marks a departure from classical models of regulation by incorporating technological infrastructure. Broadband is costlier and less accessible in rural areas and Indian reservations, adversely affecting telehealth deployment.[3] Despite increased broadband penetration enhancing healthcare delivery, the digital divide remains.[4] Broadband increases telehealth service supply elasticity, modifies opportunity costs of in-person services, and facilitates health-related information access, shifting healthcare supply and demand curves. These changes are not uniform as metropolitan areas often benefit more.[5]

By capturing the multilayered policy effects on healthcare delivery and the physician count, the study enriches the current discourse on telehealth's fiscal soundness, patterns of healthcare consumption, physician response and the accessibility implications of TPLs (Bavafa, Hitt and Terwiesch (2018); Reed et al. (2021); Phillips et al. (2023)). In contrast to other studies that might not focus on

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[3]Telehealth is crucial in reducing disease exposure during health crises, benefits patients with mobility issues or chronic conditions in Health Professional Shortage Areas (HPSAs), and can achieve outcomes similar to in-person care with cost savings (Shaver, 2022).

[4]*Figure A.II, Online Appendix*, shows the county level broadband access in the U.S. for years 2010 and 2019.

[5]*Figure II* reveals the compounded challenges faced by non-metro areas.

specific mechanisms of reimbursement, this study foregrounds the preeminence of Fee-for-Service (FFS) in the U.S. telehealth payment framework and contrasts it with Value-Based Payment (VBP) models, offering a critical lens through which the financial viability of telehealth can be evaluated within the varied landscape of reimbursement policies.

This study contributes empirically by modeling the adoption of TPLs as a treatment, the heterogeneous state-level framing of these laws that generate distinct types of Price Control, Cost Control, or their distinct combinations as treatment types, and the impacts of these controls in the form of equilibrium quantity shifts as treatment effects. The methodology represents a significant advancement in policy analysis, adopting Poisson Pseudo-Maximum Likelihood (PPML) estimator (Santos Silva and Tenreyro (2006); Gourieroux, Monfort and Trognon (1984)) in a non-linear difference-in-differences (DID) framework with staggered intervention to account for the discrete nature of count data (Chen and Roth (2024); Wooldridge (1999); Wooldridge (2023)).

The state licensure requirements and Intertate Medical Licensure Compact (IMLC) influence the physical location, remote practice capabilities of physicians and telehealth accessibility. IMLC and licensure requirements impact quantity control differently. Licensure requirements directly control the number of physicians entering the profession, while the IMLC aims to make it easier for existing physicians to practice in multiple states. This study incorporates the licensure landscape explicitly into the empirical analysis to show that IMLC might not fit the traditional narrative that such controls necessarily lead to deadweight loss or inefficiencies.

Finally, this study recognizes the differential usage of telehealth among medical specialties and assesses how TPLs affect the counts of physicians belonging to different specialties based on their telehealth interactions and modalities. This specialty-wise comparison offers a granular understanding of the impacts of telehealth legislation, augmenting the study's empirical contribution.

The results suggest that when the effect of broadband internet is considered, a different picture emerges. The control group consists of counties with mean broadband levels in states that did not adopt TPL, while the treated groups are counties with broadband at one standard deviation above the mean level, in states that adopted TPL. Price Ceiling or Price Floor positively affects physician count in metro areas but negatively in non-metro areas. Conversely, Cost Parity has a negative effect in metro areas, while a Cost Ceiling positively impacts physician count in both regions. When examining combinations of different types of Price and Cost Controls, Cost Parity tends to dominate with a net negative effect, whereas a Cost Ceiling amplifies the positive effect of a Price Ceiling. The findings challenge the conventional narratives and underscore the role of regional disparities and technology in shaping price regulation policy outcomes.

The rest of the paper is organized as follows: Section II provides the background, Section III presents the data, Section IV lays out the theoretical framework, Section V outlines the empirical framework, Section VI summarizes the results, Section VII reviews the robustness checks, and Section VIII concludes.

II BACKGROUND

The framing of TPLs generated various types of Price and Cost Controls: Since 1995, 40 states and the District of Columbia have implemented telehealth Coverage Parity mandates for insurance plans (*Panel (b), Figure I*). This means that if a service is covered when it is provided in-person, it is also considered under these mandates when offered through telehealth. Many of the states who introduced Coverage Parity also introduced Payment Parity mandates. These mandates ensure that telehealth services have the same level of reimbursement for physicians and the same costs in terms of deductibles, co-pays, and insurance for the consumer, as those for equivalent in-person services.

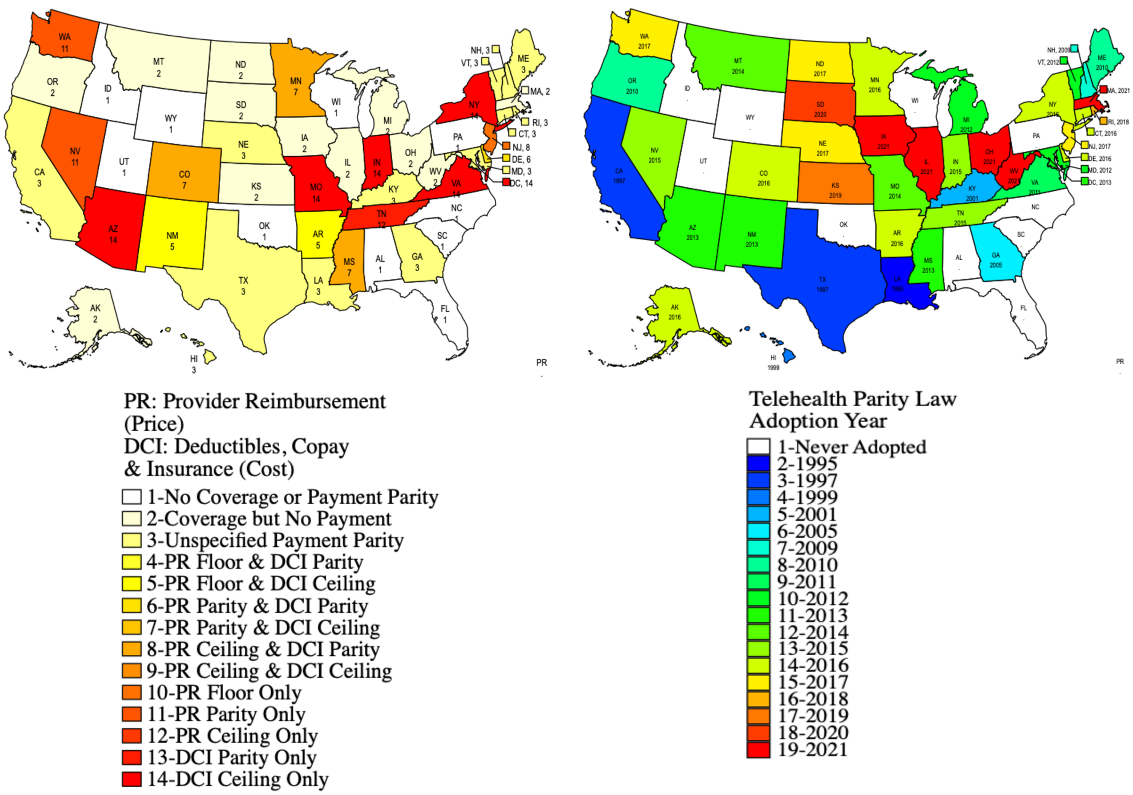
The Payment Parity stipulations are not entirely uniform across all states, largely due to the varying frames in which these laws are constructed and communicated (*Panel (a), Figure I*). Neglecting the framing could lead to missing the differential impacts. Framing effects cannot be overlooked even for the most experienced physicians (Tversky and Kahneman, 1986). While behavioral economics emphasizes perceived value and decision-making under uncertainty, in the case of TPLs, the framing could directly impact not only perceptions but also the actual current or expected financial incentives and cost structures faced by providers and patients. This leads to measurable changes in market equilibrium owing to shifts in healthcare services provision and utilization rates.

Distinct legal stipulations for Payment Parity within state laws can manifest as a type of Price Control (Price Floor, Price Ceiling, or Price Parity), or a type of Cost Control (Cost Ceiling or Cost Parity), or a combination of both, or neither.[6] A state may stipulate that reimbursement for telehealth "may not exceed" that for in-person services, establishing a "Price Ceiling"; that it be "at least as much as" in-person services, establishing a "Price Floor"; or that it be the "same rate" as in-person services, establishing exact "Price Parity". A state may stipulate that "deductibles, co-pays, and insurance" for telehealth "may not exceed" those for in-person services, establishing a "Cost Ceiling", or be the "same rate" as for in-person services, establishing "Cost Parity". A state might

[6] This study predominantly centers on the regulatory effects of Price Ceiling and Price Floor. Hence, Price Parity becomes a secondary aspect rather than a direct subject of inquiry.

FIGURE I

State-wise Telehealth Parity Laws: Framing and Staggered Adoption



(a) (b)

Note: Panel (a) shows the state level framing for the states who adopted telehealth parity laws in the United States till 2021. Panel (b) shows the staggered adoption of Telehealth Parity Laws in the United States upto 2021.

not specify the details or framing. In that case, it would be deemed to just have a Payment Parity law. Each of the types within Price or Cost Control is mutually exclusive, meaning that a state can have only one: a Price Ceiling, Price Floor, or Price Parity. Similarly, a state might specify either a Cost Ceiling or Cost Parity, but not both.

Telehealth modalities and usage: Telehealth entails direct, electronic patient-to-provider interactions and the use of medical devices to collect and transmit health information as well as to manage chronic conditions. The responses of providers to the regulations depend on their respective specialities, since specialities differ in their modalities. Currently, there are three main modalities of telehealth.[7] *Synchronous or Live Video* involves two-way interaction via videoconferences us-

[7]Telehealth incorporates telemedicine, which is a bilateral, interactive health communications with clinicians on both ends of the exchange (e.g. videoconferenced grand rounds, x-rays transmitted between radiologists or consultations where a remote practitioner presents a patient to a specialist).

ing audiovisual telecommunications technology. *Asynchronous or Store-and-Forward (SFT)* refers to the transmission of diagnostic information, videos, and digital images such as x-rays, CT scans, and EEG printouts, collected at the patient's site of care, to a specialist in another location. *Remote Patient Monitoring (RPM)*, used for the management of chronic illness, employs devices such as Holter monitors to transmit personal medical data and vital statistics (e.g., blood pressure, blood oxygen levels), to clinicians. In addition to these three main modalities, there are other "Integrated Telehealth Solutions" such as apps (*mHealth*) and digital information tools (*eHealth*).

Reimbursement models for physicians in the U.S.: Fee-for-service (FFS) and value-based-payment (VBP) are the two main reimbursement models for healthcare services. In FFS, the provider is reimbursed for each service, and the quantity of service determines the provider revenue. VBP, on the other hand, rewards the value of care provided. However, in the U.S., the typical VBP compensated services are hospital services, such as surgeries, which are typically not feasible to be carried out via telehealth. FFS is not just the main reimbursement model for physician services in the U.S., but also the main channel for telehealth pay-parity policies.

Licensure, credentialing and privileging: State licensure requirements could potentially hinder the broader usage of telehealth and affect the physician's ability to practice telehealth. The administrative burden of licensure laws could deter physicians from utilizing telehealth.[8] To address this, a model "Interstate Licensure Compact" was drafted, which aims to streamline interstate licensing and expand telehealth usage where the hospital where the patient is located to have the ultimate authority in decision-making for "privileging".[9] The license agreements or 'compacts', offer a more efficient route to practicing telehealth across multiple states. For instance, Wisconsin became part of IMLC and enacted the medical licensing legislation to successfully address doctor shortage in the area. By controlling for the effects of the Interstate Medical Licensure Compact, it is possible to isolate the impact of TPLs and ensure the results are not confounded by simultaneous policy changes.

III DATA

State Level Telehealth Parity Regulations Data: The insights into the TPLs come from the survey report Lacktman and Acosta (2021), from where the TPL language has been put together in table form by Dills (2021). The documents contain the specifics of adoptions of TPLs and their respective

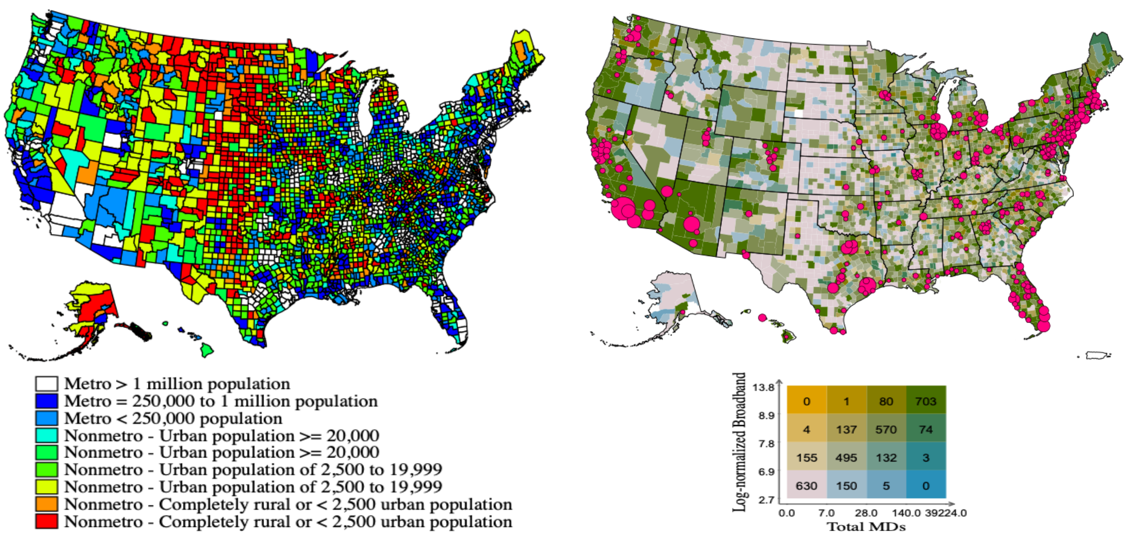
[8] According to the Federation of State Medical Boards Telemedicine Overview (2015), 80% of states require out-of-state clinicians offering telehealth to be licensed in the patient's residing state.

[9] Credentialing involves the verification of a provider's qualifications, while privileging decides what specific procedures or services the provider can offer based on those credentials.

frameworks at the state level. Various cohorts have been created based on the year each state received the treatment. Treatment indicators have been established based on the "type" of treatment received, with states receiving similar treatments—whether a type of Price Control, a type of Cost Control, or a combination of a type of Price Control with a type of Cost Control—grouped together.

FIGURE II

County-wise Degree of Urbanization and Bi-variate Distribution of Broadband Penetration and Physician Counts



(a) (b)

Note: Panel (a) shows the metro and non-metro, rural, and urban areas. The bluish shades correspond to the metro counties. The reddish-orange counties are non-metro rural and greenish-yellowish ones are non-metro urban. Panel (a) shows the bivariate distribution of broadband penetration and physician counts for 2019. The Y-axis of the legend indicates log-normalized broadband score, while the X-axis of the legend indicates Total MDs. The numbers inside the legend box are the number of counties corresponding to each row-column intersection. The pink bubbles represent the densely populated areas with a population of more than 200,000, with the size of the bubbles proportional to the population of the county. The maps are generated using the Stata package from Naqvi (2023) using shapefiles from the U.S. Census Bureau (2016).

County Level Broadband and Demographic Data: The dataset originates from the Federal Communications Commission's (FCC) Form 477 County Data on Internet Access Services (Federal Communications Commission, 2024). To the best of the current knowledge, this study is the first to utilize this novel dataset, which provides information about the number of residential broadband connections at the county level. The number of residential connections offers a more precise measurement of broadband penetration. The residential connection variable is transformed into a weighted standardized variable, through a process described in detail in *Section A.I.A, Online Appendix*. This dataset is combined with the Staff Block Estimates (Federal Communications Commission, 2020 &

2021) from where the county level control variables are obtained.

Licensure Compact Data: The Interstate Medical Licensure Compact is a cooperative tool among participating U.S. states and territories that simplifies the licensing process for physicians practicing in multiple states. The data for the states who joined the compact in 2015 and 2016 comes from Interstate Medical Licensure Compact Commission (2015-2023), official website.[10]

County Level Physician Count Data: The data containing aggregate and speciality-wise county level count of physicians, and the population demographics used as control variables come from the Area Health Resource file (AHRF) (U.S. Department of Health and Human Services, Health Resources and Services Administration, Bureau of Health Workforce, 2021-2022). The data is released on an annual basis by the Bureau of Health Workforce. Each county is uniquely classified by a "County Code", in accordance with Federal Information Processing Standards (FIPS). The sample used in the study spans from 2010 to 2019.[11] The study uses county-level counts of physicians as a proxy for the quantity of healthcare services, due to the high correlation between physician density and service availability. This is supported by literature and practical constraints, given the challenges of directly measuring healthcare service quantities. Including both outpatient and hospital-based physicians, this measure captures comprehensive service capacity, thus providing a robust indicator of healthcare service quantity as discussed in theory.

Metro and Non-Metro County Classification: The study integrates data from the 2013 Rural-Urban Continuum Codes (U.S. Department of Agriculture, Economic Research Service, 2013). It categorizes the U.S. counties based on their degree of urbanization, population size, and proximity to metro areas. This data enables evaluation of spatial distinctions such as metro and non-metro in the U.S. *Panel (a), Figure II*, displays categories of urbanization in further detail.

Table A.II, Online Appendix shows the summary statistics.

IV THEORETICAL FRAMEWORK

A. ***Insights from Conventional Model***

Reimbursement for healthcare services through a Fee-For-Service (FFS) model can interact with Price Controls in a complex manner, when third-party insurers are involved. If the TPL sets a Price Ceiling for telehealth equal to the Market Equilibrium Reimbursement Rate for In-Person services

[10] *Figure A.III, Online Appendix*, shows a map of the states which joined the compact in 2015 and 2016. *Table A.I, Online Appendix*, gives a list of all the state enactments up to 2023.

[11] *Section A.I.C, Online Appendix*, describes the sample further, and *Figure A.IV, Online Appendix*, shows the trends in physician count by cohort and by geographical area.

($MERR - I$) that is above the current Market Equilibrium Reimbursement Rate for telehealth services ($MERR - T$), the physicians might still not be able to increase their charges up to this ceiling.[12] The insurers often have established rates they're willing to pay for each service. If those established rates (Physician Rate Schedules or Physician Pay Schedules (PPS)) are below the parity law-enabled Price Ceiling, then health providers are still constrained by those rate schedules. They won't necessarily be able to charge more just because the TPL allows for a higher limit.

On the other hand, if PPS rate is higher than $MERR-T$, the TPL might not lead to a surplus of physicians offering telehealth services. It would suggest that there's already a higher willing payment above the market equilibrium. If there hasn't been an excess supply under those conditions, the TPL might not change that. If the Price Ceiling is above this equilibrium, physicians could charge more for their services up to that limit, but only if there's a demand for it. If there's no corresponding increase in demand for telehealth at this higher price, physicians are unlikely to increase their rates, and thus, it wouldn't lead to an excess supply of physicians.[13] Thus, it becomes necessary to see the Price Controls in conjunction with Cost Controls.

B. ***Price: Physician Reimbursement, Consumer Costs and Insurer Profits***

Insurer adjustments can reciprocally influence both consumer costs and provider reimbursements—a regulatory change in reimbursement rates may lead to alterations in consumer-facing expenses, such as premiums and cost-sharing, while shifts in consumer cost-sharing can impact providers' financial returns. These modifications can take several forms: adjustments in premiums, alterations to deductibles and co-pays, changes in coverage scope, and even the restructuring of provider rate schedules that may not correspond to policy rates. Additionally, insurers might re-calibrate service networks or negotiate provider rates to manage costs within their risk pools. Despite the role of insurers as intermediaries, their strategic responses to market and policy shifts still generate price signals, driving consumer and provider behavior much like traditional market interactions. In the healthcare market, this traditional direct price-consumer interaction is replaced by a tripartite relationship involving the consumer, provider, and a third-party insurer. The full price P that consumers face is not just direct expenditures like out-of-pocket costs, but also indirect costs

[12] Traditionally, Price Ceilings are envisaged as upper bounds above the equilibrium, while Price Floors are conceptualized as lower bounds below it. However, in the pre-pandemic era in places without TPLs, the telehealth reimbursement rates were established beneath $MERR - I$, with averages for telehealth consultations ranging between \$40 and \$50, contrasting with up to \$176 for in-person visits (Yamamoto (2014); Mahar, Rosencrance and Rasmussen (2018)).

[13] *Section A.II and Figure A.V, Online Appendix*, describe the peripheral aspects in further detail.

through insurance. Premiums S, divided into the provider share S_p and the insurer's share S_n, along with administrative costs A, shape the full price P that consumers encounter. The full price P is a sum of the out-of-pocket expenditure E_{oop} and the insurance premium components divided over the number of healthcare service units Y, given by: $P = E_{\text{oop}} + \frac{(S_p+S_n+A)}{Y}$. Here, $E_{\text{oop}} = \frac{D}{Y} + Co$, where D denotes the annual deductible, and Co represents the copayment for each healthcare service. S_p/Y is the portion of the insurance premium distributed towards providers' reimbursements, S_n/Y is the insurer's profit share, and A/Y is the allocation for the insurer's administrative costs.

Thus, the aspect of canonical economic models that link the price received by providers to the price paid by consumers retain some of their applicability as they still incorporate the tripartite relationship. The focus here is on these direct expenditures without including the value of consumer inputs. However, as telehealth and in-person services incorporate elements managed by both consumers and providers, the full price P can also be analyzed through the value produced using these inputs, as illustrated in the following section.

C. ***Rotations in Supply Curves: A Supply Chain Framework***

Adaptation of the Household Production Model: "Telehealth (T)" and "In-person (I)" are considered as two factors in the spirit of the household production model (Becker, 1965).[14] The impact on the physician count could depend on the effect on surplus of the physicians and the substitutability between the inputs. Price regulations distort the factor mix, create externalities and cause rotation of the marginal cost curve. Considering the supply chain framework similar to Mulligan (2024), where both physicians and patients are considered co-producers in the healthcare transaction, the production function is given by: $Y = AF(T, I)$. T signifies telehealth resources predominantly controlled by providers and I symbolizes in-person inputs primarily at the discretion of consumers. The full price P is expressed mathematically as: $P = \frac{tT}{Y} + \frac{iI}{Y}$, indicating how total revenue PY is allocated across telehealth and in-person services. Consumers undertake dual roles: first, as suppliers of I, they receive remuneration valued at iI/Y per unit of output Y consumed; second, as end-users, they

[14] T and I inputs are analogous to capital K and labor L in traditional economic frameworks, respectively. T represents telehealth resources such as digital infrastructure, software, and machines predominantly controlled by providers, much like capital in other industries. I corresponds to labor-intensive activities such as traveling, standing in queues, and waiting, which demand time and effort primarily from consumers. This distinction is used to reflect the primary control exerted by providers over telehealth technology and infrastructure (T), whereas consumers generally govern their own time and effort (I) in seeking in-person healthcare services. The setup highlights the industry norms where providers are equipped with and responsible for the technological aspects of care (T), and patients navigate the logistics of in-person engagement (I), underlining the separate but interdependent contributions of both parties to healthcare delivery.

incur the full price P, resulting in a net payment to providers of: $tT/Y = P - iI/Y$ per unit of output, where "t" and "i" are the inverse factor-supply functions derived from the strictly convex and increasing cost functions, $\Gamma_T(T)$ and $\Gamma_I(I)$, for telehealth and in-person services, respectively. The marginal costs associated with in-person services "i" and telehealth inputs "t" are captured by $i = \Gamma_I'(I)$ and $t = \Gamma_T'(T)$, respectively. To acknowledge the impacts of cost-sharing and broadband access, the market demand is now characterized by a curve $Y_R = BD(P;\gamma)$. This adapts the unregulated demand function, $Y_U = BD(P)$, to incorporate the policy parameter γ, thereby accounting for regulatory influences on consumer demand elasticity. Similarly, supply within this market is represented by the regulated market supply curve, $Y_R = S(P;\rho)$, where ρ incorporates the policy parameter. $Y_U = S(P)$ is the unregulated supply. Under the presence of a up-stream price regulation compliance condition (PRC): $\frac{tT}{Y} = \rho$, the equilibrium in the telehealth space is not necessarily optimized solely around provider reimbursements, but is also attuned to the collective value derived from healthcare services, inclusive of patient's contributions. A and B serve as shift parameters that allow for the analysis of changes in supply and demand, respectively, brought on by the integration of such policy parameters, with A eliciting supply shifts and B indicating demand shifts. The production function defined as $F(T,I)$ relates to how demand for inputs escalates with increased service provision Y, and $C(i,t,Y)$ denotes the corresponding unregulated cost function. These considerations amalgamate to form an equilibrium that is now dynamically responsive to the policy environment and distinct consumer behaviors. The equilibrium conditions are:

- Full Price (*FP*): $P = \frac{tT}{Y} + \frac{iI}{Y}$
- Final Demand (*FD*): $Y = BD(P;\gamma)$
- Production Function (*PF*): $Y = AF(T,I)$
- In-person Supply (*IS*): $i = \Gamma_I'(I)$
- Telehealth Supply (*TS*): $t = \Gamma_T'(T)$
- Price Regulation Compliance (*PRC*): $\frac{tT}{Y} = \rho$
- Cost Minimization (*CMC*): $\frac{\frac{\partial F(T,I)}{\partial T}}{\frac{\partial F(T,I)}{\partial I}} = \frac{t}{i}$

Divergence from Conventional Models: The divergence from the conventional model arises when we introduce the PRC, which, rather than adhering to CMC, which traditionally would set relative marginal costs equal to the marginal rate of substitution derived from the production function $F(T,I)$, incorporates an upstream-price compliance condition. This condition mandates that the price per unit of telehealth service (tT/Y), as a policy parameter ρ, aligns with either a legislatively mandated Price Floor or Price Ceiling, transforming the allocation of resources within the telehealth and in-person services markets. This regulation-induced adjustment distorts the market allocation away from the cost-minimizing mix of telehealth and in-person services that would naturally arise in an unregulated market.

Quality Adjustments Under Non-price Competition: An alternative view is that these regulations induce substantial changes in the product or service characteristics as market actors adapt to the imposed constraints. In case of a Price Ceiling, particularly when the supply is highly elastic, the markets will not simply collapse. Instead, there is an incentive for the providers to modify the quality or nature of the product to maintain some level of market functionality, while avoiding the total disappearance of trade – a scenario supported by the elasticity of supply and a reluctance to forego potential gains from trade. This implies a rotation of the supply curve owing to a change in the mix of the factors of production utilized. Moreover, these price regulated markets are not slack, owing to the incentive among providers to react to the willingness of the consumers to accept a lower quality product. Thus, quantity is not really independent of demand. Regulation removes the cost-minimization condition, compelling the providers to comply with the regulation, which will raise the overall costs. However, marginal costs might not necessarily rise due to adaptations. For instance, if excessive T and a minuscule I are being used instead of the cost minimizing factor mix, the marginal cost of producing an extra unit of Y would be lower since more of T, which is cheaper, can be used.

For a unit output Y, consumers are quoted the full price P that reflects both the cost of healthcare services provided and the value of consumer input. When faced with a Price Ceiling, the consumers are compelled to find alternative ways to compete due to the inability to pay higher prices, a consequence of the regulatory cap. Such alternatives may involve increased personal effort, such as being more accommodating with appointment scheduling or willing to travel greater distances for care. In contrast, a Price Floor stimulates providers to enhance their offerings. For example, they may invest in expanding telehealth services by introducing additional features or capabilities. In this regulated landscape, where price cannot serve as the primary signaling mechanism, the quality and assortment of services become the focal points of communication between healthcare providers and consumers. Telehealth is a capital-intensive, high-quality product that requires less time and effort from the consumer, whereas in-person or office-based healthcare is a low-quality product that demands more time and effort from the consumer.

Policy Parameters and Equilibrium Conditions: $E(\rho)$ exists as a point on the unregulated supply curve, where $\frac{tT}{Y}$ coincides with ρ. However, $E(\rho)$ is not an unregulated or regulated equilibrium unless the demand curve coincidentally intersects it. At $E(\rho)$, PRC would be non-binding, either as a Price Ceiling or as a Price Floor. As one goes above $E(\rho)$, the Price Floor becomes binding. As one goes below $E(\rho)$, the Price Ceiling becomes binding. Similar analogy follows for $E(\gamma)$ and Cost Ceiling or Cost Parity. Let $\rho \in [\underline{\rho}, \overline{\rho}]$ and $\gamma \in [\underline{\gamma}, \overline{\gamma}]$. Holding constant tastes (B, $D()$) and technology (A, $F()$, Γ_I, Γ_T), both the unregulated equilibrium U and any point on the unregulated supply curve are on the same demand curve in the $[Y, P]$ plane, indicating that regulation effects stem from supply rotations. Since the point $E(\rho)$, satisfies the unregulated conditions FP, PF, IS, TS, and CMC, it must also satisfy the regulated-conditions FP, PF, IS, TS, and PRC.

Factor Distortions and Production Inefficiency-Price Floor vs Price Ceiling: Irrespective of whether $MERR - T$ is close to $MERR - I$ or not, the introduction of a binding Price Floor reallocates spending towards the upstream input T at the expense of the downstream input I, which ultimately causes an uptick in t and a decline in i. If T is more elastically supplied than I, it would lead to counter-clockwise rotation in the Marginal Cost (MC) curve, and vice versa. Conversely, a binding Price Ceiling reduces T, hence t, while increasing I, and therefore i. If T is more elastically supplied than I, it would lead to clockwise rotation in the Marginal Cost (MC) curve, and vice versa. In the case of telehealth, $MERR - T$ is away from $MERR - I$, i.e., the pre-regulation physician reimbursement rate is much lower than the post-regulation rate. Thus, owing to such a unique case, even in the face of a Price Ceiling, providers will still reallocate spending towards the upstream input T at the expense of the downstream inputs I, which ultimately causes an increase in t and a decline in i. Thus, the effect could be similar to that of a Price Floor. The feasibility of these mechanisms depend on the geographical area. Typically, in areas with high broadband penetration, T will have enough supply elasticity to make such adjustments feasible. In the areas with low broadband penetration, where supply elasticity of T is much less, there will be more tendency to reallocate spending from T towards I.[15] In cases where I is also not supplied elastically enough, it could lead to a relocation or exit of the upstream input supplier or the healthcare provider.

When the model operates near an efficient factor mix, no incremental costs arise, given their capability to substitute between inputs to maintain the desired output level. Inputs T and I can be traded off along the isoquant at an exchange rate of i/t, so there is no price effect if i and t are kept constant. However, the changes in i and t will have repercussions on P, contingent on the relative

[15] Both metro and non-metro areas could have counties with high or low levels of broadband penetration, even though metro areas will have more counties with high broadband penetration. The supply elasticity of telehealth is more contingent on the degree of broadband penetration than on the degree of urbanity, as internet access is crucial for telehealth services.

elasticity of supply for T and I. The provider's ability to adjust depends on these elasticities, and the Marginal Cost (MC) curve will rotate in response. Therefore, the overall impact of a price regulation on P—whether it leads to an increase or decrease in P—hinges on the elasticity of supply for the inputs T and I. Let $\varepsilon_{\Gamma T}$ and $\varepsilon_{\Gamma I}$ are the elasticities of supply for the inputs (T) and (I), respectively. The relation between Y_R^* and Y_U^*, the regulated and unregulated equilibrium quantities, respectively, will depend upon the position of the regulated demand curve or the demand curve post regulation.

In the empirical analysis, the treated cohorts have broadband levels one standard deviation above the mean, in contrast to the "never treated" control group, where broadband levels are at the mean, approximating the counterfactual. This indicates an interaction effect between changes in policy and differences in the technological infrastructure. As one moves to a higher broadband level, the elasticity of telehealth increases. This leads to the following propositions, which prepare a theoretical context for the treatment effects in the empirical results.

Proposition 1: With $\varepsilon_{\Gamma T}$ and $\varepsilon_{\Gamma I}$ as input supply elasticities for (T) and (I), respectively—

(a) When $MERR - I$ acts as a binding Price Floor or a non-binding Price Ceiling, the supply curve rotates counter-clockwise (clockwise) around $E(\rho)$ if the sign of $\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I}$ is positive (negative), respectively.

(b) In each case, the position of the regulated equilibrium quantity E_R with respect to the unregulated equilibrium quantity E_U will depend on the position of the regulated demand curve.

For *Proposition 1* (a) to hold—specifically for the Price Ceiling and Price Floor to exhibit similar behavior—it is crucial that pre-regulation telehealth reimbursement is significantly lower than $MERR-I$, and that the Physician Pay Schedule (PPS) adjusts according to $MERR-I$, which ensures that the Price Ceiling is non-binding. As previously noted, this scenario is indeed the case with pre-regulation $MERR-T$ being considerably lower than $MERR-I$, which prompted physicians to demand parity in the first place. If PPS adjusts accordingly, this unique scenario allows physician reimbursement to rise even under a Price Ceiling (PC), resulting in the regulated supply curve ($Y_R = S_{PC}(P;\rho)$) exhibiting behavior similar to the regulated supply curve ($Y_R = S_{PF}(P;\rho)$) of a binding Price Floor (PF), as shown in *Figure III*. Conversely, if the Price Ceiling is binding, or if the PPS restricts telehealth reimbursement from rising, anticipatory adjustments will occur, causing the supply curve behavior under a binding Price Ceiling to contrast sharply with that under a binding Price Floor. Specifically, under a binding Price Ceiling, there will be a clockwise rotation in the supply curve when $\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} > 0$, and a counter-clockwise rotation in the supply curve when $\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} < 0$. This will be manifested as red-black ($\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} > 0$) and light green ($\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} < 0$)

curves exchanging positions in *Panel (b), Figure III*.

While rotations alter the slopes of demand and supply curves indicating changes in price elasticity, shocks shift these curves by changing quantities at all price levels. Shocks result from exogenous events, whereas rotations stem from varying responsiveness due to factors like technological advancements or market dynamics. This distinction leads us to *Proposition 2*.

Proposition 2: If there are demand and supply shocks and the policy parameter ρ is set as a binding Price Ceiling or Price Floor, assuming that there is a supply curve in the $[Y, T/Y]$ plane as the locus of pairs $\{Y, T/Y\}$, then -

(a) An increase in demand $(dB > 0)$ leads to a higher quantity of telehealth services provided without an increase in the upstream price $\left(\frac{t_T}{Y}\right)$, while a productivity improvement $(dA > 0)$ in telehealth services leads to greater quantity Y delivered without decreasing the upstream price $\left(\frac{t_T}{Y}\right)$.

(b) If $(dB > 0)$, the equilibrium full price (P) may increase due to the heightened demand for healthcare services. If $(dA > 0)$, the equilibrium full price P could decrease due to more efficient production of services, reflecting advances in telehealth capacity.

(c) Following *Proposition 1* (a), if $\varepsilon_{\Gamma_T} - \varepsilon_{\Gamma_I} < 0$, the positive demand shock and the supply shock both yield more considerable increases in total healthcare services quantity Y than they would in the absence of regulation.

Proposition 2 (c) results out of the fact that when $\varepsilon_{\Gamma_T} - \varepsilon_{\Gamma_I} < 0$, the regulated supply curve (light green curve in *Figure III*) is flatter than the unregulated supply (dark green) curve causing the increase in the equilibrium quantity in the regulated scenario to be more than that in the unregulated scenario.

D. ***Rotations in Demand Curves***

Cost Regulations as Demand Modulators: In healthcare market characterized by third-party insurance systems, the demand-side mechanisms for medical services diverge fundamentally from supply-side dynamics. The supply chain framework focusing on providers' allocation decisions, assuming movements along a static demand curve, a distinct model is necessary to explore demand shifts resulting from changes from consumers' point of view. Thus, Cost Ceiling and Cost Parity become pivotal in shaping demand. A Cost Ceiling, prevents the full price paid by the consumers from rising above that of in-person services. Cost Parity equalizes the full price paid for telehealth services with those for in-person services, increasing the full price.

Demand for Healthcare Services: Time Price vs Money Price: Within this framework, the approach similar to that in Acton (1975) informs the dynamic nature of demand. The utility function of individuals incorporates medical services, denoted by m, and a composite good represented by X. The constraint is the full income equation that combines monetary costs and time costs for both medical services and the other composite good. P is the money price, which is also the full price paid by the consumer in the supply chain approach. If w is the wage and τ is time required for accessing medical services, $w \times \tau$ becomes the time price per unit of medical services. The total price Π, which is the sum of money price and time price, becomes: $\Pi = P + w \times \tau$. Both money price and time price influence the demand for medical service m, depending on money price elasticity, ε_m^P, and time price elasticity, ε_m^τ, of demand for medical services, such that: $\varepsilon_m^p = \frac{P}{\Pi}\varepsilon_m^\Pi$, and $\varepsilon_m^\tau = \frac{w\tau}{\Pi}\varepsilon_m^\Pi$. This yields a prediction from the model:

$$\varepsilon_m^\tau \lesseqgtr \varepsilon_m^P \text{ as } w\tau \lesseqgtr P \tag{B1}$$

This implies that the relationship between the two elasticities is determined by the respective prices. This is consistent with quality adjustments discussed in the supply chain framework. The good requiring lower time on part of the consumer has better quality than the one requiring more time.

Changes in Consumption Mix Owing to Expected Change in Cost: The higher wages in metro areas make the time price of medical services higher compared to the money price as implied by (B1). Thus, at the same level of broadband, the demand for medical services will be more sensitive to changes in time price in metro areas, as opposed to non-metro areas, which have relatively lower wages. Moreover, the demand for medical services will be relatively more sensitive to money prices in non-metro areas than in metro areas, making the demand curve more elastic for the former, as shown in *Figure III*. A Cost Ceiling (CC) regulation would prevent P from rising above what it otherwise would, making the regulated demand curve ($Y_R = D_{CC}(P;\gamma)$) less elastic than the unregulated demand curve ($Y_U = D_U(P)$). Conversely, a Cost Parity (CP) regulation would raise P above what it otherwise would, making the regulated demand curve ($Y_R = D_{CP}(P;\gamma)$) more elastic than the unregulated demand curve. Thus, at $E(\gamma)$, where the cost for telehealth becomes the same as $MECR - I$, Cost Ceiling would cause a clockwise rotation, and Cost Parity would cause a counter-clockwise rotation in the demand curve.

Income and Substitution Effects of Broadband: An increase in broadband penetration would increase the opportunity cost of time, thus raising the time price. Whether this change results in a positive substitution effect causing an increase in demand for medical services will depend on the relative proportions of the time price to the total price of medical services and the composite good. With q as the money price and $w \times s$ as the time price per unit of the composite good X, the substitution effect of broadband on the demand for medical services will be positive if:

$$\frac{ws}{ws+q} > \frac{w\tau}{w\tau+P}, \tag{B2}$$

that is, if the time price is a larger proportion of the total price for the composite good, X, than it is for medical services, m (Acton, 1973).

If there is increase in broadband causing a rise in the opportunity cost of time, and if the time intensity of the price of the composite good is more than the time intensity of the price of medical services, the substitution effect will be positive, leading to an increased demand for medical services. The increase in demand will be more pronounced in metro areas where the demand for medical services is more sensitive to time prices. In metro areas, a Cost Parity, which causes telehealth costs to rise due to a binding $MECR-I$, will have a moderately higher effect than a non-binding Cost Ceiling regulation. Thus, for counties with broadband level 1 SD above the mean, the demand curves will fan out as shown in *Figure III*.[16] The regulated demand curve will take into account this effect of broadband and the effect of Cost Control. The quantity corresponding to the intersection of the regulated demand and supply curves will give the regulated equilibrium quantity. The differences between the unregulated and regulated equilibrium quantities, corresponding to each type of regulation, k, will give the respective equilibrium shifts. The estimates of these equilibrium shifts, quantified as ATT_k, under Price Control or Cost Control types in isolation, are given in *Table II* and *Table III*, while those under combinations of a type of Price Control with a type of Cost Control are given in *Table IV*.

The regulated equilibrium will depend on whether a type of regulation—a type of Price Control, a type of Cost Control, or a combination of both a type of Price Control with that of a Cost Control. If only a type of Price Control is in effect, then the regulated equilibrium will be the intersection of the regulated supply curve and the unregulated demand curve. If only a Cost Control is in effect, then the regulated equilibrium will be the intersection of the unregulated supply curve and the regulated demand curve. If a combination of a type of Price Control with a type of Cost Control is present,

[16] For free or highly subsidized services, where $P \approx 0$, the right-hand side of (B2) becomes greater than the left-hand side, causing the substitution effect to be negative. For a high P, the right-hand side becomes less than the left-hand side, making the substitution effect positive. The switch in the substitution effect would happen around $E(\gamma)$, where neither Price Ceiling nor Price Floor is binding, and the substitution effect is negligible.

then the regulated equilibrium will be the intersection of the regulated supply curve and the regulated demand curve. Moreover, with the broadband interaction, to get the regulated equilibrium quantity at broadband level 1 SD above the mean, the regulated supply curve with a superscript "MB" will be considered for metro areas ("NMB" for non-metro areas) in *Figure III*.[17] For broadband at mean level, the regulated supply curve with a superscript "M" will be considered for metro areas ("NM" for non-metro areas). *Proposition 3* sets the context for the rotations in the demand curve.

Proposition 3: For the supply and demand curves in the $[Y, P]$ plane as the locus of pairs $\{Y, P\}$:

(a) A Cost Ceiling causes the demand curve to rotate clockwise, while a Cost Parity causes the demand curve to rotate counter-clockwise.

(b) A one standard deviation increase in broadband causes the demand curve to rotate clockwise at $E(\gamma)$, so that the position of the regulated demand curve depends on the combined effects of broadband and the type of Cost Control (Ceiling or Parity) specified.

Broadband-Enhanced Telehealth Supply Elasticity Assumption (BETSEA): At the mean broadband level, $\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} < 0$, and a one standard deviation increase in broadband increases the supply elasticity of telehealth to a point where $\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} > 0$.

The supply elasticity of telehealth depends on a multitude of factors, among which broadband is a crucial one. An increase in broadband will increase the supply elasticity of telehealth. Specifically, a one standard deviation (henceforth 1 SD) increase in broadband will raise the telehealth supply elasticity to a point where the switch (from $\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} < 0$ to $\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} > 0$) occurs. The implications of *BETSEA* are discussed further in *Section VI*, while discussing the results for *Table IV*.

The following proposition sets the context for the subsequent determination of regulated equilibrium quantities.

Proposition 4: Let the superscript "MB" denotes "metro areas with broadband 1 SD above the mean", while referring to *Figure III*. For supply and demand curves in the $[Y, P]$ plane as the locus of pairs $\{Y, P\}$—

(a) If only a type of Price Control is in place with broadband level 1 SD above the mean, then conditional on *BETSEA* being satisfied, the regulated equilibrium will lie on the regulated supply curve ($Y_R = S_{PF}^{MB}(P; \rho)$ for Price Floor, and $Y_R = S_{PC}^{MB}(P; \rho)$ for Price Ceiling), where $\varepsilon_{\Gamma_T} - \varepsilon_{\Gamma_I} > 0$ (red-black curve with superscript 'MB').

[17] Thus, the final equilibrium quantity shifts could be better understood by looking at the results where the treatment is the combination of a type of Price Control with a type of Cost Control, as actually specified by the states (*Table IV*), rather than looking at types of either Price Control or Cost Control in isolation (*Table III*).

FIGURE III

Price Floor and Price Ceiling

(a)
MERR−I
Floor

(b)
MERR−I
Ceiling

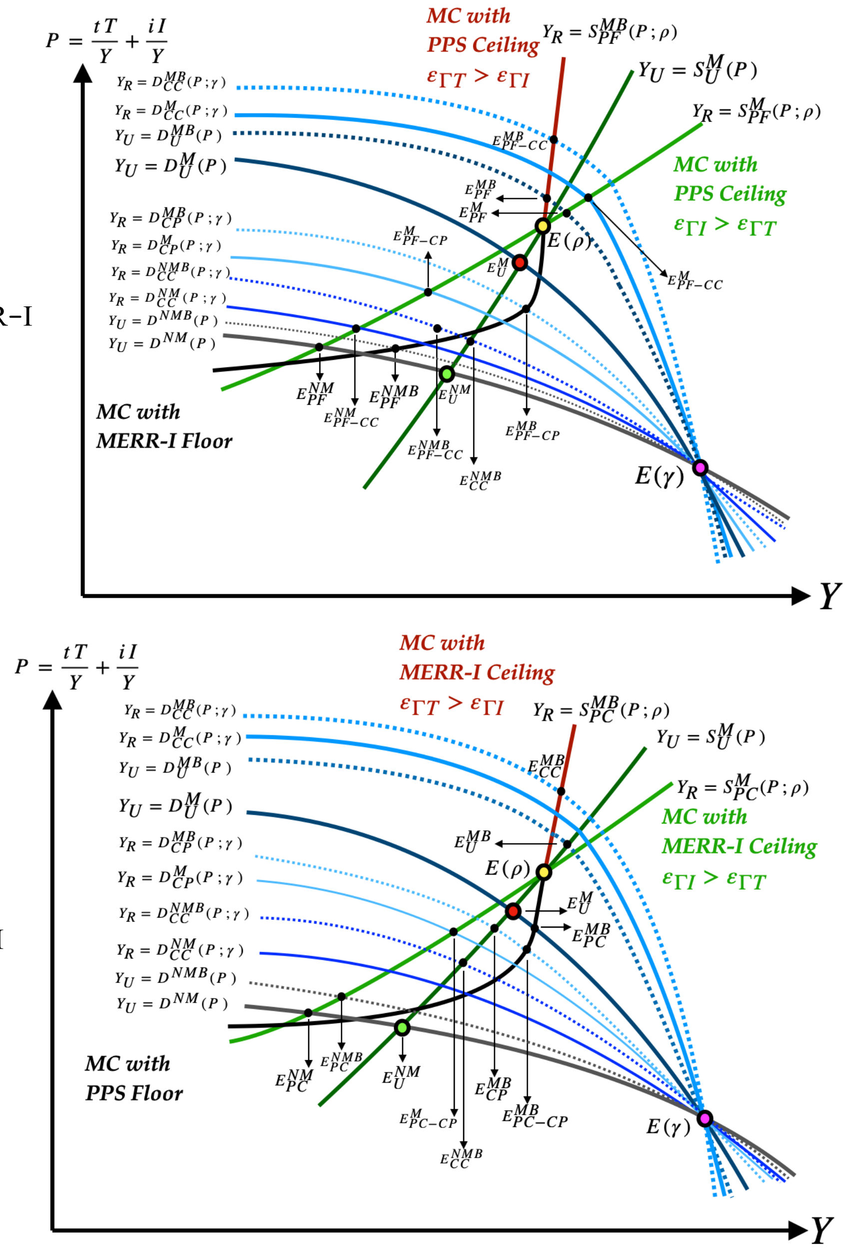


Figure 3 Note: Panel (a) shows the supply and demand curve rotations with $MERR - I$ as the floor (PPS as the ceiling), while Panel (b) shows the supply and demand curve rotations with $MERR - I$ as the Price Ceiling (PPS as the Price Floor). The dark green supply curve denotes the unregulated supply ($Y_U = S_U^M(P)$) when the broadband is at the mean level ($\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} < 0$) and there is no Price Control. As given in *Proposition 1* (a), the light green supply curve ($Y_R = S_{PF}^M(P;\rho)$) denotes the regulated supply when the broadband is at the mean level but there is a Price Control in place. The red/black supply curve denotes the regulated supply (e.g., $Y_R = S_{PF}^{MB}(P;\rho)$) when the broadband is 1 SD above the mean, ($\varepsilon_{\Gamma T} - \varepsilon_{\Gamma I} > 0$), and a Price Control is specified.

Figure 3 Note-continued: As the red supply curve crosses $E(\rho)$, the Price Floor becomes binding, and the red supply curve continues as a black supply curve crossing $Y_U = S_U^M(P)$ once more and becoming horizontal. The rotations in the blue and grey demand curves are as per *Proposition 3*. The superscripts M and NM stand for Metro and Non-metro, respectively. MB and NMB stand for Metro and Non-metro when the broadband is 1 SD above the mean, respectively. The solid blue and grey curves denote the demand curves at the mean broadband level, while the dotted blue and grey curves denote the demand curves when the broadband is 1 SD above the mean. The subscripts PC, PF, CC, and CP denote Price Ceiling, Price Floor, Cost Ceiling, and Cost Parity, respectively. The yellow and pink circles with black rings denote $E(\rho)$ and $E(\gamma)$, respectively. The red circle and the green circles with black rings denote the unregulated equilibriums for metro (E_U^M) and non-metro (E_U^{NM}) areas, respectively. The equilibrium quantities are denoted by black dots. The ATT described in the results for metro (non-metro) areas will be the distances between the projections of red (green) circles with black boundaries and the projections of black dots corresponding to each treatment type, on the quantity axis.

(b) If only a type of Cost Control is specified with broadband level 1 SD above the mean, then conditional on *BETSEA* being satisfied, the regulated equilibrium will lie on the regulated demand curve ($Y_R = D_{CC}^{MB}(P;\gamma)$ for Cost Ceiling, or $Y_R = D_{CP}^{MB}(P;\gamma)$ for Cost Parity), where $\varepsilon_{\Gamma_T} - \varepsilon_{\Gamma_I} > 0$ (dotted blue curves with superscript "MB").

(c) If a combination of a type of Price Control with a type of Cost Control is in place with broadband level 1 SD above the mean, then conditional on *BETSEA* being satisfied, the regulated equilibrium will lie on the respective regulated supply and demand curves, depending on the type of Price Control-Cost Control combination specified (red-black curve and dotted blue curves with superscript "MB").

(d) In any of the above regulated scenarios described in (a), (b), and (c), if broadband level is 1 SD above the mean, but *BETSEA* is not satisfied, then depending upon the type of regulation specified, the regulated equilibrium will lie on the intersection of the respective regulated supply curve, where $\varepsilon_{\Gamma_T} - \varepsilon_{\Gamma_I} < 0$ (light green curve with superscript "M"), and the regulated demand curve (dotted blue curves with superscript "MB").[18]

While *Proposition 4* is about metro areas, a similar discussion ensues for non-metro areas, with the superscript for metro areas "M" replaced by "NM".[19]

It is to be noted that $E(\rho)$ and $E(\gamma)$ are different from equilibrium points. These are points where the physician reimbursement and consumer costs equal the regulatory parameters, ρ and γ, re-

[18]The unregulated supply curve at broadband level 1 SD above the mean ($Y_U = S^{MB}(P)$) is not shown in *Figure III*, as it is of no consequence to estimating the treatment effects. This is because the baseline scenario is the unregulated equilibrium at mean broadband level (dark green curve, $Y_U = S^M(P)$), and the treated outcome is regulated equilibrium at broadband level 1 SD above the mean.

[19]Non-metro areas would have distinct supply curves, just as they have their own separate demand curves, apart from those for metro areas. However, to maintain clarity and avoid visual clutter, these supply curves are intentionally omitted from the graphical representation in *Figure III*. The supply curves for metro areas have been applied to non-metro areas too. This approach does not alter the predictions of the model.

spectively. $E(\rho)$ might coincide with the equilibrium point only if the demand curve passes through it, while $E(\gamma)$ might coincide with the equilibrium point only if the supply curve passes through it.

Table I—: Predictions from the Model

				Price Controls			
				Price Floor		**Price Ceiling**	
				M	**NM**	**M**	**NM**
				$+$	$-$	$+$	$-$
Cost Controls	**Cost Ceiling**	**M**	$+$	$+$	N/A	$+$	N/A
		NM	$+$	N/A	$-$	N/A	$-$
	Cost Parity	**M**	$-$	$-$	N/A	$-$	N/A
		NM	$-$	N/A	$-$	N/A	$-$

Note: "N/A" denotes "Not Applicable". "$+$" denotes a positive effect, while "$-$" denotes a negative effect on healthcare service quantity or physician count. Row 4 from top and column 4 from left denote the effects for Price Controls and Cost Controls, individually. Rows 5 to 8 from top and columns 5 to 8 from left denote the effects of combinations of types of Price Control with those of Cost Control.

This study doesn't explicitly examine the short-run and long-run effects of regulation on telehealth supply elasticity. In the short run, there is a clockwise rotation when telehealth supply elasticity is less than that of in-person care (light green curve at mean broadband level in *Figure III*), and there is a counterclockwise rotation in the long run when telehealth supply elasticity exceeds that of in-person care (red-black curve at broadband level 1 SD above mean in *Figure III*). However, this study, spanning 2010 to 2019, lacks the temporal scope to distinguish short-run and long-run behaviors. Instead, the switch in sign ($\varepsilon_{\Gamma_T} - \varepsilon_{\Gamma_I} < 0$ to $\varepsilon_{\Gamma_T} - \varepsilon_{\Gamma_I} > 0$) mimics the transition from short-run to long-run behaviour when telehealth becomes relatively more elastic with time.[20]

Table I shows the predictions from the model, which are also encapsulated in *Figure III*.

V EMPIRICAL FRAMEWORK

A. ***Model Specification and Data Generating Process***

The data-generating process (DGP) is specified as follows:

$$Y_{j(i)t} = \exp[\beta_0 + \beta_1 M_{it} + \beta_2 M_{j(i)t} - \beta_3 D_{it} - \beta_4 D_{j(i)t}]\varepsilon_{j(i)t} \tag{1}$$

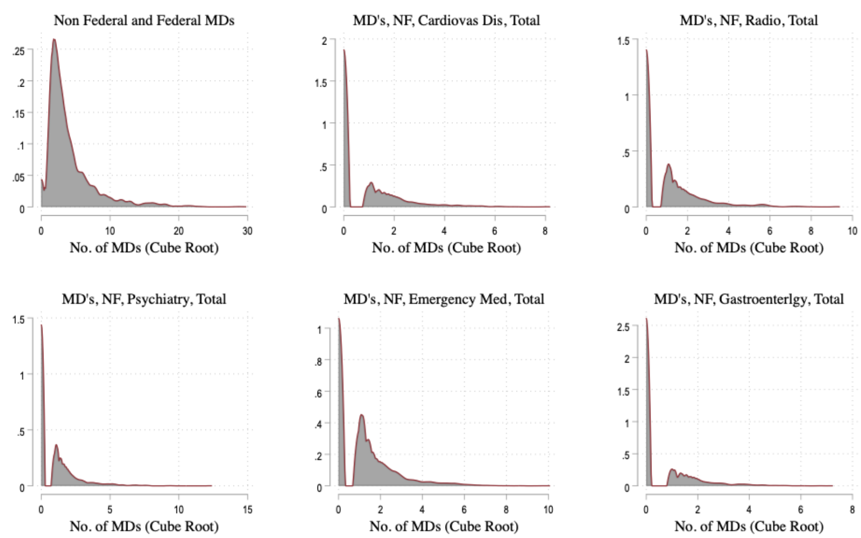
β_0 is the natural log of a constant. In the panel data setting, *i* is construed as "state", $j(i)$ as "county" in state *i* such that $j(i) \in i$, and *t* as "year". $Y_{j(i)t}$ denotes the count of physicians at county *j(i)* in a given year. $\varepsilon_{j(i)t}$ is the error term with an expectation equal to 1. β_1 signifies

[20] Standardized broadband, which is the third term in the triple interaction term (*Table III*) incorporates this by comparing counties at broadband level 1 SD above the mean to those at mean broadband level. At 1 SD above the mean, telehealth is more elastic, as implied by *BETSEA*. This provides insights akin to short-run and long-run impacts without separately analyzing such temporal effects.

the degree of "conducive" nature of the state's policy environment, indicating how factors that are favorable to medical practice can lead to an increase in the physician count. For instance, a state specifying a Price Floor as part of it's TPL could be conducive to physicians locating in a given state. β_2 captures the "attractiveness" of the county-level as signified by the county-level characteristics $M_{j(i)t}$, which could include population, standardized broadband, logged median household income, per capita risk-adjusted Medicare expenditure, and the number of hospital admissions per population. Conversely, β_3 and β_4 measure the degree of "friction" induced by state and county-level variables, respectively, which discourages physician settlement or leads to their departure. D_{it} could include state-level frictional components, such as Cost Parity, which could make telehealth unaffordable for consumers. $D_{j(i)t}$ could include county-level frictional components, such as the percentage of poverty, or the percentage of people aged 65 and older without health insurance, which could make a county less attractive for physicians. Unobserved time-invariant factors that could influence a physician's location are captured in the error term $\varepsilon_{j(i)t}$.

FIGURE IV

Specialty-wise Density Plots of Physician Counts



Note: Total Non-Federal and Federal MDs for specialties (in clockwise direction): Cardiovascular diseases, Radiology, Gastroenterology, Emergency Medicine & Psychiatry. The cube root transformation moderates the influence of outliers, so that the non-zero values are spread out to allow for a more distinctive visualization of the distribution, enabling better identification of patterns in the data.

B. *Estimation Approach*

As shown in *Figure IV*, $Y_{j(i)t}$ is a count variable with zeroes, estimating the log-linearized equation by least squares (OLS) can lead to significant biases, especially if the true model is nonlinear in its parameters, and can result in inconsistent estimates due to heteroskedasticity. Firstly, logarithm of zero is undefined. Secondly, even if the counts are strictly greater than zero or transformed as $ln(1 + Y_{j(i)t})$, the expected value of the log-linearized error will depend on the covariates, which will make OLS biased. Further, multiplicative models estimated using the non-linear least squares (NLS) method can be inefficient as it ignores heteroskedasticity. The best way to estimate this model would be to write it in the multiplicative form and then estimate it using Poisson Quasi Maximum Likelihood Estimator (QMLE) or Pseudo Maximum Likelihood Estimator (PMLE), which can very well account for the the zero values of $Y_{j(i)t}$ (Santos Silva and Tenreyro, 2006).[21] After adding county and time fixed effects, and covariates $X_{j(i)t}$, the DiD model in a generalized multiplicative form becomes:

$$\begin{aligned} Y_{j(i)t} = \exp\Bigg(&\beta_0 + \lambda_{j(i)} + \gamma_t + \sum_{k=1}^{K} \beta_{1k}(M_{ik} \times Post_{kt} \times B_{j(i)t}) + \\ &\sum_{k=1}^{K} \beta_{2k}(M_{ik} \times Post_{kt}) + \sum_{k=1}^{K} \beta_{3k}(Post_{kt} \times B_{j(i)t}) + \sum_{k=1}^{K} \beta_{4k}(M_{ik} \times B_{j(i)t}) + \\ &\sum_{k=1}^{K} \beta_{5k} M_{ik} + \beta_6 B_{j(i)t} + \sum_{k=1}^{K} \beta_{7k} Post_{kt} + \beta_8' X_{j(i)t} \Bigg) \varepsilon_{j(i)t} \end{aligned} \quad (2)$$

K is the total number of types of treatment or regulation being incorporated. The part $\sum_{k=1}^{K} \beta_{5k} M_{ik} + \beta_6 B_{j(i)t} + \beta_8' X_{j(i)t}$ can be broken down into conducive, attractive and frictional components, depending on whether the sign of the coefficients is positive or negative.[22] "k" is the type of treatment as determined by the framing of the TPL. If the sign of the coefficient β_{5k} is positive (or negative), the state-level treatment type is a conducive (or a frictional) component. If the sign of a coefficient in the vector β_8' is positive (or negative), the county-level control variable is an attractive (or a frictional) component. There are six different indicators, one indicating whether the state adopted the TPL or not, and five for the types of framing. The triple interaction term incorporates a DiD framework, where the state-level treatment variables are interacted with the post-treatment indicator, which is further interacted with the standardized broadband.[23] The model is estimated with and without the broadband interaction $B_{j(i)t}$.

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[21] PPML is preferred even though QPML and PPML are used alternately in the literature (Gourieroux, Monfort and Trognon, 1984).

[22] The decision to logarithmize a co-variate or not was based on whether it was approximately log-normally distributed after taking natural logs or not (Beyer, Schewe and Lotze-Campen, 2022).

[23] *Please refer to Section III, Online Appendix* for the peripherral aspects of the estimation strategy.

Since TPLs, cannot be reversed after adoption, there is no reversibility with staggered entry. After ensuring that there is no perfect multicollinearity, the $ATT_k s$, where k is the treatment type, are identified if teh assumptions of "Conditional No Anticipation Assumption" and "Conditional Indexed Parallel Trends" in levels are satisfied. Since the latter is mostly unreasonable, a more likely assumption is the ratio version of the parallel trends assumption, which allows one to get the counterfactual percentage change in the mean outcome for the treated group (denoted by "$D_{j(i)} = 1$") using the observed percentage change for the control or never treated group (denoted by "$D_{j(i)} = 0$").[24] This is implied by an exponential conditional mean function. This is the only known nonlinear estimation method where including unit-specific dummies does not lead to the incidental parameters problem. After incorporating covariates, the Poisson PMLE, given in Chen and Roth (2024) and formalized in Wooldridge (2023), gives a consistent estimate of $\theta_{\text{ATT(k)}}\%$, if the ratio version of parallel trends holds conditional on covariates, $\varepsilon_{j(i)t}$ has a mean of 1 conditional on covariates, and $Y_{j(i)t}$ takes the exponential functional form.[25] The state-level main effects M_{ik} will be dropped since they are constant within groups and will be subsumed into the county fixed effects $\lambda_{j(i)}$, while the main $Post_{kt}$ effects for each treatment type will be subsumed into the time fixed effects γ_t. Thus, (2) gets reduced to:

$$\begin{aligned} Y_{j(i)t} = \exp\Bigg(\lambda_{j(i)} + \gamma_t + \sum_{k=1}^{K} \beta_{1k}(M_{ik} \times Post_{kt} \times B_{j(i)t}) + \sum_{k=1}^{K} \beta_{2k}(M_{ik} \times Post_{kt}) + \\ \sum_{k=1}^{K} \beta_{3k}(M_{ik} \times B_{j(i)t}) + \sum_{k=1}^{K} \beta_{4k}(Post_{kt} \times B_{j(i)t}) + B_{j(i)t} + \beta_6' X_{j(i)t}\Bigg)\varepsilon_{j(i)t} \end{aligned} \tag{3}$$

The parameters of main interest are the coefficients of the double interaction (*Table II*), or the triple interaction (*Table III*): β_{13} to β_{16}. These denote the $ATTs$ for Price Floor, Price Ceiling, Cost Parity, and Cost Ceiling, respectively. All the specifications include the term M_{i1}, which denotes whether the state adopted the telehealth parity law or not, and corresponds to β_{11}, and the term M_{i2}, which denotes whether the state adopted Price Parity, signifying exact equality between physician reimbursement for telehealth and that for in-person services, and corresponds to β_{12}. The data sam-

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[24] It is assumed that if the ratio version of the parallel trends assumption is given by: $\frac{E[Y_{j(i)t}(0) \mid D_{j(i)} = 1, \text{Post}_t = 1]}{E[Y_{j(i)t}(0) \mid D_{j(i)} = 1, \text{Post}_t = 0]} = \frac{E[Y_{j(i)t}(0) \mid D_{j(i)} = 0, \text{Post}_t = 1]}{E[Y_{j(i)t}(0) \mid D_{j(i)} = 0, \text{Post}_t = 0]}$ is satisfied, then the Conditional Indexed Parallel Trends Staggered (CIPTS) is satisfied.

[25] The percentage $ATTs$ are given by:
$\theta_{\text{ATT(k)}}\% = \frac{E[Y_{j(i)t}(1) \mid D_{kj(i)} = 1, \text{Post}_{kt} = 1] - E[Y_{j(i)t}(0) \mid D_{kj(i)} = 1, \text{Post}_{kt} = 1]}{E[Y_{j(i)t}(0) \mid D_{kj(i)} = 1, \text{Post}_{kt} = 1]}$.

ple spans from year 2010 to year 2019. States treated in or before 2011 were categorized as "always treated", removed to avoid skewing the results and treated as missing data for those years, while states treated in 2018 or later were labeled "never treated." A span of two years before the first treatment helps establish the baseline conditions, while a two-year period after the last treatment underscores the persistence or decay of the treatment effects over time. Consequently, the first treated cohort comprises states treated in 2012, and the last treated cohort includes states treated in 2017.

VI RESULTS

A. *Without Broadband Interaction*

Table II provides the results without considering broadband interaction. Including both the non-specific post-treatment indicator and the types of framing in the model for the decomposition of the overall treatment effect into specific component effects, β_{12} to β_{16}. This helps identify not only whether treatment as a whole has an effect, but also whether specific types of treatment have different effects.

When the framing effects are taken into account, the results indicate that Price Floor has a positive effect for the metro subsample, and a negative effect for the non-metro subsample. The standard errors suggest more precise estimates for the metro subsample compared to the non-metro subsample. The Interstate Compact shows a positive effect across all models, more pronounced in non-metro areas, with relatively precise estimates indicated by smaller standard errors. On the other hand, Price Ceiling and Cost Ceiling in the last three columns, have negative effects, while Cost Parity has a positive effect, although the estimates are less precise due to the comparatively larger standard errors. In summary, the findings corroborate the premise that the effects of TPLs on the physician count diverge not only by region, but also by how the laws are framed.

B. *With Broadband Interaction*

Table III provides the results with broadband interaction. When the post-treatment indicators are interacted with the standardized broadband index, a different picture emerges. The Price Floor shows a positive effect for the aggregate sample and the metro subsample.[26] Price Ceiling has a positive effect in the full sample and the metro subsample, similar to that of the Price Floor. The estimates for these effects are relatively precise, indicating that price controls generally act as

[26]The interpretation in this case, for instance, would be: In column 1, the coefficient of 0.0318 on the triple interaction term suggests that in a county within a state that enacted a Price Floor policy, a one standard deviation increase in broadband is associated with an increase in the expected physician count by a factor of $e^{0.0318} = 1.0323$, or about 3.23% more than what would have been expected in the same county, at the mean broadband level, within the same state had the state not adopted the policy, holding other variables constant.

Table II—: PPML Estimates Without Broadband Interaction

	Without Considering Framing			Considering Framing		
	Full sample	Non-metro	Metro	Full sample	Non-metro	Metro
Post Price Floor	___	___	___	0.0270	-0.0179	0.0385
				(0.0117)	(0.0182)	(0.0093)
Post Price Ceiling	___	___	___	-0.0169	-0.0511	-0.0133
				(0.0121)	(0.0209)	(0.0113)
Post Cost Parity	___	___	___	0.0106	___	0.0035
				(0.0118)		(0.0110)
Post Cost Ceiling	___	___	___	-0.0015	-0.0060	-0.0017
				(0.0057)	(0.0125)	(0.0058)
Post Payment Parity	-0.0003	0.0097	-0.0014	-0.0003	0.0188	-0.0027
	(0.0034)	(0.0055)	(0.0036)	(0.0050)	(0.0093)	(0.0053)
Broadband	0.0047	-0.0073	0.0030	0.0043	-0.0080	0.0024
	(0.0018)	(0.0680)	(0.0018)	(0.0018)	(0.0664)	(0.0017)
Post Interstate Compact	0.0089	0.0212	0.0101	0.0076	0.0195	0.0076
	(0.0040)	(0.0067)	(0.0040)	(0.0039)	(0.0073)	(0.0038)
Log Population	0.8674	0.9951	0.7880	0.8567	0.9877	0.7644
	(0.0631)	(0.1093)	(0.0666)	(0.0657)	(0.1103)	(0.0697)
Observations	22332	14354	7978	22332	14354	7978

Note I: The table shows the PPML estimates of the difference-in-difference design. The dependent variable is the count of Federal and Non-Federal MDs in a given county in a given year. Standard errors in parentheses are clustered at the county level. The first three columns show ATT without accounting for the framing of TPLs, while the last three columns do account for the framing (ATT_k, where k is the treatment type). All models include county and year fixed effects and controls (not shown): total hospital admissions and log transformed - population, median household income, std risk adjusted per capita medicare costs, percentage poverty, unemployment rate for population aged 16 or more, population with age 65 or more without health insurance, and controls (shown): log transformed population and broadband. "___" indicates either no output or omitted output.

Note II: "Post Payment Parity" which represents the non-specific "Average Treatment Effect on the Treated" (ATT) is shown here, and has been included in all subsequent specifications but not shown. The purpose of showing it here is to demonstrate how incorporating the framing affects the treatment effects. Additionally, "Post Price Parity" is included in all specifications but not shown, since our main interests are Price Floor and Price Ceiling.

Note III: In subsequent tables, Broadband and Log Population are not shown.

conducive factors for metro areas. For the non-metro areas, Price Floor and Price Ceiling show negative effects suggesting that they act as frictional components for non-metro areas. However, the higher standard errors suggest imprecision or high variability. If there is a Cost Parity, it could deter consumers from accessing healthcare services through telehealth. This reduction in demand could consequently reduce the revenue for third-party insurers or physicians, leading to a decrease in physician count.

Table III—: PPML Estimates With Broadband Interaction

	Fed & Non-Fed MDs			Radiologists		
	Full sample	Non-metro	Metro	Full sample	Non-metro	Metro
Post Price Floor=1 ×	0.0318	-0.3077	0.0171	0.0973	-3.7324	0.0566
Broadband	(0.0058)	(0.3380)	(0.0064)	(0.0280)	(1.8465)	(0.0227)
Post Price Ceiling=1 ×	0.0350	-0.3189	0.0321	0.0372	0.0069	0.0540
Broadband	(0.0055)	(0.2187)	(0.0061)	(0.0220)	(1.3571)	(0.0253)
Post Cost Parity=1 ×	-0.0319	___	-0.0280	-0.0346	___	-0.0485
Broadband	(0.0070)		(0.0072)	(0.0233)		(0.0264)
Post Cost Ceiling=1 ×	0.0007	0.2221	0.0011	0.0158	0.5766	0.0166
Broadband	(0.0033)	(0.1164)	(0.0036)	(0.0088)	(0.5574)	(0.0096)
Post Interstate Compact	0.0089	0.0215	0.0100	0.0069	0.0200	0.0070
	(0.0040)	(0.0068)	(0.0040)	(0.0038)	(0.0071)	(0.0037)
Observations	22332	14354	7978	12188	5890	6298

Note: The coefficient estimates for Post Interstate Compact are not shown in subsequent tables.

The effect for Cost Parity is negative for the full sample and metro subsample, and the relatively small standard errors suggest these estimates are quite precise, confirming that it is a frictional component. Cost Ceiling, on the other hand, tends to have an opposite effect, suggesting that Cost Ceiling tends to be a conducive component. A Cost Ceiling could have significant implications for non-metro areas by causing an increase in demand for telehealth services, subsequently increasing the physician count in those regions. The estimated effects are considerable, especially for non-metro subsample. However, the larger standard errors indicate imprecision, which implies caution in interpretation. The Cost Ceiling does not appear to have any substantial impact on the physician count in the aggregate sample or metro areas, where the estimates are relatively more precise. This result aligns with the discussion in *Section IV.D.* about the demand in non-metro areas being more sensitive to money price than in metro areas. Most of the estimates for Radiologists, who are among the highest telehealth users, are relatively more pronounced and are discussed further in subsequent sections where specialty-wise estimates are compared. The relatively higher precision of the coefficient estimates for the Interstate Compact suggests that being in a compact state allows physicians in non-metro areas to provide in-person and telehealth services not only to in-state patients but also to out-of-state patients. Such regulations enhance the supply of medical services and improve allocative efficiency in the healthcare market, challenging conventional models that suggest quantity controls must lead to deadweight loss and inefficiency.

C. Price Control-Cost Control Combinations With Broadband Interaction

If the Price Ceiling is above the current equilibrium, theoretically, physicians could charge more for their services up to the Price Ceiling, but only if there's a demand for it. If there's no corresponding increase demand for telehealth at this higher price, physicians are unlikely to increase their rates, and thus, the non-binding Price Ceiling wouldn't typically lead to an excess supply of physicians. Thus, it becomes necessary to see the Price Controls in conjunction with the Cost Controls. *Table IV* shows the PPML estimates for the types of Price Control and the types of Cost Control, either in isolation, or in combination with each other, as actually specified by the states. Price Floor and Cost Ceiling combination turns out to be a conducive factor for aggregate physician count and Radiologists in metro areas, while being a frictional factor for non-metro areas. Price Parity and Cost Parity combination turns out to be a frictional factor for the full sample and metro subsample. This indicates that even though Price Parity might have a conducive effect akin to that of a Price Floor, the frictional effect of Cost Parity dominates it. The estimates for Radiologists, who are among the most intensive telehealth users, are discussed while discussing the results of *Table V*.

***Linking Table IV results with Figure IV*:** The results from *Table IV* confirm the theoretical predictions encapsulated in *Proposition 1* to *Proposition 4*, and graphically represented in *Figure IV*. The red (green) circle with black ring portrays the unregulated equilibrium in metro (non-metro) areas. The black dots represent the regulated equilibriums corresponding to each of the treatment types—Price Floor-Cost Ceiling, Price Parity-Cost Parity and Price Ceiling-Cost Parity (combinations), and Price Parity, Price Ceiling and Cost Ceiling, in isolation, all interacted with broadband and corresponding to Rows 1 to 6, respectively, in *Table IV*. The estimates quantify the shifts from unregulated equilibrium to the respective equilibrium quantities for each type of regulation specified. These shifts are the distances between the projections of the red circle with black ring (for metro),

Table IV—: PPML Estimates for all "Price Control-Cost Control" Combinations

	Fed & Non-Fed MDs			Radiologists		
	Full sample	Non-metro	Metro	Full sample	Non-metro	Metro
Post PF & CC=1 ×	0.0325	-0.0911	0.0189	0.1181	-3.1206	0.0796
Broadband	(0.0068)	(0.3293)	(0.0074)	(0.0292)	(1.7955)	(0.0241)
Post PP & CP=1 ×	-0.0938	___	-0.0950	-0.3876	___	-0.3867
Broadband	(0.0103)		(0.0122)	(0.0741)		(0.0787)
Post PC & CP=1 ×	0.0006	___	0.0026	0.0081	___	0.0109
Broadband	(0.0064)		(0.0065)	(0.0134)		(0.0137)
Post PP only=1 ×	0.0011	0.0389	0.0021	0.0248	-0.9369	0.0256
Broadband	(0.0039)	(0.1862)	(0.0042)	(0.0101)	(1.3292)	(0.0108)
Post PC only=1 ×	0.0368	-0.3247	0.0348	0.0398	0.0419	0.0591
Broadband	(0.0058)	(0.2191)	(0.0064)	(0.0213)	(1.3569)	(0.0245)
Post CC only=1 ×	0.0006	0.2711	0.0019	0.0219	0.7117	0.0243
Broadband	(0.0039)	(0.1392)	(0.0041)	(0.0082)	(0.6208)	(0.0087)
Observations	22332	14354	7978	12188	5890	6298

Note: The abbreviations are as follows: PF - Price Floor, PP - Price Parity, PC - Price Ceiling, CC - Cost Ceiling, and CP - Cost Parity. In the subsequent discussion, a "row" refers collectively to the lines corresponding to the estimates and the standard errors for an interaction term.

or green circle with black ring (for non-metro), and the projections of the black dots, on the quantity axis in *Figure III*. For instance, E^{MB}_{PF-CC} in Panel (a), *Figure III*, represents the regulated equilibrium for Price Floor-Cost Ceiling combination (interacted with broadband). The positive estimate for metro subsample is signified by the regulated equilibrium quantity (corresponding to E^{MB}_{PF-CC}) lying on the right side of the unregulated equilibrium quantity (E^{M}_{U}). The distance between the X-axis projections of the two points signifies the magnitude of the coefficient estimate.

The estimate for the Price Floor-Cost Ceiling combination (distance between projections of E^{MB}_{PF-CC} and E^{M}_{U}) is more in magnitude than that for the Price Floor considered in isolation in *Table IV* (distance between projections of E^{MB}_{PF} and E^{M}_{U}). This shows that the conducive effect Price Floor is bolstered further by the conducive effect of Cost Ceiling.

The estimates for Price Parity, for the aggregate sample and the metro subsample in *Table IV*, have signs similar to those of Price Floor for the corresponding columns in *Table III*. However, their magnitudes differ. This is because, Price Parity requires the physician reimbursement for telehealth to be exactly the same as $MERR - I$, as opposed to Price Floor, which would take the physician reimbursement for telehealth above $MERR - I$. Thus, Price Parity makes the physicians more constrained than a Price Floor, which only puts a lower bound on their reimbursement. For metro sub-sample, Price Parity shows a positive effect when seen in isolation (*Row 4, Table IV*), and a negative effect when combined with Cost Parity (*Row 2, Table IV*), suggesting that the negative effect or frictional nature of Cost Parity dominates the conducive effect of Price Parity.

These effects depend on *BETSEA*. If the assumption is not met, the regulated equilibrium for the Price Parity (or Floor)-Cost Parity combination will still be in the vicinity of the light green curve ($Y_R = S^M_{PF}(P;\rho)$), as opposed to the red-black curve ($Y_R = S^{MB}_{PF}(P;\rho)$), and the regulated equilibrium, instead of being in the vicinity of E^{MB}_{PF-CP}, will instead be in the vicinity of E^{M}_{PF-CP}, implying a strongly negative estimate.[27] This is more plausible for specialties which use telehealth extensively, such as Radiology, where the supply elasticity of telehealth might not increase as much, owing to the strictly convex and increasing cost function $\Gamma_T(T)$. Thus, for such a specialty, the regulated equilibrium E^{M}_{PF-CP} will be more likely than E^{MB}_{PF-CP}, even at broadband level 1 SD above the mean, which is evident by the high negative estimates for Radiologists (full sample and metro sub-sample, *Row 2, Table IV*). Thus, it becomes necessary to study the specialty-wise effects.

Price Ceiling is a conducive component, while Cost Parity is a frictional component for metro areas (*Rows 2 and 3, Table III*). However, for a combination of both, the effects tend to cancel out, resulting in a minuscule coefficient estimate (*Row 3, Table IV*). Moreover, when there is only a Cost Ceiling and no Price Control, the ATT will be positive for the metro subsample, and positive and more substantive in magnitude for the non-metro sub-sample. This is because the demand in non-metro areas is more price sensitive, causing a flatter demand curve, and hence, a more substantive equilibrium shift, E^{NM}_{U} to E^{NMB}_{CC}, as shown in *Figure III*.

D. ***Specialty-wise Estimates for Heavy Telehealth Users***

The results discussed in previous subsections present valuable insights by discriminating the treatment effects by treatments types and geography. However, since telehealth usage differs in scope and nature according to specialties, it is expected that the effect of TPLs interacted with broadband will differ according to specialties.

[27] Price Floor does not occur in isolation in the sample. It occurs only in combination with a type of Cost Control. Price Parity can be used as an approximation of Price Floor's behavior in combination with Cost Parity.

Table V—: Specialty-wise PPML Estimates for Heavy Telehealth Users (Except RPM Users)

	Psychiatrists			Emergency Physicians		
	Full sample	Non-metro	Metro	Full sample	Non-metro	Metro
Post Price Floor=1 ×	0.0807	0.1249	0.0950	0.1325	2.6131	0.1281
Broadband	(0.0293)	(2.0840)	(0.0300)	(0.0274)	(1.8127)	(0.0364)
Post Price Ceiling=1 ×	0.0116	0.0051	0.0272	0.0271	-0.7074	0.0156
Broadband	(0.0263)	(1.6324)	(0.0286)	(0.0375)	(0.6878)	(0.0422)
Post Cost Parity=1 ×	0.0303	___	0.0153	-0.0115	___	0.0003
Broadband	(0.0304)		(0.0318)	(0.0407)		(0.0443)
Post Cost Ceiling=1 ×	0.0111	0.9092	0.0098	0.0057	0.0021	0.0074
Broadband	(0.0094)	(0.5362)	(0.0106)	(0.0073)	(0.5455)	(0.0081)
Observations	12398	5890	6508	14771	7903	6868

Table V shows the specialty-wise break up of our estimates for Emergency Physicians (leading in video conferencing and interacting with other healthcare professionals) and Psychiatrists (second only to Radiology in interacting with patients). Radiologists (results shown in *Table III* and *Table IV*) lead in the telehealth modality which involves storing and forwarding of data and interacting with patients.[28] The Price Floor shows positive effects for all three specialties in both the full sample and the metro subsample. The effect is the strongest for Emergency Physicians, followed by Psychiatry, and then Radiology in metro areas. In metro areas with typically higher demand, Price Floor allows physicians to get reimbursed more than they otherwise would. The relatively precise estimates for the metro subsample suggests that Price Floor is a significantly conducive component for metro areas, irrespective of the specialty. For the non-metro subsample, the estimates for Price Floor, particularly for Psychiatrists and Emergency Physicians, indicate less precision, underscoring variability in telehealth usage patterns. It is important to note that these specialties rely heavily on telehealth, which reduces the scope for substitution to in-person services. This reliance implies stronger rotations in the supply curves and more pronounced estimates.

For non-metro areas, Price Floor has a negative effect of high magnitude for Radiologists, indicating that a Price Floor acts as a frictional component for this specialty. However, the relatively

[28]The usage of telehealth prior to the COVID-19 pandemic in 2016, differed by specialty and by area (Kane and Gillis, 2018). The modalities considered were: Videoconferencing, Remote Patient Monitoring (RPM), or Storing and Forwarding Data.

large standard errors indicate less precision and significant variability. Price Ceiling shows a positive effect for Radiology in metro areas. Cost Parity appears to act as a frictional element for Radiologists and aggregate physician count in metro areas. Conversely, Cost Ceiling is expected to make telehealth cheaper for consumers, acting as a conducive component. The effects of Cost Parity are particularly pronounced for Radiology, with relatively robust estimates. The estimates for Price Floor in *Table V* appear more amplified and show more conduciveness than those for the Price Floor in *Table III*, while the estimates for the Price Ceiling in *Table V* appear more subdued compared to those in *Table III*. Specialties that use telehealth intensively for patient interactions may use more telehealth to capitalize on higher reimbursement opportunities when a Price Floor is present, or they may relocate to areas with more favorable policy environments with better technological infrastructure when faced with a Price Ceiling, thus moderating the conducive effect of a Price Ceiling observed in the aggregate sample in *Table III*.

E. ***Specialty-wise Estimates for a Light Telehealth User and a RPM User***

Table VI—: Specialty-wise PPML Estimates for a Heavy Telehealth User (RPM) and a Light Telehealth User

	Cardiologists			Gastroenterologists		
	Full sample	Non-metro	Metro	Full sample	Non-metro	Metro
Post Price Floor=1 ×	-0.0400	0.6499	-0.0166	-0.0037	5.3501	0.0157
Broadband	(0.0334)	(2.3075)	(0.0377)	(0.0459)	(8.9145)	(0.0472)
Post Price Ceiling=1 ×	0.0083	0.6503	0.0022	0.0510	1.2735	0.0280
Broadband	(0.0254)	(2.0979)	(0.0271)	(0.0236)	(2.2740)	(0.0252)
Post Cost Parity=1 ×	-0.0065	___	-0.0037	0.0014	___	0.0194
Broadband	(0.0298)		(0.0309)	(0.0255)		(0.0268)
Post Cost Ceiling=1 ×	-0.0038	-0.1072	-0.0058	0.0059	-1.0452	0.0026
Broadband	(0.0100)	(0.8141)	(0.0110)	(0.0118)	(0.9073)	(0.0133)
Observations	9687	3839	5848	7828	2440	5388

Table VI shows the estimates for Cardiologists—the biggest RPM (Remote Patient Monitoring) users—and for Gastroenterologists—who are among the specialties that use telehealth the least. Most of the coefficients exhibit considerable variability and imprecision, indicating that the physician count for specialties with either extensive RPM usage or minimal telehealth use is not significantly affected by the TPLs, as compared to the specialities with heavy telehealth usage or to the specialties which use modalities other than RPM. RPM requires relatively much lower patient input. This indicates that the scope for using patient input and it's impact on supply and demand is crucial while determining the effect of TPLs. This further bolsters this study's theoretical predictions, which rely on the mechanism of Price Controls distorting the input mix, and Cost Controls changing the consumption mix, implying that for specialties using telehealth less or lacking scope for consumer input, the TPLs would not have a significant impact.

In the results discussed in most of the tables so far, the signs of the coefficients for metro and non-metro areas are mostly opposite, and the sign of the coefficients for the full sample aligns with that of the metro areas. This indicates that the aggregate impact is dominated by the effect in metro areas, despite the larger sample size of non-metro areas. Several factors can explain this phenomenon. Firstly, there is a scale effect owing to the higher baseline density of physicians in metro areas, meaning that percentage changes result in substantial absolute changes. Secondly, while both treated metro and non-metro areas have broadband levels standardized to 1 SD above the mean, metro areas likely have a greater number of such counties, benefiting from existing infrastructure, stronger competition, better availability of resources, and higher patient demand. Consequently, metro areas can more effectively leverage increased broadband to enhance telehealth services. Finally, the implementation and support mechanisms for telehealth policies are often more robust in metro areas, which might benefit from targeted initiatives, training programs, and financial incentives that facilitate adoption. In non-metro areas, the absence or lesser extent of such support can hinder effective implementation. These factors collectively result in metro area impacts that are significant enough to influence the overall sample, despite the larger sample size of non-metro areas. This demonstrates the critical role of metro dynamics in shaping the overall effectiveness of the TPLs.

VII ROBUSTNESS CHECKS

To ensure balance and comparability of treatment and control groups, logistic regression-based Propensity Score Matching (PSM) with multiple explanatory variables and comprehensive model diagnostics were performed. Multicollinearity was evaluated, and sensitivity analyses were conducted (*Section A.IV, Online Appendix*).

To ensure the correctness of the functional form while using the Fixed Effects Poisson Estimator, the heteroskedasticity-robust Ramsey's Regression Specification Error Test (RESET) was applied (Ramsey, 1969). County and year fixed effects were included to control for unobserved, time-invariant characteristics and common time trends. The test showed that there are no signs of misspecification (*Table A.III, Online Appendix*).

Some of the estimates show higher standard errors, particularly for the non-metro subsample. Non-metro counties differ significantly in their infrastructure leading to greater inherent variability or instability in responses to policy changes in these areas. Additionally, the complexity of the model further contributes to this issue. Nevertheless, the use of cluster-robust standard errors at the county level corrects for both heteroskedasticity and autocorrelation within counties, and accounts for intragroup correlation, resulting in more accurate standard errors and reliable estimates.

A placebo test for pre-treatment trends was conducted by assigning a fictitious treatment period. This test showed no significant pre-treatment differences between treated and control groups, suggesting that the treatment effect estimates are not driven by pre-existing trends or other exogenous factors (*Table A.IV, Online Appendix*).

Figure A.IV, Online Appendix, presents the trends in the number of physicians by cohort, and by metro or non-metro areas. Due to the smaller relative changes in physician counts, graphical verification of parallel trends is not feasible. Instead, the ratio version of the parallel trends assumption was tested by conducting a PPML event study, where "relative time from treatment" was interacted with treatment indicator and standardized broadband variable. The results support the assumption (*Column (a), Table A.V, Online Appendix*). To test the no-anticipation assumption, PPML model with broadband interaction on the lag of count of MDs was estimated. The results support the assumption that the future treatment does not affect current outcomes (*Column (b), Table A.V, Online Appendix*).

VIII CONCLUSION

This study addresses an important gap in the literature by considering the role of non-price attributes in analyzing the impact of Price Control or Cost Control, while assessing the effect of Telehealth Parity Laws on physician count in the presence of broadband in the pre-pandemic period. The staggered adoption and heterogeneity in the framing of these regulations have seldom been taken into account. The study finds that the effect on physician count at the county level differs according to the framing by each state. When accounting for broadband penetration, a different picture emerges, showing that the mediating effects of broadband cannot be neglected. The conventional literature on price regulations predicts shortages or inefficiencies due to regulations, while supply chain approaches predict opposite effects for Price Ceiling and Price Floor. The study shows that such assertions are not necessarily true. By studying the Cost Controls in conjunction with Price Controls, the study finds rotations in demand curve as significant determinants of equilibrium shifts, along with rotations in supply curve. The study adds new theoretical insights, which are bolstered by the empirical results. The actual impact of a type of Price Control or Cost Control depends on whether it is used in isolation or combination, as well as on the geographical area—whether it is metro or non-metro. The study finds that the impact of TPLs on different specialties depends not just on the type of interaction but also on the modality used. These findings have significant policy implications. The usage of telehealth has grown rapidly following the COVID-19 pandemic, while discussions on Price Controls have gained new momentum. As telehealth usage solidifies, and healthcare professionals and hospitals expand capacity, and measures are taken to improve broadband access, this study contributes to both theoretical and practical discourses, and seeks to inform future policy formulations.

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