Effects of Subsidies on Welfare and Market Structure in the U.S. Broadband Industry*

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February 2, 2026

Abstract

Broadband plays an important role in modern economic activity, yet remains unaffordable or uncompetitive for many U.S. households, prompting historic public investment. Two flagship initiatives, the Affordable Connectivity Program (ACP) and the Broadband Equity, Access, and Deployment (BEAD) program, form the core of the federal broadband policy. However, their effects on welfare and market structure remain poorly understood. Using rich data on markets, providers, and broadband products, I combine a difference-in-differences design with continuous treatment intensity and a structural model of demand, entry, and product choice to quantify their effects. The ACP, a \$30 monthly household subsidy, increases social surplus and generates up to \$1.90 in welfare per dollar spent. The BEAD program, which subsidizes providers' fixed costs, expands entry and product variety, but also raises marginal costs and prices, with larger welfare gains per dollar spent of up to \$10.70, which peaks at intermediate subsidy intensities (25–50%) in the long run. These findings highlight a key policy trade-off: demand-side subsidies yield immediate, cost-effective affordability gains, while supply-side subsidies reshape competition to foster long-term efficiency, albeit at higher fiscal cost.

JEL classification codes: D22, L13, L52, L96, L98
Keywords: Digital infrastructure; Public subsidies; Market structure; Welfare analysis; Digital divide

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*I thank Mathieu Marcoux, Max Lesellier, Joshua Lewis, William Arbour, Mohamed Coulibaly, Alexandre Pavlov, Fansa Koné, and Eugène Dettaa for the insightful discussions and valuable comments. I am also grateful to the participants at the seminar hosted by the Competition Bureau of Canada, the 2025 Bank of Canada Graduate Student Paper Award Workshop, the 64th Annual Conference of the Société canadienne de science économique (SCSE), the CIREQ–UdeM Seminar, the Industrial Organization Study Group, and the QPESF Workshop for helpful feedback. I acknowledge financial support from the J.W. McConnell Foundation Chair in American Studies. I also gratefully acknowledge the allocation of computing resources provided by the Digital Research Alliance of Canada. All usual disclaimers apply.

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1 Introduction

Broadband has become a critical infrastructure for modern economic activity, driving productivity, supporting employment, and fostering regional development (Bertschek et al., 2016). The COVID-19 pandemic underscored this role: households with broadband could work, study, and access healthcare remotely, whereas those without broadband were left behind. However, U.S. broadband markets remain highly concentrated, with over three in five Americans depending on a single provider and often paying prices up to five times higher than in competitive markets.[1] The fundamental challenge is economic: deploying high-speed networks requires substantial upfront investment.[2] High fixed costs discourage private investment in sparsely populated areas, where revenue rarely covers expenses. However, connecting these households generates large social benefits (e.g., in education, healthcare, and economic opportunities) that firms cannot monetize. This gap between private and social returns is a classic market failure that warrants policy intervention (Tirole, 1988; Bourreau et al., 2020). The 2021 Infrastructure Investment and Jobs Act (IIJA) responds with \$65 billion subsidies. Its two flagship programs address distinct barriers: the Affordable Connectivity Program (ACP, \$14.2 billion) helps low-income households afford services, while the Broadband Equity, Access, and Deployment (BEAD, \$42.45 billion) program subsidizes network buildout. Yet, as of 2024, over one-third of Americans still lack competitive options or high-speed access.[3] The persistence of unmet needs despite these unprecedented subsidies underscores the need for a rigorous evaluation of their effectiveness in ensuring that public funds achieve their intended goals.

In this paper, I address three questions: (i) How do subsidies alter welfare and market structure? (ii) What is the optimal level of subsidy to implement, and (iii) is it more effective to target supply or demand? Answering these questions is critical for three reasons. First, the magnitude of public investment in one of the nation's largest broadband affordability initiatives underscores its significance. The IIJA allocated unprecedented funding to broadband subsidies, highlighting the need to evaluate their effective deployment.[4] Second, the broadband market is characterized

[1] Executive Order 14036 on Promoting Competition in the American Economy.

[2] According to the 2023 Fiber Deployment Report, underground fiber costs 11–24 per foot and aerial fiber 4–9 per foot, with labor accounting for over two-thirds of costs. See Fiber Deployment Annual Report 2023, p.2.

[3] FCC 2024 Broadband Progress Report, p. 4, §3.

[4] https://docs.fcc.gov/public/attachments/DOC-380259A1.pdf

by high fixed costs and limited competition, conditions under which government initiatives often have complex and unintended effects on key equilibrium outcomes and market structures. Third, policymakers face a trade-off between short-term affordability, promoted by ACP, and long-term market sustainability, supported by the BEAD program. However, empirical evidence on how to balance the competing objectives of short-term affordability and long-term sustainability is scarce, leaving a critical gap that this paper seeks to fill.

I construct a rich dataset at the market, provider, and product levels by merging FCC Form 477 data, the Urban Rate Survey, the American Community Survey, and hand-collected federal program records.[5] I begin with a difference-in-differences design with continuous treatment intensity, exploiting cross-state variation in per-capita subsidy allocation intensity to trace how broadband prices and service quality evolve following the announcement of federal broadband funding. The reduced-form evidence indicates that states more exposed to subsidy allocations experience relative declines in prices and improvements in product quality compared with the pre-intervention period. While informative, difference-in-differences cannot disentangle demand- and supply-side effects, simulate counterfactual subsidy policies, or capture firms' strategic responses. Therefore, to quantify these mechanisms and evaluate policy counterfactuals, I estimate a structural model of a two-stage game. In the first stage, firms choose their product offerings. In the second stage, they observe demand and compete on prices à la Nash-Bertrand. Since introducing a product involves both marginal and fixed costs that jointly determine profitability, firms compute equilibrium profits for all possible product configurations and select the set that maximizes expected profits. I estimate the model in the same order, beginning with demand and pricing in the second stage and recovering fixed costs from entry decisions in the first stage. Demand is estimated following Berry (1994), a framework well suited to broadband's differentiated products, whereas the entry stage follows Fan and Yang (2024) which is more convenient to model markets with many firms and product choices.

The estimated demand system suggests that, on average, a 1% increase in broadband prices results in a 5.85% decrease in broadband demand *ceteris paribus*. This estimate is consistent with

[5]Section 2.2 and Appendix A provide details on the data sources, cleaning procedures, and variable construction.

values reported in the literature.[6] The first-stage estimates indicate substantial heterogeneity in fixed costs, which increase with market size. Average fixed costs (in millions of dollars) range from 0.49–1.25 in small markets, 0.97–3.01 in medium markets, and 1.79–6.26 in large markets.[7] These costs, which encompass salaries, rent, and insurance, are difficult to validate because of scarce public data, but they align broadly with the figures reported in the industry sources.[8]

Using the estimated structural model, I conduct counterfactual policy analyses to address the research questions. First, the BEAD program, a 75% reduction in firm-fixed costs, induces significant firm entry (13.9–19.5%) and product expansion (12.6–16.7%), but also raises marginal costs and prices as firms expand into high-cost areas and compete for scarce skilled labor. The social surplus rises by 3.4–4.7%, although gains and benefit-cost ratios diminish at higher subsidy intensities, suggesting an optimal range of 25–50% reduction in firm-fixed costs. In contrast, the ACP, a $30 monthly household subsidy, generates larger welfare gains, increasing the social surplus by 7.6–8.8% with benefit–cost ratios between $1.28 and $1.91, while leaving the market structure largely unchanged. These results reveal a central policy trade-off: ACP is more cost-effective in improving affordability, whereas the BEAD program promotes long-run competition and infrastructure expansion at higher fiscal costs but yields cost-effectiveness in the long run.

This paper makes two contributions to the literature: methodological and empirical. Methodologically, it advances research on the broadband market structure by integrating demand estimation into models of firms' endogenous product choices and entry decisions. While most prior studies have either examined how market structure affects competition (e.g., Xiao and Orazem (1999); Flamm and Varas (2022); Gadiraju et al. (2018)) or estimated consumer demand without modeling firms' strategic supply responses (e.g., Espín and Rojas (2024)), few have combined both elements. Kearns (2024), the most closely related work, links demand estimation to entry but in a setting with few players and incomplete information. In contrast, this paper introduces a structural entry framework that allows firms to choose among many potential products while accounting for strate-

[6]For instance, in the U.S. broadband industry, Kearns (2024) estimates own-price elasticities of -4.73, -4.46, and -4.16 for low-, middle-, and high-income households, respectively. Similarly, Goetz (2019) reports a mean own-price elasticity of -5.9. In the Colombian broadband market, Hidalgo (2024) estimates an own-price elasticity of -4.6. Additionally, in the U.S. cable industry, which is closely related to the U.S. broadband industry, Crawford and Yurukoglu (2012) find mean own-price elasticities of -4.1 for cable services and -5.4 for satellite services.

[7]Standard deviations range from 1.14 to 1.15 for small markets, 2.16–3.00 for medium markets, and 0.35–5.00 for large markets.

[8]https://businessplan-templates.com/blogs/running-costs/internet-service-provider

gic interactions under complete information. By leveraging recent advances in moment-inequality methods for entry games to a setting with many firms and rich product portfolios (e.g., Fan and Yang (2024)), the model captures key institutional features of the U.S. broadband market that existing studies abstract from. Second, this paper empirically contributes to the literature on public investment in broadband infrastructure. Bourreau et al. (2020) show that State Aid programs in Europe since 2003 have expanded broadband coverage, often complementing private investment. In the U.S., Kearns (2024) evaluates local subsidy effects on closing the digital divide in Seattle, while Espín and Rojas (2024) study the ACP and the BEAD program but hold the market structure fixed, limiting their assessment of the BEAD program. In contrast, this paper provides the first nationwide evaluation of ACP and the BEAD program in a structural framework that jointly models demand and supply, allowing subsidies to influence prices, product variety, entry, and welfare through both consumer adoption and firms' strategic responses. Related evidence from Wilson (2025) shows that municipal broadband investment can spur private investment via dynamic preemption, a finding that is consistent with my results on subsidy-induced market expansion.

The remainder of this paper is organized as follows. Section 2 presents an overview of the industry background and data. Section 3 introduces the empirical model. Section 4 discusses the estimation strategy. Section 5 presents the empirical results. Section 6 provides counterfactual experiments. Finally, Section 8 concludes the paper.

2 Industry Background and Data

This section provides an overview of the industry background, along with a detailed description of the data and their respective sources.

2.1 Industry Background

2.1.1 Current Landscape

The U.S. broadband industry is a crucial sector that fuels economic growth and boosts productivity. This analysis examines the residential broadband usage that has benefited from significant government funding programs aimed at improving accessibility. Broadband is offered in several forms, with internet service providers (ISPs) competing through differences in speed, data limits, and pricing.

Traditionally, local telephone and cable companies have been the primary providers of broadband services. Telephone companies deliver the internet through Digital Subscriber Line (DSL) technology, utilizing older copper wires installed on telephone poles. In contrast, cable companies provide broadband using coaxial cables, which were originally deployed for television services. Today, the broadband industry has expanded with more companies, including large nationwide providers and smaller local providers. Local governments participate in the market in most states, except in a few states, including Texas, where state laws significantly restrict municipal governments from directly providing broadband services to residents.[9] [10] Most U.S. households connect to the internet through one of the following technologies: DSL, cable, fixed wireless, or fiber optics.[11] Fixed wireless transmission of the internet via radio signals from a fixed tower to a receiver at the customer's location makes it a practical solution for rural and remote areas where wired infrastructure is costly or impractical. It offers relatively high speed and low installation costs. In contrast, fiber-optic broadband uses thin glass or plastic strands to transmit data as light pulses, offering superior speed, reliability, and bandwidth. It supports symmetrical upload and download speeds, low latency, and high-demand applications such as streaming, clouding services, and remote work. However, fiber deployment requires a significant investment and is primarily available in urban and suburban areas.

The literature has identified several key aspects of the U.S. broadband industry. A major finding is that broadband services are a significant financial burden for many American households. Furthermore, competition among residential ISPs is limited in most local markets, with some areas offering fewer options for consumers (Flamm and Varas, 2022). These challenges contribute to what the federal government calls the "digital divide". This term refers to the gap between individuals, households, and geographic regions that have access to modern information and communication technology (ICT), such as broadband internet, and those that do not. Factors such as socioeconomic status, geographical location, and digital literacy contribute to this disparity, resulting in unequal access to opportunities for education, employment, healthcare, and social par-

[9] https://www.baller.com/wp-content/uploads/BallerStokesLideStateBarriers7-1-20.pdf

[10] https://broadbandnow.com/report/municipal-broadband-roadblocks-2023

[11] See Appendix B for illustrative images.

ticipation. Recognizing the digital divide as a major obstacle to economic and social inclusion, especially for underserved and rural communities, the federal government has introduced various subsidy programs aimed at bridging this gap. These initiatives focus on making internet services more affordable and expanding broadband infrastructure to improve access.

2.1.2 Subsidies

The U.S. federal government introduced significant investments through the IIJA, which was passed by Congress in 2021. This initiative aims to enhance broadband accessibility and affordability through two primary objectives: direct consumer subsidies provided by the ACP and provider-focused investments through the BEAD program. The total funding allocated under these programs was approximately \$65 billion, with \$14.2 billion dedicated to ACP and \$42.45 billion allocated to the BEAD program.

ACP was introduced as a successor to the Emergency Broadband Benefit (EBB). The EBB program, which began in February 2021 and ended later in 2021, reached nearly nine million low-income households, providing a subsidy of up to \$50 per month for eligible households to help cover internet costs. Following the conclusion of the EBB, the ACP was launched, enrolling 20 million households and offering a monthly discount of up to \$30 for eligible households, and \$75 for those residing in qualifying tribal lands. Additionally, eligible households could receive a one-time discount of up to \$100 to purchase a laptop, desktop computer, or tablet from participating providers, provided they contributed between \$10 and \$50 to the purchase price.[12]

The BEAD program was the most significant investment targeting broadband providers, with the goal of reducing deployment costs and encouraging market entry. The program typically allocates funds to states based on the number of underserved areas within their jurisdictions, which is further confirmed by the data (see Figures 1 and 2). These underserved areas were identified based on their geographic location and defined according to the FCC criteria for unserved areas as broadband-serviceable locations that either have no access to broadband services or lack access to reliable broadband services with speeds of at least 25 and 3 megabits per second (Mbps) for downloads and uploads, respectively, and a latency of less than or equal to 100 milliseconds.[13]

[12] https://www.fcc.gov/acp

[13] https://broadbandusa.ntia.doc.gov/

Consequently, states cannot independently influence the amount of subsidies they receive or negotiate for fund allocations.

2.2 Data

This paper uses publicly available data from five distinct sources, with the first being the Urban Rate Survey (URS).[14] URS data are collected annually by the FCC from a randomized sample of ISPs operating in a small number of urban census tracts. The sampling unit is the pairing of a census tract and ISP. The dataset spans the period from 2015 to 2024 and refers to data from the previous year, effectively covering the period from 2014 to 2023. ISPs are required to report various plan characteristics, including advertised download speeds (downstream), advertised upload speeds (upstream), data allowances, prices charged to consumers, and weights for all plans offered in the sampled tracts. The weight variable is computed by the FCC and is intended to indicate how widely the plan is available in a given census tract. Therefore, this does not necessarily indicate the number of subscribers using each plan.

The second source is the FCC Deployment Data.[15] These data are collected semiannually by the FCC (in June and December) and span the period from 2014 to 2021. ISPs are required to complete the form and certify the accuracy of all the information provided. The ISPs report data for census blocks that offer internet services at speeds above 200 kilobits per second (download and upload). The dataset includes information on ISPs and details of whether the provided technology is a DSL, fixed wireless, cable modem, or fiber optics. The ISPs also report the maximum download speed, maximum upload speed, and whether the service is intended for residential use, business use, or both. In this study, I focus on residential broadband access; therefore, I only consider plans designed for residential usage.

The third source is the American Community Survey (ACS).[16] This dataset provides annual estimates of demographic data based on the latest U.S. census. I extracted relevant demographic variables at the state level, such as median income (inflation-adjusted), median age, number of housing units, number of residential broadband subscribers, number of satellite subscribers, and the number of housing units without broadband.

[14] https://www.fcc.gov/economics-analytics/industry-analysis-division/urban-rate-survey-data-resources
[15] https://broadband477map.fcc.gov/#/data-download
[16] https://www.census.gov/programs-surveys/acs

The fourth source is the U.S TIGER/Line Shapefiles[17], from which I extracted the total area of each state to compute the population density.

Finally, I collected the amount of subsidy from the BEAD program allocated to states from the U.S. government website.[18]

All the five data sources were assembled to construct a unique dataset. To account for inflation, prices were adjusted to 2023 dollars using the Consumer Price Index (CPI) provided by the Bureau of Labor Statistics (BLS). This study faces three notable limitations worth mentioning. First, the FCC does not report the number of subscribers who choose each plan. Consequently, the market share for each plan is not readily available. Second, although the URS data were collected at the census-tract level, the publicly available dataset does not identify the specific census tracts in which each ISP operates. This lack of granularity makes it challenging to conduct detailed analyses at a more localized level. Third, the URS dataset was derived only from a sample of urban census tracts, thus limiting its representativeness to all areas, including rural regions.

Several adjustments have been made to overcome these limitations. First, owing to the lack of market share data, I assume that plan availability (measured by the weight in the URS) is proportional to the number of residential broadband subscribers reported in the ACS. This assumption allowed me to approximate the market share and demand by combining these weights and subscriber counts. Second, to address the lack of census tract identifiers, I aggregated the data at the state level to create a feasible unit of analysis. Third, although the URS is based only on a sample of urban census tracts, it serves as an official benchmark for federal policies and programmes nationwide. It is worth emphasizing that URS prices are used as reference points to ensure that consumers in areas receiving government intervention are charged reasonable prices. Therefore, using URS data to represent national trends is not a major concern. For comparison, the Bureau of Labor Statistics (BLS) relies on data from urban census tracts or blocks to compute CPI and related metrics, which are widely used as proxies for national economic indicators.

The final dataset is structured at the market-provider-product level and consists of 19 providers, with providers holding a market share of less than 1% aggregated into a single group referred to as "other providers".[19] Providers can offer different product technologies, such as DSL, fixed wire-

[17] https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html

[18] https://www.ntia.gov/funding-programs/internet-all

[19] The market definition in this analysis is based on a combination of the state and year.

less, cable modem, or fiber. As a result, the consumer choice set consists of available technologies and an outside option, which includes non-broadband alternatives, such as no subscription, wireline, or cell phone services.

Table 1: Observed Market Shares

Products					Aggregate Providers		
DSL	Fixed Wireless	Cable	Fiber	Outside good	All Top 19	Other	All Products
0.155	0.024	0.415	0.139	0.268	0.617	0.115	1.000

Note: All Products' Column represents the sum of all the products' market shares or sum of the providers (all 19), Other, and the Outside good market shares.

Table 1 presents the observed market from the data and shows that all 19 providers account for 61.7% of the total market share. The remaining providers, each with less than 1% market share, collectively account for 11.5% of the total market share. Finally, outside goods account for 26.8% of the total market share.

Table 2: Summary Statistics

	Mean	**Std. Dev**	**Min**	**Max**	**Observation**
A. Endogenous variables					
Price (2023 dollar)	89.62	29.31	36.97	244.71	2595
Subscriber Count	378,671.70	621,350.10	80.83	7,018,170	2595
Market size	4,070,837	3,705,298	269,469	14,800,000	2595
B. Plan characteristics					
Download speed (Mbps)	395.01	1130.52	0.25	22254.17	2595
Upload speed (Mbps)	265.71	1057.75	0.13	10,000	2595
Plan with allowance (%)	0.65	0.44	0.00	1.00	2595
Plan with high speed (%)	0.77	0.42	0.00	1.00	2595
C. Market level variables					
Median income	63,667	14,402.13	18,626	108,210	494
Median age	38.68	2.40	30.5	45.10	494
Housing units density	85.09	300.38	0.21	2318.94	494
Herfindahl–Hirschman Index (in %)	25.681	14.123	1.597	70.770	494

Table 2 presents descriptive statistics of the main URS variables used to estimate the structural model. Panels A, B, and C show that there is a lot of variability in the main endogenous variables, product characteristics variables, and exogenous market-level variables. Here, market size is defined as the number of housing units, as defined in the U.S. Census.

I supplement the data described in Table 2 with the FCC deployment data to build the pool of products. The full dataset consists of 6,369 observations structured at the state-year-provider-product level. A product is considered to be in the market if it has an associated price charged to consumers. Conversely, if no price is charged, then the product is treated as a potential product that can be introduced into the market. This distinction is based on the nature of FCC deployment data, which consists of advertised products. In this dataset, ISPs report the maximum download and upload speeds for each product offered in a given census block. However, not all products reported by ISPs in this dataset are available in the market.

Using the institutional context and established data, I outline the empirical strategy. I begin with a difference-in-differences approach to assess the effects of subsidies on prices and service quality. To explore counterfactual policy scenarios, I estimate a structural model of broadband demand and supply with endogenous entry and product offerings.

3 Empirical Model

The analysis begins with a difference-in-differences design that exploits cross-state variation in subsidy allocation intensity, providing reduced-form evidence of how state-level exposure to federal broadband funding affects prices and service quality following the IIJA. To go beyond reduced-form effects, I complement this approach with a structural model that sheds light on the underlying behavioral mechanisms that drive the observed difference-in-differences results.

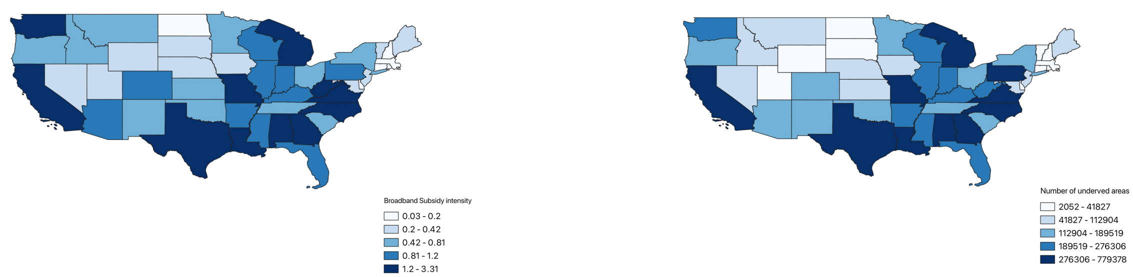
3.1 Difference-in-Differences with Continuous Treatment

In this section, I estimate a difference-in-differences model that exploits the continuous variation in subsidy intensity across states. By design, all states receive some level of subsidy (e.g., all treated units), so identification comes from differences in treatment intensity rather than from treated–control comparisons. Figure 1 illustrates the institutional mechanism underlying the subsidy allocation. Panel A shows the subsidy allocations, while Panel B displays the number of underserved areas as reported in the 2021 BEAD Report (based on 2020 FCC coverage data). The two panels reveal a mechanical link in the allocation rule: states with more underserved areas receive larger allocations. Figure 2 further highlights the strong correlation between subsidy intensity and the number of underserved areas.

Figure 1: Subsidy Allocation and Underserved Areas

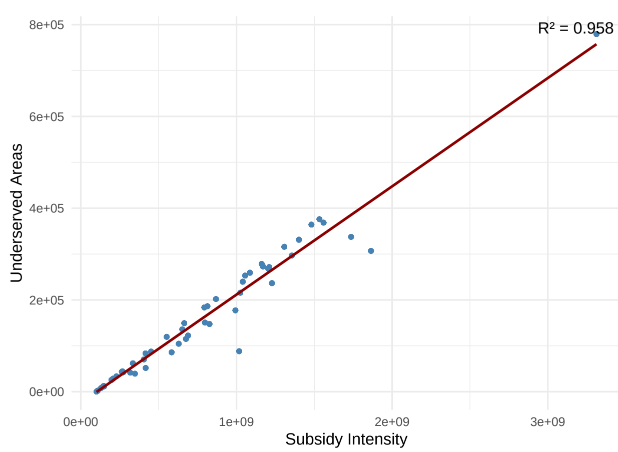
(a) Panel A: Subsidy Allocation (2021)

(b) Panel B: Number of underserved areas



Note: (1) This figure shows the per-capita BEAD subsidy allocations (Panel A) and number of underserved census blocks (Panel B). States with more underserved areas receive larger allocations, reflecting the mechanical link in the BEAD allocation formula. (2) The number of underserved areas is reported in the 2021 BEAD Report, based on 2020 FCC coverage data.

Figure 2: Relationship between Subsidy Intensity and Underserved Areas



Note: This figure shows that nearly 96% of the total variation in subsidy allocations is explained by the pre-determined number of underserved areas, underscoring the importance of controlling for this variable.

This motivates the use of subsidy intensity as a continuous treatment variable but also highlights its endogeneity. Importantly, BEAD allocations are determined and announced at the state level, whereas firm-level subgrants and network deployment occur with a lag. Consequently, the difference-in-differences design should be interpreted as estimating the exposure effect of the BEAD allocation intensity at the state level. Throughout the paper, the difference-in-differences estimates are therefore interpreted as intention-to-treat (ITT) effects, capturing the impact of exposure to subsidy allocations rather than the effects of completed network deployment or realized infrastructure build-out. In particular, the estimates reflect how outcomes evolve differentially across states receiving higher per-capita allocations following the policy announcement through channels such as anticipation effects, state-level planning and coordination, complementary investments, and early adjustments by market participants.[20]

Subsidy allocations are mechanically linked to the number of underserved areas and are therefore not randomly assigned. Moreover, they reflect underlying structural characteristics such as housing unit density, rurality, and median income (see Figure 9 in Appendix D). To mitigate confounding and allow for differential post-policy trends correlated with pre-existing state characteristics, I control for pre-intervention covariates interacted with event time.

The specification of the difference-in-differences design in the continuous treatment is written as follows[21]:

$$y_{it} = \alpha + \sum_{\substack{j=2016 \\ j \neq 2020}}^{2023} \beta_j \log\left(\frac{\text{subsidy}_i}{\text{pop}_i}\right) \mathbf{1}\{t=j\} + \sum_{\substack{j=2016 \\ j \neq 2020}}^{2023} \theta_j' X_i \mathbf{1}\{t=j\} + \lambda_i + \lambda_{rt} + \varepsilon_{it}. \tag{1}$$

The variable y_{it} denotes the outcome of interest, defined as the average broadband price or speed in gigabits per second (Gbps) in state i at year t. The term λ_i captures state fixed effects, which control for unobserved, time-invariant differences across states, whereas λ_{rt} represents region-year fixed effects, which absorb shocks that are common to states within a region in a given year.[22] The variable subsidy_i denotes the subsidy allocated to state i at $t = 2021$ and pop_i is the population

[20] Several studies examine firms' anticipatory behavior in the broadband market in response to policy exposure; see, for example, Wilson (2025) and Bourreau et al. (2020).

[21] Another possible specification is proposed by Callaway et al. (2024) (see Remark 3.1). However, in my setting, the limited number of units (states) prevents me from comparing those receiving low subsidies (below the 10th percentile) with those receiving high subsidies (above the 90th percentile).With a small number of states, it is not possible to rely on asymptotic approximations for valid inference under this specification.

[22] The analysis defines the usual five regions based on state-level groupings: Northeast, Midwest, South, West, and a standalone category for Rhode Island.

size in state i. The notation $\mathbf{1}\{\cdot\}$ denotes the usual indicator function. The coefficients β_j are the parameters of interest, capturing the average differential change in outcome y_{it} associated with a one-unit increase in log per capita subsidy allocation relative to 2020. The β_j before $j = 2020$ are falsification tests that capture the relationship between the subsidy allocation intensity and the outcomes before the subsidy program occurred. Their pattern and statistical significance are a direct test of the common trends assumption. Following standard practice, I omit $t = 2020$, the year immediately preceding policy implementation, from the set of indicators to serve as the baseline. The vector X_i includes pre-intervention ($t = 2020$) state-level covariates, such as the number of underserved areas and the share of workers that work remotely to account for differential exposure to COVID-19 and related shocks. The associated coefficients θ_j are allowed to vary flexibly over time. Finally, ε_{it} is the idiosyncratic error term that captures unobserved factors that affect the outcome.[23]

The identifying assumption of treatment effects β_t in (1) relies on a conditional parallel trends assumption. Specifically, in the absence of exposure to the IIJA program, states with different subsidy intensities would have followed parallel outcome trajectories over time, conditional on pre-policy characteristics X_i and included fixed effects. In addition, I assume that conditional on the observed pre-intervention characteristics and fixed effects, the treatment intensity is mean-independent of unobserved shocks that affect the outcome:

$$\mathbb{E}[\varepsilon_{it} \mid \text{subsidy}_i/\text{pop}_i, X_i, \lambda_i, t, \lambda_{rt}] = 0. \tag{2}$$

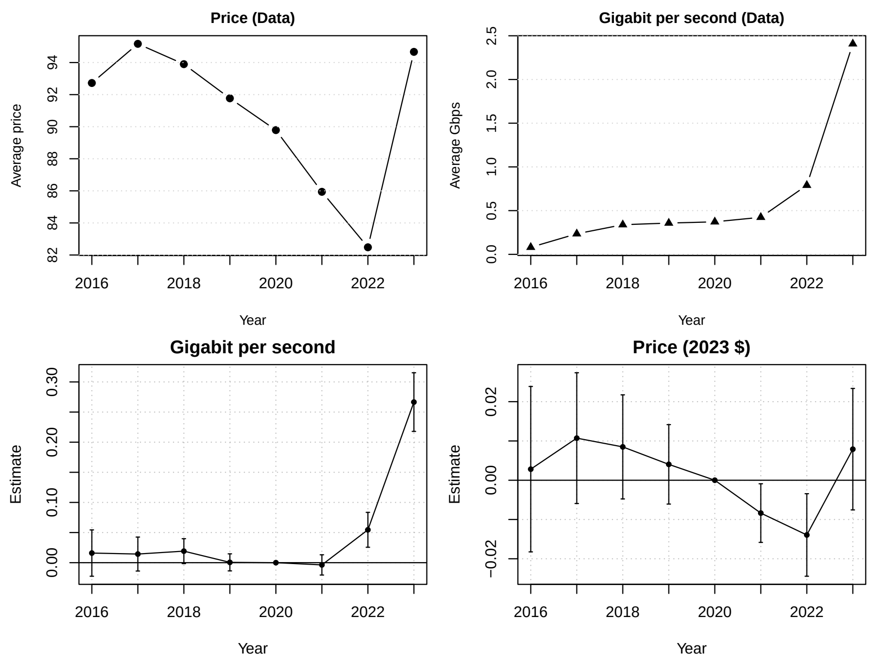
The assumption defined in (2) implies that after conditioning for pre-treatment covariates, state fixed effects, and region-by-time fixed effects, cross-state variation in per-capita subsidy allocations is conditionally exogenous to the contemporaneous unobserved determinants of the outcome. Together, these assumptions allow the coefficients β_t to be interpreted as causal differences in the post-allocation outcomes associated with differential exposure to BEAD funding.

The top-row panel of Figure 3 displays the trends in average broadband prices (in 2023 dollars) and service quality measured in gigabits per second (Gbps). While prices fluctuate between \$82 and \$95 over time, the service quality increases steadily. The sharp increase in Gbps from 2022 to 2023

[23] As a robustness check, I also report the difference-in-differences main results by only controlling by region fixed-effect and with no covariates X_i in Figure 10 in Appendix D.

coincides with a notable jump in product quality, suggesting substantial technological- or policy-driven improvements. The second-row panels show the results of the difference-in-differences regression specified in equation (1). Standard errors are clustered at the state level to account for serial correlation within states.

Figure 3: Difference-in-Differences Estimates



Note: (1) The second row of this figure reports the estimates and 95% CIs for β_t from (1). Standard errors are clustered at the state level. 2020 is omitted as the reference year; (2)The first two rows of the figure display the data: the average price (in 2023 dollars) and average speed (in gigabits per second). The last row shows the corresponding estimates generated by the model in (1).

The coefficients for the pre-event periods are close to zero and not statistically significant, supporting the parallel trend assumption. The results suggest that states that are more exposed to subsidy allocations experience differential post-2021 changes in prices and service quality. However, the effects on average prices become statistically insignificant at $t = 2023$, consistent with the gradual pass-through of infrastructure investments and rising marginal costs documented in the structural analysis. It is worth noting that excluding X_i from specification (1) yields estimates that are nearly identical to the baseline results (Figure 3 versus Appendix D). This similarity suggests that the allocation rule does not mechanically drive the estimated DiD effects. While controlling for underserved areas is conceptually important, the results indicate that state and region–year fixed effects absorb most of the cross-state variation correlated with this variable.

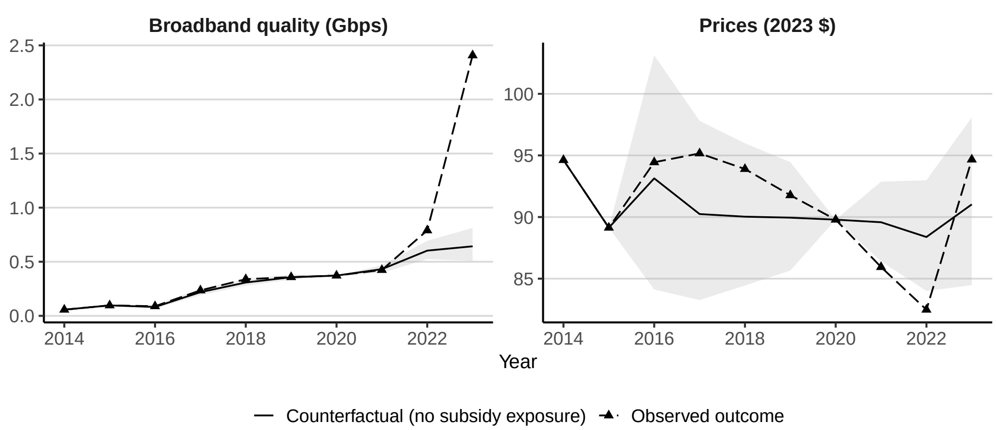
To quantify the aggregate effect of subsidy allocations on national broadband prices and quality, I construct counterfactual price and quality paths representing outcomes that would have prevailed in the absence of subsidy exposure, starting in 2021. Specifically, for each year t, the counterfactual outcome y_t^{cf} is defined as

$$y_t^{cf} = y_t - \beta_t \times \overline{\log\left(\frac{\text{subsidy}}{\text{pop}}\right)}, \tag{3}$$

where y_t denotes the observed national average price or broadband quality (measured in Gbps), β_t is the estimated treatment effect coefficient for year t, and $\overline{\log\left(\frac{\text{subsidy}}{\text{pop}}\right)}$ denotes the cross-state average of the log per-capita subsidy allocation. Intuitively, y_t^{cf} corresponds to the observed outcome net of the component attributable to exposure to the subsidy program.

Figure 4 reports the observed and counterfactual national average broadband quality and average price from 2014 to 2023. These counterfactual paths should be interpreted as exposure-based benchmarks rather than as the full equilibrium outcomes absent network deployment. Prior to 2021, the observed and counterfactual trends closely overlap and are statistically indistinguishable within the 95% confidence intervals, consistent with the common pre-trends documented in Figure 3.

Figure 4: Observed and Counterfactual Annual Outcomes



Note: The figure displays observed annual average prices and broadband quality (Gbps) and the corresponding counterfactual outcomes absent subsidy allocations. Counterfactuals are constructed using the estimated β_t from (1) and the average log per-capita subsidy allocation across states. The gray shaded region denotes the 95% confidence region for y_t^{cf}.

Beginning in 2021, the counterfactual broadband quality path lies below the observed trajectory, which is consistent with the interpretation that higher subsidy exposure contributes to improvements in broadband quality. Conversely, the counterfactual price path exceeds the observed price trajectory from 2021 onward, indicating a reduction in average prices following exposure to higher subsidy intensity.

The difference-in-differences reveals encouraging reduced-form patterns: broadband service quality improves and prices decline more rapidly in states with higher BEAD allocation intensity following the IIJA. However, while informative, these trends do not allow me to distinguish between the effects of supply- and demand-side programs, nor do they capture the underlying strategic behavior of firms that shape these outcomes. Crucially, they provide limited guidance for policy design, particularly in answering questions such as how the market would respond to a larger or smaller subsidy? What is the optimal subsidy level? How do price, entry, and product variety evolve under alternative scenarios? To address these questions, I estimate a structural model for the broadband industry that explicitly incorporates consumer demand and firms' endogenous entry and product decisions. This framework complements the difference-in-differences design by allowing for counterfactual simulations that quantify how subsidies reshape the market structure, cost pass-through, and welfare outcomes. It provides a unified lens to evaluate both the behavioral mechanisms at play and the fiscal efficiency of alternative subsidy designs.

3.2 Structural Model

3.2.1 Model Setup

Consider a framework in which the markets (defined as a combination of state and year) and firms (or providers) are indexed by $i \in \mathscr{N}$ and $f \in \mathscr{F}$, respectively. The products in market i are denoted by $j \in \mathscr{J}_i$ with the cardinalities of the markets, firms, and products represented by N, F, and J_i, respectively.

Each product is produced by a single firm. The set of products offered by firm f in market i is denoted by $\mathscr{J}_{fi}$, and the total set of products available in market i is $\mathscr{J}_i = \bigcup_{f \in \mathscr{F}} \mathscr{J}_{fi}$.

In each market i, firm f decides whether to offer product j by setting decision variable $Y_{ji} \in \{0,1\}$, where $Y_{ji} = 1$ if product j is offered and $Y_{ji} = 0$ if product j is not offered.

The full portfolio of products available in market i is represented as $Y_i \in \{0,1\}^{J_i}$. Similarly, the portfolio offered by firm f in market i is denoted by Y_{fi}, where Y_{-fi} represents the portfolio of competing firms.

Let $r_{fi}(Y_i)$ denote the variable profit of firm f from portfolio Y_i in market i. The fixed cost of introducing product j to market i is denoted FC_{ji}. For portfolio Y_{fi} offered by firm f in market i, the total fixed cost incurred by firm is given by

$$\mathrm{FC}_{fi}(Y_{fi}) = \sum_{j \in \mathscr{J}_{fi}} Y_{ji} \cdot \mathrm{FC}_{ji}.$$

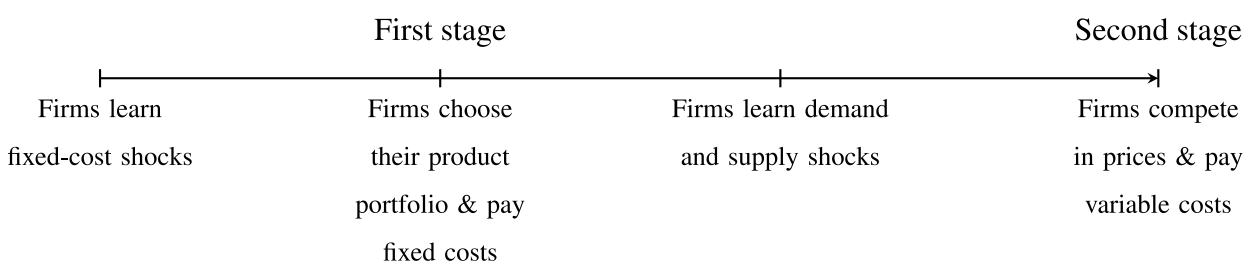
Based on the available information $\mathscr{I}_f$, each firm f chooses its product portfolio Y_{fi} by solving the following optimization problem:

$$\max_{Y_{fi} \in \mathscr{Y}_{fi}} \mathbb{E}\left[r_{fi}\left(Y_{fi}, Y_{-fi}\right) - \mathrm{FC}_{fi}\left(Y_{fi}\right) | \mathscr{I}_f\right] \tag{4}$$

where, $\mathscr{Y}_{fi} = \left\{Y_{fi} = (Y_{ji})_{j \in \mathscr{J}_{fi}} \mid Y_{ji} \in \{0,1\}\right\}$ and $\mathscr{Y}_{-fi} = \left\{Y_{-fi} = (Y_{ji})_{j \in \mathscr{J}_{-fi}} \mid Y_{ji} \in \{0,1\}\right\}$.

Optimization problem (4) can be solved using a two-stage game. In the first stage, firms decide which products to offer; in the second stage, they set prices as presented in Figure 5.

Figure 5: Timeline of the model



First stage: Product offering decision

Each firm f is endowed with a set of products $\mathscr{J}_f$. Firms observe the characteristics of these products, as well as the product, market, and year fixed effects, and the fixed costs associated with all potential product offerings. Additionally, firms have knowledge of the distribution of demand shocks (ξ) and marginal cost shocks (η), although these are unobservable to econometricians. In the estimation framework, I nonparametrically recover the empirical distributions of ξ and η.

Based on this information, firms determine their product offerings by solving the following optimization problem,

$$\max_{Y_{fi} \in \mathscr{Y}_{fi}} \mathbb{E}_{(\xi,\eta)} \left[r_{fi} \left(Y_{fi}, Y_{-fi} \right) \mid \mathscr{I}_f \right] - \mathrm{FC}_{fi} \left(Y_{fi} \right). \tag{5}$$

Second stage: Pricing competition

At this stage, demand shocks ξ and marginal cost shock η are realized, and firms observe the realization of these shocks and set prices in a Nash-Bertrand in a complete information game. Typically, firms choose prices by solving the following optimization problem,

$$\max_{\{p_{ji}, j \in \mathscr{J}_{fi}\}} r_{fi} \left(Y_{fi}, Y_{-fi} \right). \tag{6}$$

The fact that firms know only the distribution of demand and marginal cost shocks in the first stage and the realization in the second stage after they commit to the product offering decision is referred to as the timing assumption. In the broadband industry, the timing assumption can be justified by considering the nature of the technology implementation and its associated timelines. Broadband deployment typically requires a significant upfront investment in infrastructure, such as laying fiber-optic cables, setting up data centers, or configuring wireless networks. These processes often involve long planning and execution phases, regulatory approval, and coordination with local governments, making the decision to enter a market or to roll out specific services a long-term commitment.[24]

I estimate the structural model in two stages. Estimating such a model requires back out of the demand parameters, marginal, and fixed costs associated with offering broadband services. This section describes how I estimate each part sequentially, starting with consumer demand and moving backward to firm decisions. I also address key econometric challenges, such as dealing with multiple equilibria in firms' entry and product choices.

[24] This timing assumption has been used in several studies. Examples include Fan and Yang (2024) for the brewery industry, Eizenberg (2014) in the personal computer industry, and Hidalgo (2024) for the broadband industry.

4 Estimation

This section presents the strategies used to estimate the model. First, I solve the second stage of the analysis following the methodology outlined in Berry (1994).[25] Next, I proceed to the first stage, where I construct moment inequalities leading to bounds of the parameters of interest using the approach proposed by Fan and Yang (2024). For inference in models defined by moment inequalities, I rely on the techniques developed by Chernozhukov et al. (2019).

4.1 Demand

I follow Berry (1994) and assume that the indirect utility of household h from choosing product $j \in \mathscr{J}_i$ in market $i \in \mathscr{N}$ takes the following form:

$$U_{hij} = \delta_{ji} + \nu_{hig} + (1-\rho)\,\varepsilon_{hji}, \tag{7}$$

where $g \in G$ is the number of product groups, δ_{ji} is the utility from the observed characteristics of product j and ε_{hji} is the idiosyncratic utility shock. The term δ_{ji} is further specified as $\delta_{ji} = X'_{ji}\beta + \alpha p_{ji} + \xi_{ji}$, where $X_{ji} = \left(X_{jki}\right)_{k=1}^{K}$ is a K-dimensional vector of observable characteristics of product j,[26], p_{ji} is the price of product j, ξ_{ji} is an unobserved (by the econometrician) characteristic of product j, (α, β) are $K+1$ taste parameters, and ν_{hig} is unobserved (by the econometrician) and common to all products in group g is a group-specific variable whose distribution function depends on the within-group taste correlation parameter $0 \leq \rho < 1$.

Following Ciliberto et al. (2021) and Aguirregabiria et al. (2024), I consider a nested logit model with two nests: one with all inside goods and the other with the outside good. Let d_{jg} be a dummy variable equal to 1 if $j \in J_i$ and 0 otherwise. I can then rewrite (7) as follows:

[25] This paper departs from Fan and Yang (2024), who employ a random-coefficients demand model. While such models allow for richer substitution patterns, they may generate non-unique pricing equilibria in multiproduct settings (Nocke and Schutz, 2018), complicating welfare and entry counterfactuals. I therefore follow Berry (1994), which delivers a unique closed-form pricing solution and ensures a stable mapping from demand primitives to prices. This tractability is essential for evaluating firms' endogenous product offerings and entry decisions. I nonetheless rely on Fan and Yang (2024)'s framework to recover fixed-cost parameters in the entry stage.

[26] In this paper, I consider the download speed, upload speed, data allowance, and high/low speed product

$$U_{hij} = \delta_{ji} + \sum_{g \in G} d_{jg} \nu_{hig} + (1-\rho)\, \varepsilon_{hji}, \tag{8}$$

Let $\tilde{s}_{ji}$ denote the observed market share of product j in market i, and let $\tilde{s}_{j/g}$ denote the observed market share of product j as a fraction of the total market share of group g.

$$\log\left(\tilde{s}_{ji}\right) - \log\left(\tilde{s}_{i0}\right) = X'_{ji}\beta + \alpha p_{ji} + \rho \log\left(\tilde{s}_{j/g}\right) + \xi_{ji}. \tag{9}$$

In the model defined in (9), p_{ji} and $\log\left(\tilde{s}_{j/g}\right)$ are endogenous variables. Price p_{ji} is endogenous because it is influenced by factors correlated with demand shock ξ_{ji}, often interpreted as the unobserved quality of product j. Endogeneity of $\log\left(\tilde{s}_{j/g}\right)$ arises because of simultaneity issues.

To address these endogeneity issues, I rely on the instrumental variables approach proposed by Berry (1994) for p_{ji}, employing instruments such as[27]

$$\frac{1}{J_i - 1} \sum_{l \in \mathscr{J}_i, l \neq j} X_{lki}, \quad \forall k = 1, \cdots, K$$

average characteristics of all exogenous products in market i (excluding product j), including upstream and downstream speed and high-speed indicators. The intuition behind using these instruments is twofold. First, the characteristics of rival products influence their pricing decisions, which in turn affect the price of product j, ensuring instrument relevance. Second, these characteristics are assumed to not directly impact consumers' utility from product j except through their effect on prices, thus satisfying the exclusion restriction. For $\log\left(\tilde{s}_{j/g}\right)$, I rely on the instrument proposed by Aguirregabiria et al. (2024), using the number of all products in market i (excluding product j) and the previous set of instruments used for price endogeneity. Furthermore, I report the first-stage instrumental variable regressions in Appendix E.1, the results of which justify the strength of the instruments used.[28]

The estimation of the model in (9) is performed using a two-stage least-squares (2SLS) ap-

[27] I am fully aware that other types of instruments have been proposed in the literature, as well as the potential weakness of the BLP-type instrument, especially when J_i is sufficiently large. However, in my dataset, the number of products J_i is approximately nine on average, which is relatively small for asymptotics to apply.

[28] The first-stage results (Table 12) confirm the relevance of the instruments. The F-statistics for joint instrument significance are 40.9 for the nest equation and 28.2 for the price equation, both well above the conventional threshold of 10, indicating that BLP-type instruments are strong in this context.

proach. In the first stage, I regress the endogenous variables on the instruments and exogenous characteristics, controlling for state and provider fixed effects. In the second stage, I estimate the model in (9), addressing the endogeneity problem while controlling for state, year, and product fixed effects.

The estimation of the model in (9) allows me to recover the empirical distribution of demand shocks ξ_{ji}. Moreover, it allows for the computation of consumer welfare CS_i in market i, which is written as

$$\mathrm{CS}_i = -\frac{1}{\alpha} \cdot \log \left(1 + \left(\sum_{j \in \mathscr{J}_i} \exp \left(\frac{\delta_{ji}}{1-\rho} \right) \right)^{1-\rho} \right) \cdot M_i \cdot s_i \left(p_i, X_i, \xi_i \right), \tag{10}$$

where

$$s_i \left(p_i, X_i, \xi_i \right) = \frac{\exp \left(\delta_{ji} / \left(1-\rho \right) \right)}{\left(D_g \right)^{\rho} \left(\sum_{g'} \left(D_{g'} \right)^{1-\rho} \right)}, \tag{11}$$

where $D_g = \sum_{j \in \mathscr{J}_g} \exp \left(\delta_{ji} / \left(1-\rho \right) \right)$, $\delta_{ji} = X'_{ji} \beta + \alpha p_{ji} + \xi_{ji}$, and $\mathscr{J}_g$ set of products belonging to group g.

4.2 Oligopoly Price Competition

The variable profit r_{fi} of firm j in market i is given by,

$$r_{fi} = \sum_{j \in \mathscr{J}_f} \left(p_{ji} - mc_{ji} \right) M_i Y_{ji} s_j \left(p_i, X_i, \xi_i \right), \tag{12}$$

where mc_{ji} is the marginal cost of product j, $s_j \left(p_i, Y_i, X_i, \xi_i \right)$ is the market share of product j in market i, M_i is the market size defined as the number of housing units in market i. I follow the literature and assume that firms set prices according to the Bertrand-Nash equilibrium in a complete information game.

The first order conditions resulting from the optimization problem are written as,

$$s_j \left(p_i, X_i, \xi_i \right) + \sum_{j \in \mathscr{J}_{fi}} \left(p_{ji} - mc_{ji} \right) \frac{\partial s_j \left(p_i, X_i, \xi_i \right)}{\partial p_{ji}} = 0, \tag{13}$$

To solve (13), I define $S_{jr} = -\partial s_r \left(p_i, X_i, \xi_i \right) / \partial p_{ji}, \quad j, r = 1, \ldots, J_i$.

$$\Omega^*_{jr} = \begin{cases} 1 & \text{if } \exists f : \{r, j\} \subseteq \mathscr{J}_{fi} \\ 0 & \text{otherwise,} \end{cases}$$

and Ω is $J_i \times J_i$ matrix with $\Omega_{jr} = \Omega^*_{jr} \odot S_{jr}$, where $\odot$ is the Hadamard product. Hence, the first order conditions in (13) become

$$p_i - mc_i = \Omega^{-1} s_j \left(p_i, X_i, \xi_i\right), \tag{14}$$

The marginal cost mc_i is nonparametrically recovered from (14), and is further specified as follows:

$$\log\left(mc_{ji}\right) = X'_{ji}\gamma + \eta_{ji}, \tag{15}$$

where η_{ji} denotes the marginal cost shock.

I estimate the model in (15) using ordinary least squares (OLS) and control for state, year, and product fixed effects. Subsequently, I recover the empirical distribution of marginal cost shocks. With these in hand, along with demand shocks, I estimate the expected variable profits and counterfactuals resulting from any type of product-offering configuration.

4.3 Product Offerings

In this section, I consider a simultaneous, static, and discrete choice game of complete information. This setup follows the seminal contributions of Bresnahan and Reiss (1991) and Berry (1992).[29] The primary objective is to recover the fixed costs associated with product-offering decisions. To estimate the fixed costs, the following specification is adopted:

$$\mathrm{FC}_{ji} = W_i\theta + \sigma_\zeta \zeta_{ji}, \quad \zeta_{ji} \xrightarrow{d} \mathscr{N}(0,1), \tag{16}$$

where θ and σ_ζ are the parameters of interest to be estimated, ζ_{ji} is the unobserved market and product heterogeneity affecting fixed costs, and W_i consists of fixed cost shifters, which are explanatory variables that influence fixed costs. In this case, W_i includes dummy variables indicating whether a market falls into a specific category (small, medium, or large). These dummies help

[29]These models have been widely adopted in the literature (Aradillas-López, 2020).

account for systematic differences in fixed costs across different market sizes.

Estimating this type of model poses notable challenges because of the presence of multiple equilibria. Specifically, for a given set of parameters and unobserved fixed-cost shifters, the model can predict multiple equilibria, thus rendering it incomplete. The existing literature offers three main approaches to address this issue. The first aggregates observed data to ensure that the model predicts a unique equilibrium (Bresnahan and Reiss, 1991; Berry, 1992). The previous insight applies only to models with two players making binary decisions and cannot be readily extended to the more complex setting considered in this study. The second approach imposes an equilibrium selection mechanism (Bjorn and Vuong, 1984; Bajari et al., 2010), which typically adds another layer of complexity to the model, as it requires estimating the selection rule, potentially introducing a risk of misspecification. The third approach avoids imposing restrictions on the equilibrium selection mechanism and relies on tools from moment inequality literature to estimate the parameters of interest.[30] In this study, I adopt the latter approach, as it provides a more robust solution than other methods. Specifically, I leverage the recent method proposed by Fan and Yang (2024), which offers an efficient way to compute bounds. of parameter. This framework is particularly well suited for the present study, as it accommodates a large number of players and products, which is an essential feature of the U.S. broadband industry.

Assumption 1. *Any observed decision Y_{ji} is not a dominated strategy for all products $j \in \mathscr{J}_i$.*

In this section, I closely follow Fan and Yang (2024) to illustrate the construction of the bounds of the parameters of interest.[31] Under Assumption 1,

$$\Pr\left(Y_{ji} = 1 \text{ is dominant}\right) \leq \Pr\left(Y_{ji} = 1\right) \leq \Pr\left(Y_{ji} = 1 \text{ is not dominated}\right) \tag{17}$$

I denote $Y_{-ji} = (Y_{ki}, k \in \mathscr{J}_i : k \neq j)$. To simplify the notation, the minimum and maximum values

[30] Tamer (2003), Ciliberto and Tamer (2009), Ciliberto et al. (2021), Fan and Yang (2024), Wollmann (2018), Eizenberg (2014), and Pakes et al. (2015), among other.

[31] For a detailed exposition of the heuristic results underlying this section, readers can refer to Fan and Yang (2024).

are taken over the elements Y_{-ji}.

$$Y_{ji} = 1 \text{ is dominant } \Leftrightarrow \zeta_{ji} < \min_{Y-ji} \left\{ r_{fi}\left(Y_{ji} = 1, Y_{-ji}, X_{ji}\right) - r_{fi}\left(Y_{ji} = 0, Y_{-ji}, X_{ji}\right) \right\} - \mathrm{FC}_{ji},$$
$$Y_{ji} = 1 \text{ is not dominated } \Leftrightarrow \zeta_{ji} < \max_{Y-ji} \left\{ r_{fi}\left(Y_{ji} = 1, Y_{-ji}, X_{ji}\right) - r_{fi}\left(Y_{ji} = 0, Y_{-ji}, X_{ji}\right) \right\} - \mathrm{FC}_{ji}.$$

Given a set of observed covariates X_{ji} and the change in firm f variable profit as Y_{ji} turns from zero to one is defined as,

$$\Delta_j\left(Y_{-ji}, X_{ji}\right) = r_{fi}\left(Y_{ji} = 1, Y_{-ji}, X_{ji}\right) - r_{fi}\left(Y_{ji} = 0, Y_{-ji}, X_{ji}\right). \tag{18}$$

Hence,

$$F_\zeta\left(\min_{Y-ji}\{\Delta_j\left(Y_{-ji}, X_{ji}\right)\} - \mathrm{FC}_{ji}\right) \leq \Pr\left(Y_{ji} = 1 | X_{ji}, W_{ji}\right),$$
$$\Pr\left(Y_{ji} = 1 | X_{ji}, W_{ji}\right) \leq F_\zeta\left(\max_{Y-ji}\{\Delta_j\left(Y_{-ji}, X_{ji}\right)\} - \mathrm{FC}_{ji}\right).$$

Assume that the presence of rivals reduces a firm's profit. Then,

$$\begin{aligned} \underline{\Delta}_j\left(X_{ji}\right) &= \min_{Y_{-ji}} \Delta_j\left(Y_{-ji}, X_{ji}\right) \approx \Delta_j\left(1, \ldots 1, X_{ji}\right) \\ \overline{\Delta}_j\left(X_{ji}\right) &= \max_{Y_{-ji}} \Delta_j\left(Y_{-ji}, X_{ji}\right) \approx \Delta_j\left(0, \ldots 0, X_{ji}\right). \end{aligned} \tag{19}$$

Finally, the bounds of the parameters can be derived as follows,

$$F_\zeta\left(\underline{\Delta}_j\left(X_{ji}\right) - \mathrm{FC}_{ji}\right) \leq \Pr\left(Y_{ji} = 1 | X_{ji}, W_{ji}\right) \leq F_\zeta\left(\overline{\Delta}_j\left(X_{ji}\right) - \mathrm{FC}_{ji}\right), \tag{20}$$

$$\begin{aligned} \mathrm{L}\left(Y_{ji}, \underline{\Delta}_j\left(X_{ji}\right), W_i, \theta, \sigma_\zeta\right) &= F_\zeta\left(\underline{\Delta}_j\left(X_{ji}\right) - \mathrm{FC}_{ji}\right) - 1\left(Y_{ji} = 1\right), \\ \mathrm{H}\left(Y_{ji}, \overline{\Delta}_j\left(X_{ji}\right), W_i, \theta, \sigma_\zeta\right) &= 1\left(Y_{ji} = 1\right) - F_\zeta\left(\overline{\Delta}_j\left(X_{ji}\right) - \mathrm{FC}_{ji}\right), \end{aligned} \tag{21}$$

$$\begin{aligned} &\mathbb{E}\left[\mathrm{L}\left(Y_{ji}, \underline{\Delta}_j\left(X_{ji}\right), W_i, \theta, \sigma_\zeta\right) | X_{ji}, W_i\right] \leq 0, \\ &\mathbb{E}\left[\mathrm{H}\left(Y_{ji}, \overline{\Delta}_j\left(X_{ji}\right), W_i, \theta, \sigma_\zeta\right) | X_{ji}, W_i\right] \leq 0. \end{aligned} \tag{22}$$

Let $g^{(k)}(\cdot), k = 1, \dots, K$ be non-negative functions of X_{ji} and W_i. Thus, (22) can be transformed from conditional to unconditional expectations.

$$\begin{aligned}
&\mathbb{E}\left[\mathrm{L}\left(Y_{ji}, \underline{\Delta}_j\left(X_{ji}\right), W_i, \theta, \sigma_\zeta\right) g^{(k)}\left(W_i, X_{ji}\right)\right] \leq 0, \\
&\mathbb{E}\left[\mathrm{H}\left(Y_{ji}, \overline{\Delta}_j\left(X_{ji}\right), W_i, \theta, \sigma_\zeta\right) g^{(k)}\left(W_i, X_{ji}\right)\right] \leq 0.
\end{aligned} \tag{23}$$

I average (23) across all potential products in each market to mitigate any correlations between the decisions of firms operating in the same market. Consequently, the asymptotic is driven by the number of markets rather than a combination of the number of products and markets.

$$\begin{aligned}
&\mathbb{E}\left[\frac{1}{J_i} \sum_{j \in \mathscr{J}_i} \mathrm{L}\left(Y_{ji}, \underline{\Delta}_j\left(X_{ji}\right), W_i, \theta, \sigma_\zeta\right) g^{(k)}\left(W_i, X_{ji}\right)\right] \leq 0, \\
&\mathbb{E}\left[\frac{1}{J_i} \sum_{j \in \mathscr{J}_i} \mathrm{H}\left(Y_{ji}, \overline{\Delta}_j\left(X_{ji}\right), W_i, \theta, \sigma_\zeta\right) g^{(k)}\left(W_i, X_{ji}\right)\right] \leq 0.
\end{aligned} \tag{24}$$

At this stage, the function $g^{(k)}(\cdot)$, along with the cutoffs $\underline{\Delta}_j(X_{ji})$ and $\overline{\Delta}_j(X_{ji})$, are essential for computing these moment inequalities. In what follows, I discuss how I defined the function $g^{(k)}(\cdot)$ and the cutoffs $\underline{\Delta}_j(X_{ji})$ and $\overline{\Delta}_j(X_{ji})$.

The computation of the cutoffs $\underline{\Delta}_j\left(X_{ji}\right)$ and $\overline{\Delta}_j\left(X_{ji}\right)$ is achieved under three distinct scenarios[32]: (i) only a single product j is in the market, (ii) all products are in the market, and (iii) a given product j is removed from the market while keeping all other products in the market. Scenario (i) allows for the computation of $\overline{\Delta}_j\left(X_{ji}\right)$, whereas scenarios (ii) and (iii) allow for the computation of $\underline{\Delta}_j\left(X_{ji}\right)$. To compute these counterfactual scenarios, I rely on the algorithm provided in Canay et al. (2023)[33], which I restate in Appendix F.1.

To construct the set $\mathscr{G}$ of functions $g^{(k)}(\cdot)$, I discretize $\underline{\Delta}_j\left(X_{ji}\right)$, $\overline{\Delta}_j\left(X_{ji}\right)$ and the ratio $\overline{\Delta}_j\left(X_{ji}\right)/\underline{\Delta}_j\left(X_{ji}\right)$ were constructed using the 25th, 50th, and 75th percentiles, respectively. These percentiles were selected under the assumption that they provide informative summaries of X_{ji}. This parsimonious discretization is used to prevent excessive occurrence of zeros in the moment inequalities in (24). Set $\mathscr{G}$ consists of the interactions between these discretized percentiles, market category W_i, and

[32] I normalize the profit to zero when none of the products for a given firm f are in the market.

[33] A similar algorithm was used by Ciliberto et al. (2021)

their interactions.[34]

The variable profit is measured in monetary units (dollars), allowing the fixed cost parameters θ and σ_ζ to be separately identified directly in dollars rather than only up to the scale factor σ_ζ as is common in frameworks in which variable profit is specified in a semi-reduced form (e.g., Ciliberto et al. (2021)). Identifying these parameters in dollars enables a meaningful cost–benefit analysis (see Section 11). The following section explains how this identification was achieved in this paper.

4.3.1 Identification

The identification of the fixed-cost parameters θ and σ_ζ relies on the exogenous variation in product characteristics and market sizes X_{ji} and W_i, combined with the equilibrium structure of firms' product-portfolio choices. Parameter θ, which captures how fixed costs vary with market size, is identified from the differences in entry patterns across market size categories. These size categories generate distinct moment inequalities (24) that link the observed entry outcomes to fixed-cost heterogeneity. The variance parameter σ_ζ governing the unobserved component of fixed costs is partially identified using the entry-decision inequality in (6). The variation in the observed covariates identifies the expected variable profits, whereas the observed equilibrium product portfolio Y_i further restricts σ_ζ through the implied variance of the truncated normal distribution. Assumption 2 ensures that σ_ζ is pinned down for estimation.

Assumption 2. *The observed decision Y_i is a pure-strategy equilibrium for all $i \in \mathcal{N}$.*

Proposition 1. *Under Assumption 2, the variance σ_ζ is partially identified via a truncated normal distribution with mean $W_i\theta$.*

Proof: See Appendix C. □

4.3.2 Inference

The moment inequalities in (24) form the basis of the inference procedure used to estimate the parameters of interest θ and σ_ζ. The identified set is defined as any combination of (θ, σ_ζ) that

[34] Similar functions was used by Fan and Yang (2024), Canay et al. (2023), Eizenberg (2014), Wollmann (2018), among others.

satisfies (24).

$$\Theta_0 = \left\{ \left(\theta, \sigma_\zeta\right) \in \Theta : \mathbb{E}\left[m\left(X_{ji}, W_i, \theta, \sigma_\zeta\right)\right] \leq 0 \right\}, \tag{25}$$

where m is an $\mathbb{R}^{2|\mathscr{G}|}$-valued function that stacks the functions inside expectations in (24). The inference procedure relies on the framework developed by Chernozhukov et al. (2019). This framework enables the construction of confidence sets for points in the identified set that are uniformly consistent in level over the relevant class of distributions of the observed data with a prespecified probability of $1-\alpha$. Typically, this is performed by inverting the test for the following null hypothesis:

$$\mathrm{H}_\theta : \mathbb{E}\left[m\left(X_{ji}, W_i, \theta, \sigma_\zeta\right)\right] \leq 0. \tag{26}$$

Concretely, the resulting test (26) takes the following expression,

$$\phi_n\left(\theta, \sigma_\zeta\right) = \mathrm{I}\left\{ T_n\left(\theta, \sigma_\zeta\right) > c_n\left(1-\alpha, \theta, \sigma_\zeta\right) \right\}, \tag{27}$$

where $c_n\left(1-\alpha, \theta, \sigma_\zeta\right)$ is the critical value, and the function T_n is the test statistic defined as follows:

$$T_n\left(\theta, \sigma_\zeta\right) = \max_{1 \leq l \leq 2|\mathscr{G}|} \frac{\sqrt{n}\overline{m}_{n,l}\left(\theta, \sigma_\zeta\right)}{\hat{\sigma}_{n,l}\left(\theta, \sigma_\zeta\right)}, \tag{28}$$

where

$$\overline{m}_{n,l}\left(\theta, \sigma_\zeta\right) = \frac{1}{n}\sum_{i \in \mathscr{N}} m_l\left(X_{ji}, W_i, \theta, \sigma_\zeta\right), \; \hat{\sigma}_{n,l}\left(\theta, \sigma_\zeta\right) = \frac{1}{n}\sum_{i \in \mathscr{N}} \left(m_l\left(X_{ji}, W_i, \theta, \sigma_\zeta\right) - \overline{m}_{n,l}\left(\theta, \sigma_\zeta\right)\right)^2.$$

Finally, the confidence set consists of vectors of parameters that lie within the identified set and are not rejected by the test statistic T_n defined in (28). That is, the confidence set C_n collects all points $\left(\theta, \sigma_\zeta\right) \in \Theta$ satisfying the following condition

$$C_n = \left\{ \left(\theta, \sigma_\zeta\right) \in \Theta : \phi_n\left(\theta, \sigma_\zeta\right) = 0 \right\}. \tag{29}$$

The computation of the confidence set C_n boils down to the computation of the test statistic $T_n\left(\theta, \sigma_\zeta\right)$ (which is readily available) and the critical value $c_n\left(1-\alpha, \theta, \sigma_\zeta\right)$.

To compute the critical value, I follow the two-step procedure proposed by Chernozhukov et al. (2019). Appendix H details the method and its implementation for the test statistic in (28). Finally, I construct the confidence set in (29) by performing a grid search over 10,000 points for the parameter vector (θ, σ_ζ)

I now present the empirical results of the estimated model, including demand elasticities, markups, and the distribution of fixed costs across markets. These estimates serve as the basis for the subsequent counterfactual policy simulations.

5 Empirical Results

5.1 Demand and Supply

Table 3 reports the estimation results of the demand system along with the marginal cost models. The latter is derived from demand system estimation using the pricing competition model.

I provide two estimation results for demand: an OLS estimation, which does not consider price endogeneity, and a 2SLS estimation, wherein I leverage the instrumental variables presented in Section 4 to properly address price endogeneity while controlling for fixed effects. The marginal cost model is estimated using OLS, and I also control for fixed effects.

The demand estimation shows that consumers dislike higher prices *ceteris paribus*. They tend to prefer the downstream product under a certain cutoff, but dislike it when the downstream exceeds this cutoff. This can be explained by the fact that consumers often prefer faster download speeds up to a certain level, which satisfies typical usage requirements (e.g., streaming, browsing, and gaming). Beyond this threshold, marginal utility diminishes because most consumers do not need extreme speed, and they might perceive it as over-provisioning, which does not justify the additional costs. Finally, consumers tend to dislike products that have allowance caps. Consumers often view data caps or allowances as restrictive and inconvenient, particularly if they lead to overage charges or reduced speeds after exceeding the cap. This perception can decrease the attractiveness of capped plans compared with unlimited plans, even if they are priced similarly. The marginal cost estimation shows that the downstream product and high-speed features strongly increase marginal costs. However, upstream products tend to decrease marginal costs, which consumers typically value less. High-speed broadband requires more advanced infrastructure, such as fiber optics, and higher operational costs to maintain quality (e.g., reducing congestion). This finding is consistent with the marginal cost increase for providers that offer higher speeds.

Table 3: Estimation Results for Demand and Marginal Cost

	Demand ($\log(\tilde{s}_j/\tilde{s}_0)$)		Marginal Cost ($\log(cm_j)$)
	OLS	**2SLS**	**OLS**
Intercept	0.598^{***}	-	-
	(0.044)		
Price (100 $)	-0.259^{***}	-2.754^{***}	-
	(0.041)	(0.569)	
Within Share (ρ)	0.921^{***}	0.646^{***}	-
	(0.006)	(0.059)	
Upstream (in Gbps)	-0.549^{***}	0.331	-0.296^{***}
	(0.069)	(0.276)	(0.050)
Upstream^2	0.012^{**}	-0.071^{***}	0.008
	(0.004)	(0.013)	(0.004)
Downstream (in Gbps)	0.900^{***}	0.873^{*}	0.566^{***}
	(0.073)	(0.355)	(0.053)
Downstream^2	-0.038^{***}	-0.040^{**}	-0.024
	(0.003)	(0.015)	(0.002)
With Allowance	-0.021	-0.266^{*}	-0.024
	(0.024)	(0.109)	(0.018)
High Speed	0.295^{***}	0.061	0.166^{***}
	(0.028)	(0.097)	(0.0161)
Observation	2595	2595	2595
R^2	0.928	0.687	0.558
State Fixed Effect	No	Yes	Yes
Year Fixed Effect	No	Yes	Yes
Provider × Product Fixed Effect	No	Yes	Yes
% of Negative Implied Marginal Costs	-	-	0.000

5.1.1 Model Prediction and Elasticities

Table 4 presents the distribution of the observed and predicted market shares.

The model's predicted mean market share is 0.139, which closely aligns with the observed mean of 0.132, indicating that it accurately captures the central tendency of the data. However, the predicted standard deviation (0.234) exceeds the observed standard deviation (0.178), suggesting that the model accounted for considerable variability. The predicted maximum market share (0.962) is slightly higher than the observed maximum (0.841). Overall, the predicted market share is consistent with the observed data, reflecting the robustness of the model.

Table 5 summarizes the distribution of own-price elasticities derived from the demand system

Table 4: Summary Statistics of Market Share

	Mean	Stand. Dev.	Min	Max
Data	0.132	0.178	0.000	0.841
Model prediction	0.139	0.234	0.000	0.962

estimation by income level and the overall sample. Income levels were categorized based on the median income percentiles as follows: low-income states included those below the 33rd percentile, medium-income states included those between the 33rd and 67th percentiles, and high-income states included those above the 67th percentile.

Table 5: Own-Price Elasticities by Income Level

	Mean	Median	Stand. Dev.	Min	Max
Low income	-5.62	-5.49	3.17	-19.00	-0.10
Medium income	-6.05	-5.88	2.90	-15.10	-0.14
High income	-5.88	-5.73	2.84	-15.50	-0.06
Overall	-5.85	-5.73	2.98	-19.04	-0.06

On average, a 1% increase in prices results in a 5.85% decrease in demand *ceteris paribus*. Medium-income states tend to be more elastic to demand than are other income states.

These elasticities align with the findings for the broadband and related industries. For example, Kearns (2024) reports elasticities by income level as follows: -4.73 for low-income, -4.46 for middle-income, and -4.16 for high-income. Similarly, Goetz (2019) finds an average own-price elasticity of -5.9. In the Colombian broadband market, Hidalgo (2024) estimates an average elasticity of -4.6. In the cable industry, Crawford and Yurukoglu (2012) reports elasticities of -4.1 for cable and -5.4 for satellite services.

5.1.2 Markups

Table 6 presents the markups obtained nonparametrically from the demand system estimation. The table includes two types of markups: absolute markup, defined as the price charged to consumers minus the marginal cost, and relative markup as a percentage, defined as the absolute markup divided by the price charged to consumers.

Table 6: Markups by Income Level

	Absolute Markup				Relative Markup (in %)			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Low income	1.78	1.12	0.45	9.20	2.22	1.57	0.25	13.00
Medium income	2.70	2.18	0.53	11.50	3.27	2.91	0.44	19.20
High income	2.38	1.68	0.55	9.58	2.96	2.33	0.36	16.70
Overall	2.29	1.76	0.46	11.46	2.82	2.38	0.25	19.21

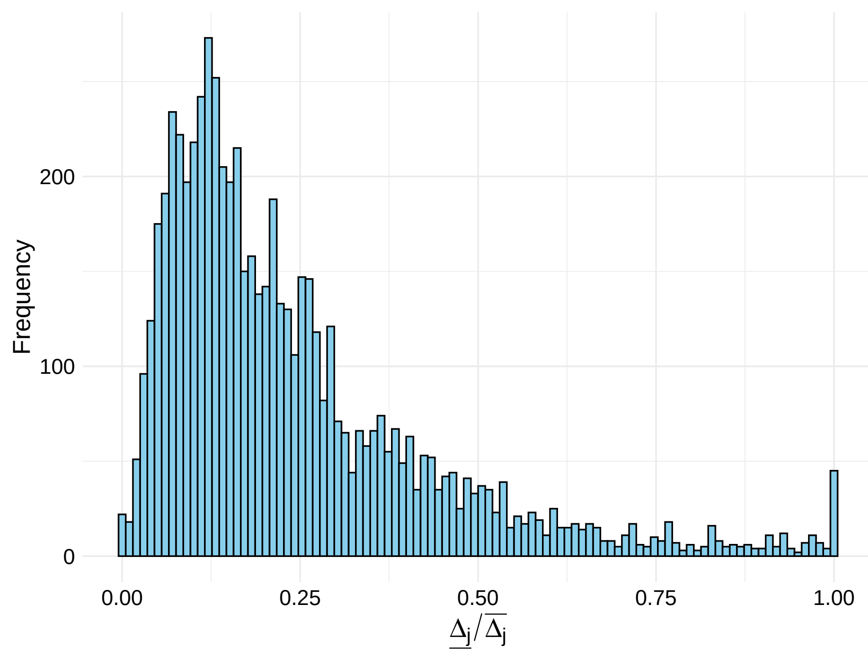
Note: Income levels are categorized as in Table 5.

In terms of absolute markups, medium-income states face the highest average absolute markup (2.70) and exhibit the highest variability (standard deviation: 2.18). In contrast, the low-income group experiences the lowest average markup (1.78) with the smallest variability (standard deviation: 1.12). Medium-income states also show the widest range of absolute markups, spanning from 0.53 to 11.50. For relative markups (percentages), the medium-income states again have the highest average (3.27%) and largest variability (standard deviation: 2.91%). Low-income states report the lowest mean relative markup (2.22%), whereas the maximum relative markup (19.20%) is observed in medium-income states. Overall, the mean absolute markup across all states is 2.29%. The mean relative markup is 2.82%. Medium-income states consistently face the highest markups, both absolute and relative, and exhibit high variability. These findings suggest that pricing strategies may disproportionately affect these states.

5.2 Product Offerings

Figure 6 presents the distribution of the cutoffs for the ratio of $\underline{\Delta}_j\left(X_{ji}\right)$ to $\overline{\Delta}_j\left(X_{ji}\right)$, which defines the moment inequalities in (24). The median of this ratio is approximately 0.183, and the distribution exhibits substantial variability. This variability is crucial for computing meaningful bounds on the fixed-cost estimates. It is important to note that these cutoffs are independent of the parameters; therefore, they are computed using the algorithm described in Appendix F.1 and saved for subsequent use. Additionally, I define W_i as a vector of discrete variables that represents whether the market is small, medium, or large. Similar to Fan and Yang (2024), this classification is based

Figure 6: Distribution of the ratio of cutoffs



on the quartiles of market size. Specifically, markets below the first quartile are classified as small, those between the first and third quartiles as medium, and those above the third quartile as large.

Table 7 presents the projected 95% confidence intervals for the estimated fixed costs, measured in millions of dollars and adjusted to 2023 dollars. In the broadband industry, typical fixed costs include expenses such as salary, rent, and insurance. The table reports these fixed cost estimates by market size category, along with the corresponding standard deviations for each category.[35]

Fixed costs increase with market size, highlighting the influence of market size on fixed-cost structures. Small markets exhibit fixed costs ranging from \$0.076 million to 1.254 million, likely owing to reduced operational scales or less stringent infrastructure requirements. Medium-sized markets, with a broader range of fixed costs (\$0.970-3.006 million), indicate the intermediate levels of investment necessary to serve a larger consumer base while managing moderate operational complexities. Large markets, which have the highest fixed costs (\$1.788-6.258 million), reflect the need for significant infrastructure, distribution networks, and regulatory compliance to meet the demands of a large consumer base.

[35]The fixed cost estimates are consistent with those presented in https://businessplan-templates.com/blogs/running-costs/internet-service-provider

Table 7: Estimates of Fixed Costs: Projected 95% Confidence Intervals

	CI-LB	CI-UB
Market size (θ)		
Small market	0.490	1.254
Medium market	0.970	3.006
Large market	1.788	6.258
Market-size specific Stand. Dev (σ_ζ)		
Small market	1.142	1.156
Medium market	2.156	2.995
Large market	0.354	4.990

Note: (1) All estimates are expressed in millions of USD, adjusted to 2023 prices; (2) CI-LB and CI-UB represent the confidence interval lower and upper bound, respectively.

Table 7 also reports the standard deviations specific to market sizes. For small markets, the standard deviation is between \$1.142 million and \$1.156 million. Medium markets display a broader range of standard deviations, from \$2.156 million to \$3.995 million, whereas large markets exhibit standard deviations ranging from \$0.354 million to \$4.990 million. These variations indicate differing levels of fixed cost dispersion depending on market size, with larger markets experiencing greater variability owing to the complexity of operations and scale.

6 Counterfactual Policy Analysis

Building on the estimated structural model, I conduct counterfactual policy simulations that align with the stated objectives of federal initiatives. This section begins by outlining the design of the counterfactual scenarios and explaining how they are incorporated into the model. I then present the simulation results and discuss their implications for market outcomes and policy effectiveness.

6.1 Counterfactual Policy Designs

In this section, I present the policy frameworks of the two principal federal subsidy programs for the broadband industry as delineated in the 2021 Biden Infrastructure Act[36]: the ACP and BEAD Program. These initiatives address distinct aspects of the broadband market, demand, and supply, and serve as the foundation for counterfactual simulations designed to evaluate their prospective impact. The ACP seeks to enhance broadband affordability for households through direct subsidies,

[36] https://www.congress.gov/bill/117th-congress/house-bill/3684

whereas the BEAD program aims to expand infrastructure deployment in underserved and unserved areas. The overarching aim is to ensure reliable, affordable, and high-speed broadband access across the United States.

Below, I present the institutional details of each program and explain how I incorporate them into the model to evaluate their effects on equilibrium outcomes, such as prices, welfare,firm entry, and product variety.

6.1.1 Affordable Connectivity Program

The ACP aimed to improve broadband affordability for low-income households by subsidizing the demand. Eligible households receive a monthly discount of up to $30 on broadband bills. They are also eligible for a one-time discount of up to $100 toward the purchase of a device, such as a laptop or tablet, provided they contribute between $10 and $50 toward the cost.

A household qualifies for ACP if its income is at or below a certain threshold as defined in the Federal Poverty Guidelines, or if a member of the household participates in certain federal or state assistance programs, such as Medicaid, Federal Public Housing Assistance, or tribal-specific programs, or meets the eligibility criteria for a participating broadband provider's low-income plan.[37] To enroll, households must confirm their eligibility by contacting the FCC, either by phone or email. Furthermore, participating providers must allow recipient households to apply the affordable connectivity benefit to any of their internet service offerings and may not require the households to submit to a credit check to apply the benefit. Such providers must also conduct public awareness campaigns in service areas to highlight the existence of the program and the value and benefits of broadband.

Given the data limitations, it is nearly impossible to account for all the components of program eligibility. To replicate ACP in my model, I proceed as follows: First, I use the poverty rate in each market as a proxy for ACP eligibility. Although this measure reflects a stricter income threshold, it offers a conservative and consistent approximation of the share of low-income households at market level. Second, I model subsidized prices through a price discrimination scheme that reduces broadband prices by $30 for households below the poverty line, while keeping prices unchanged for those above it. Then, I simulate the impact of these subsidized prices and assess their effects on

[37] https://docs.fcc.gov/public/attachments/DOC-380259A1.pdf

various equilibrium outcomes.

6.1.2 Broadband Equity, Access, and Deployment Program

Supply-side interventions under the BEAD Program were introduced as part of the IIJA. The primary objective of the program is to incentivize broadband deployment, particularly in underserved (lacking access to 100/20 Mbps) or unserved (lacking access to 25/3 Mbps) areas. The National Telecommunications and Information Administration (NTIA) is responsible for classifying these areas within each state and defining them as locations without adequate broadband access. Based on this assessment, funds were allocated to the states in proportion to the number of underserved and unserved locations. All U.S. states, the District of Columbia, Puerto Rico, American Samoa, Guam, U.S. The Virgin Islands and Commonwealth of the Northern Mariana Islands are eligible entities under the BEAD program and may be applied for funding.

An eligible entity is responsible for distributing funds to ISPs. Although the program's design has been finalized, its implementation is yet to begin.[38] Applicants seeking BEAD program funding must have submitted a Letter of Intent and met the requirements outlined in the Qualification Application. These include certifying compliance with applicable laws and demonstrating sufficient financial and managerial capacities. BEAD program funds are disbursed on a reimbursement basis, which means that subgrantees must initially cover project costs and submit appropriate documentation for reimbursement. The grant can cover up to 75% of eligible project costs, requiring a minimum 25% match from the subgrantee.[39]

Eligible Entities are also encouraged to secure matching contributions exceeding 25% from ISPs wherever feasible to reduce the federal share and extend the impact of BEAD program funding.

To replicate the expected impact of the program, I implement a counterfactual experiment that simulates a subsidy scheme aimed at reducing firms' fixed costs by 75%. I then look for the optimal subsidy level via different cost-sharing rules, such as a reduction in fixed costs by 25% and 50%, among others. This experiment enables an evaluation of the potential effects of the BEAD program on key equilibrium outcomes, including welfare, prices, and market structure.

[38] https://www.ntia.gov/funding-programs/internet-all/broadband-equity-access-and-deployment-bead-program(timeline).

[39] See https://broadbandusa.ntia.doc.gov/sites/default/files (page 3).

6.2 Counterfactual Policy Results

To conduct the counterfactual simulation, I follow the approach outlined in Fan and Yang (2024) and draw fixed costs to ensure that the observed equilibrium constitutes a pure strategy Nash equilibrium. This step is necessary to guarantee that the baseline is comparable across all the counterfactual simulations. The procedure is implemented using Algorithm G.1. Once the fixed costs have been determined, Algorithm G.2 is applied to construct the bounds on the objects of interest.[40]

Demand versus supply-side interventions

Table 8: Effects of Supply Side Subsidies on Outcomes

	Baseline		BEAD		Change (%)	
	LB	UB	LB	UB	LB	UB
Social Surplus	69.517	89.534	71.869	93.723	3.388	4.686
Producer Surplus	0.446	0.891	0.427	0.884	−4.299	−0.786
Consumer Surplus	69.025	88.685	71.417	92.873	3.472	4.722
Average Price	60.295	83.876	71.065	86.718	3.384	17.855
Average Marginal Cost	60.032	83.423	70.795	86.266	3.408	17.949
Average Market Shares	0.097	0.107	0.0955	0.107	−1.404	0.000
Product Variety	0.428	0.478	0.482	0.558	12.561	16.736
Firm Entry	0.526	0.621	0.599	0.742	13.893	19.506

Note: (1) Surplus values are in USD billion; (2) Prices and costs are in USD per unit; (3) LB and UB refer to the lower and upper bounds; (4) I draw 100 fixed cost parameter vectors from the confidence region, compute equilibrium outcomes for each, and construct confidence intervals using the 2.5th and 97.5th percentiles across the parameter vectors.

Table 8 presents the simulation outcomes predicted for supply-side interventions in accordance with the BEAD program, which entails a 75% reduction in firm fixed costs. The findings suggest that such policy interventions stimulate significant market entry and product expansion: firm entry increases by 13.9%-19.5% and product variety grows by 12.6%-16.7%, reflecting heightened competition and expanded consumer choice. This shift in market structure leads to a reduction in the

[40] Due to the large number of providers grouped under "Other providers", I do not treat this aggregated category as a distinct player in the entry game in the counterfactual simulations. Furthermore, since "other providers" are present in all markets and their identities are unknown, I assume that players take the observed decision of this group as given. This assumption slightly simplifies the computational burden by reducing the number of potential Nash equilibria. A similar approach was adopted by Aguirregabiria et al. (2024).

average firm's market share and a decline in producer surplus, likely due to intensified competition. At the same time, the average marginal costs rise by 3.4%-17.9% as firms expand into higher-cost areas, consistent with the program's targeting of underserved and/or high-cost areas, and face increased demand for inputs, particularly skilled labor. These results are consistent with the documented labor constraints in broadband deployment. The 2023 Fiber Broadband Association report notes a significant shortage of skilled technicians.[41] Such shortages are likely to contribute to rising marginal costs under the BEAD program, as firms compete for limited labor to scale up deployment. Additionally, firms adjust their product portfolios by offering higher-quality services, typically at greater costs, in areas where such products were previously unavailable. These developments collectively contribute to an increase in average prices of 3.4%-17.8%. Despite the rise in prices, the overall social surplus improves by 3.4%-4.7%, primarily driven by gains in the consumer surplus. This reflects welfare gains from increased variety despite a moderate cost pass-through.

Table 9 presents the simulation outcomes predicted for the demand-side program, consistent with ACP, which provides direct financial assistance to consumers. The findings reveal notable improvements in welfare driven by simultaneous increases in both consumer and producer surplus.

Table 9: Effects of Demand Side Subsidies on Outcomes

	Baseline		ACP		Change (%)	
	LB	UB	LB	UB	LB	UB
Social Surplus	69.517	89.534	74.768	97.375	7.563	8.763
Producer Surplus	0.446	0.891	0.476	0.965	6.837	8.288
Consumer Surplus	69.025	88.685	74.247	96.456	7.561	8.753
Average Price	60.295	83.876	58.667	80.986	−3.437	−2.701
Average Marginal Cost	60.032	83.423	58.180	80.220	−3.842	−3.084
Average Market Shares	0.097	0.107	0.099	0.110	2.684	2.890
Product Variety	0.428	0.478	0.429	0.479	0.326	0.374
Firm Entry	0.526	0.621	0.526	0.624	0.000	0.504

Note: (1) Surplus values are in USD billion; (2) Prices and costs are in USD per unit; (3) LB and UB refer to the lower and upper bounds; (4) I draw 100 fixed cost parameter vectors from the confidence region, compute equilibrium outcomes for each, and construct confidence intervals using the 2.5th and 97.5th percentiles across the parameter vectors.

Specifically, the total social surplus rises by 7.6-8.8%, with the majority of gains accruing to

[41] See Fiber Deployment Annual Report 2023, last section on p. 10.

consumers, as consumer surplus increases by 7.6-8.8%. Producer surplus also improves modestly, by 6.8-8.3%, reflecting a more favorable market environment in which firms can benefit from increased demand without facing heightened competitive pressures. In contrast, the ACP, modeled as a $30 reduction in broadband prices for eligible households, leads to substantial welfare gains: social surplus increases by 7.6%-8.8%, producer surplus by 6.8%-8.3%, and consumer surplus by 7.5%-8.7%. However, its impact on the market structure is limited. The subsidy directly reduces the financial burden on consumers, resulting in a decrease in average prices by 2.7%-3.4% and marginal costs by 3.1%-3.8%, likely because of the more efficient utilization of existing capacity and reduced input intensity. While the average firm's market share expands by 4.7%-5.2%, firm entry remains virtually unchanged at 0.1%-0.6%, and product offerings show only a marginal growth of 0.3%-0.4%. These findings indicate that demand-side subsidy effectively boosts consumer and firm welfare by increasing demand. However, it fails to incentivize new firms to enter and induce them to introduce new products.

Supply-side subsidies promote market expansion and competition, reduce costs, and squeeze firm profits. Importantly, while supply-side BEAD subsidies achieve the goal of boosting competition and product offerings, they also generate unintended cost pressures, increasing marginal costs and prices, a result that contrasts with standard expectations from increased market competition. This finding underscores the importance of accounting for input market friction and capacity constraints when designing broadband subsidy policies.

Demand-side subsidies increase prices and demand but do not alter the market structure. The choice between these policies depends on whether policymakers prioritize market growth, competition, or direct consumer benefits.

Table 10: Effects on Outcomes at Different BEAD Intensities

	Baseline		BEAD 25% fixed-cost subsidy				BEAD 50% fixed-cost subsidy				BEAD 75% fixed-cost subsidy			
	Level		Level		Change (%)		Level		Change (%)		Level		Change (%)	
	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB	LB	UB
Social Surplus	69.517	89.534	70.149	91.442	0.909	2.131	70.902	92.493	1.992	3.306	71.869	93.723	3.388	4.686
Producer Surplus	0.446	0.891	0.438	0.892	−1.923	0.101	0.432	0.886	−3.260	−0.591	0.427	0.884	−4.299	−0.786
Consumer Surplus	69.025	88.685	69.672	90.587	0.938	2.145	70.434	91.649	2.042	3.341	71.417	92.873	3.472	4.722
Average Price	60.295	83.876	65.404	84.570	0.828	8.472	68.643	85.115	1.478	13.844	71.065	86.718	3.384	17.855
Average Marginal Cost	60.032	83.423	65.101	84.128	0.845	8.444	68.359	84.682	1.510	13.871	70.795	86.266	3.408	17.949
Average Market Shares	0.097	0.107	0.097	0.107	−0.012	−0.123	0.097	0.107	−0.176	0.139	0.096	0.107	−1.404	0.000
Product Variety	0.428	0.478	0.436	0.505	2.022	5.711	0.452	0.528	5.776	10.617	0.482	0.558	12.561	16.736
Firm Entry	0.526	0.621	0.532	0.668	1.205	7.484	0.556	0.701	5.794	12.900	0.599	0.742	13.893	19.506

Note: (1) Surplus values are in USD billion; (2) Prices and costs are in USD per unit; (3) LB and UB refer to lower and upper bounds; (4) I draw 100 fixed cost parameter vectors from the confidence region, compute equilibrium outcomes for each, and construct confidence intervals using the 2.5 and 97.5 percentiles across parameter vectors.

7 Cost-Benefit Analysis

To make welfare results more actionable for policymakers, I complement the structural analysis with a simple cost–benefit analysis. Using the estimated welfare changes (in billions of dollars) as the benefits and program spending as the costs, I compute the benefit-cost ratios (BCR). Specifically, for each program, I compute the BCR as

$$\text{BCR} = \frac{\text{Total Welfare Gains}}{\text{Program Expenditure}},$$

where Total Welfare Gains denotes the change in total surplus, defined as the sum of consumer and producer surpluses relative to the no-subsidy baseline, and Program Expenditure represents the total fiscal cost of the subsidy program, calculated as the sum of payments made under the policy.[42]

To calculate the ACP cost, I multiply the \$30 subsidy by the number of eligible subscribers in the dataset. For the BEAD program, I compute the total cost using the distribution of firms' fixed costs using (16) over a grid of 100 fixed-cost values based on the estimates reported in Table 7. The bounds are then computed by taking the minimum and maximum values across the implied grid of 100 total fixed costs. The program cost is obtained by multiplying these bounds by the corresponding subsidy rates of 25%, 50%, and 75%. Importantly, the BEAD program is a one-time investment that generates a stream of benefits over a long horizon and must be incorporated into the computation of the BCR.[43]

Table 11 presents the annual cost–benefit analysis (CBA) of the ACP and BEAD programs. The results highlight a clear contrast between demand- and supply-side subsidies. For ACP, the BCR ranges from 1.28 to 1.91, indicating that affordability subsidies deliver welfare gains above their costs, although the magnitude remains modest. In contrast, the BEAD program yields far greater fiscal returns. At a 25% subsidy rate, the BCR ranges from 6.70 to 10.70, and at 50% it remains strong at 7.34–8.30. At 75%, while absolute welfare gains continue to rise, the BCR stabilizes

[42] I limit the Program Expenditure costs that can be captured within the model, recognizing that it is nearly impossible to account for all relevant costs, such as administrative expenses, monitoring and compliance costs, or indirect fiscal effects, which lie outside the scope of the structural framework.

[43] I adopt a time horizon of $T = 25$, following Grunvalds et al. (2017), which supports a 25-year "industry-accepted" lifetime. For the discount rate, I consider a range consistent with U.S. federal guidelines provided in the OMB Circular A-4. Furthermore, I do not take into account dynamic adjustments (e.g., depreciation of infrastructure, technology upgrades, shifts in demand.

at around 7.83–8.31, reflecting the diminishing efficiency of additional subsidies. This suggests that most welfare improvements can be achieved at moderate subsidy levels (25–50%), with higher intensities offering lower incremental returns relative to the cost. From a policy perspective, these findings suggest that ACP plays a useful role in improving household affordability, whereas BEAD is more cost effective for long-term digital inclusion. Moreover, the evidence points to an optimal range for BEAD subsidies at 25–50%, where welfare gains are maximized relative to fiscal costs. Appendix I examines the sensitivity of the results to alternative discount rates and time horizons, showing findings that are broadly consistent with the recommended optimal range.

Table 11: Annual Cost-Benefit Analysis of ACP and BEAD Programs

		ΔSocial Surplus (Billion $)		Program Cost (Billion $)		BCR	
Program	Subsidy level	LB	UB	LB	UB	LB	UB
ACP	$30/month household subsidy	5.251	7.841	4.103	4.103	1.280	1.911
BEAD	25% fixed-cost subsidy	11.005	33.224	1.003	2.427	6.697	10.704
BEAD	50% fixed-cost subsidy	24.117	51.526	2.006	4.854	7.338	8.300
BEAD	75% fixed-cost subsidy	40.956	72.944	3.009	8.381	7.834	8.308

Notes: (1) LB and UB denote lower and upper bounds, respectively. (2) Annual welfare gains are $0.632–1.908 (25%), $1.385–2.959 (50%), and $2.352–4.189 (75%) billion. (3) Welfare gains are discounted over a 25-year horizon based on Grunvalds et al. (2017), whereas program costs are incurred upfront. (4) The discount rate is set to $\delta = 3$, which follows OMB Circular A-4 (2023). (5) The Benefit–Cost Ratio (BCR) is computed as discounted benefits divided by discounted costs at each rate.

8 Concluding Remarks

This paper examines the impact of subsidies on consumer welfare and the market structure in the U.S. broadband industry, focusing on two types of interventions introduced by Congress in 2021: demand-side subsidies targeting consumers and supply-side programs aimed at providers. These interventions primarily seek to enhance consumer accessibility and support the development of broadband infrastructure.

Using a difference-in-differences design with continuous treatment intensity, I analyze how broadband prices and service quality evolve across states with different levels of exposure to federal broadband subsidies. The reduced-form evidence indicates that states receiving higher per-capita allocations experience relative declines in prices and improvements in product quality following the policy announcement. Reduced-form analyses are valuable because they enable credible causal inference on policy exposure and shed light on the timing and persistence of program effects on key outcomes such as prices and quality. However, they are inherently limited in their ability to uncover underlying behavioral mechanisms or to evaluate counterfactual policy designs. To overcome these limitations, I estimate a structural model of a two-stage game in which firms first choose their product portfolios and then compete in prices. Demand elasticities, markups, and marginal costs are recovered from the demand system following Berry (1994). The supply-side estimation of product offerings and entry builds on Fan and Yang (2024), which is well suited to settings with many firms and rich product choice sets.

The results from the structural model estimation reveal that consumers dislike higher prices, tend to prefer faster download speeds up to a certain threshold, and generally avoid products with data caps. On the supply side, marginal costs increase significantly with downstream speed and high-performance features, reflecting infrastructure and quality maintenance costs. Furthermore, fixed costs increase with market size. After validating the model using industry evidence, I use the estimated parameters to simulate policy-relevant counterfactual scenarios and assess the effects of subsidy programs on key equilibrium outcomes. The findings suggest that a supply-side subsidy, modeled as a reduction in firms' average fixed costs, promotes market expansion by increasing firm entry and product variety. Conversely, demand-side subsidies reduce prices and stimulate demand but have a minimal impact on market structure. Overall, consumer surplus gains are significantly larger under demand-side subsidies than under supply-side interventions. Consumer-side subsidies deliver immediate and cost-effective affordability gains, whereas infrastructure subsidies reshape market competition to generate long-term efficiency, albeit at higher fiscal costs.

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Appendix

A Data Construction

A.1 Urban Rate Survey

The primary data source is the Urban Rate Survey (URS), which is obtained from the following link: https://www.fcc.gov/economics-analytics/industry-analysis-division/urban-rate-survey-data-resources. The dataset spans 2014 to 2024, with each release referring to the previous calendar year (i.e., 2013 to 2023). For each year, I extracted the state identifier, technology type, presence of a data cap, provider name, average upload and download speeds, price (as captured by the *TotalCharge* variable), and the corresponding plan availability weight. I harmonize provider names to account for subsidiaries operating under different labels. Using the *Technology* variable, broadband products are classified into four categories: DSL, fixed wireless, cable, and fiber optics. Finally, I aggregated the data at the state–year–provider–product level.

A.2 FCC Deployment Data

I collected data from the FCC's Form 477 deployment dataset for the years 2014 to 2023, available at: https://broadband477map.fcc.gov/#/data-download. I begin by retaining broadband plans intended for household use. For each year, I extracted the state, provider name, DBA name, maximum advertised download and upload speeds, and technology code. I then computed the average download and upload speeds at the state-provider-DBA-technology level. Using the *technology code* variable, broadband products are classified into four categories: DSL (codes 20 to 29), fixed wireless (code 60), cable (codes 40 to 43), and fiber optics (code 50). Finally, I focus on the top 19 providers (including subsidiaries), which include Comcast, Charter, Frontier, CenturyLink, Verizon, Cable One, Inc., Consolidated Communications, GCI Communication Corp., Hawaiian Telcom, Inc., Mediacom, Midcontinent Communications, New England, Puerto Rico, Starpower Communications, Suddenlink Communications, CSC Holdings LLC, Time Warner, and a residual "Other" category.

A.3 American Community Survey

I extracted data from the American Community Survey (ACS) for 2014 to 2023, available at: https://www.census.gov/programs-surveys/acs. The key variables include the following:

- B25001: Total number of housing units
- B01002: Median age
- S1903: Median household income
- S1701: Poverty rate
- S2801: Broadband subscription rate
- S0801: Home workability in 2020

For each variable, I used 5-year estimates when available. In years in which the 5-year estimates are not published, I rely on the corresponding 1-year estimates. The final dataset was aggregated at the state–year level.

A.4 Final Dataset

First, I estimate the market share of each provider in the dataset, assuming that plan availability in the Urban Rate Survey (URS) is proportional to the number of broadband subscribers reported in the American Community Survey (ACS). Providers with market shares below 1% are grouped into the residual "Other" category. This yields a set of the top 20 providers (including subsidiaries), which includes: Comcast, Charter, Frontier, CenturyLink, Verizon, Cable One, Inc., Consolidated Communications, GCI Communication Corp., Hawaiian Telcom, Inc., Mediacom, Midcontinent Communications, New England, Puerto Rico, Starpower Communications, Suddenlink Communications, CSC Holdings LLC, Time Warner, and "Other." To mitigate the influence of extreme values on the price variable, I winsorize prices at the 1st and 99th percentiles, replacing observations below the 1st percentile and above the 99th percentile with the respective cutoff values. All prices are then adjusted for inflation and expressed in 2023 dollars using the Consumer Price Index (CPI) from the U.S. Bureau of Labor Statistics, available at: https://data.bls.gov/pdq/SurveyOutputServlet. Finally, all data sources were merged to construct a comprehensive panel dataset at the state, year, provider, and product levels.

B Broadband Products

Figure 7: Differentiated products

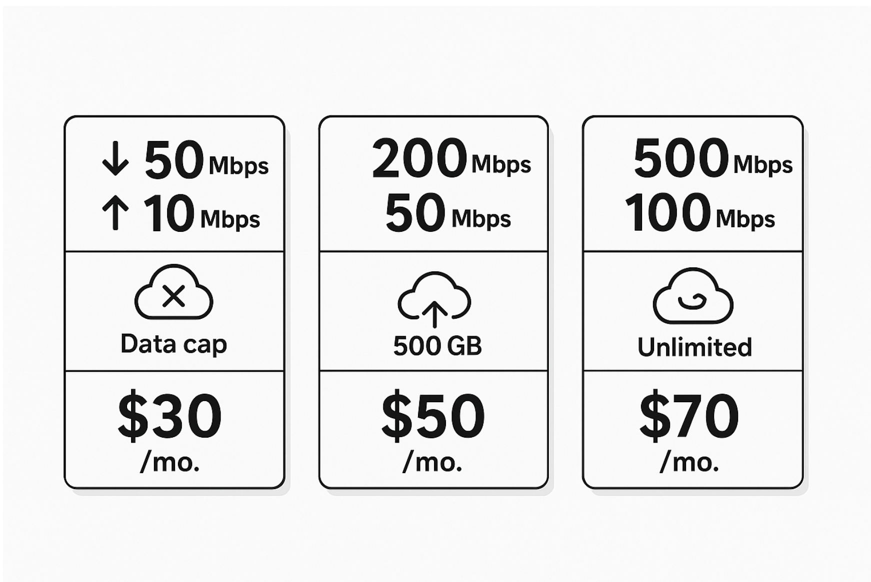
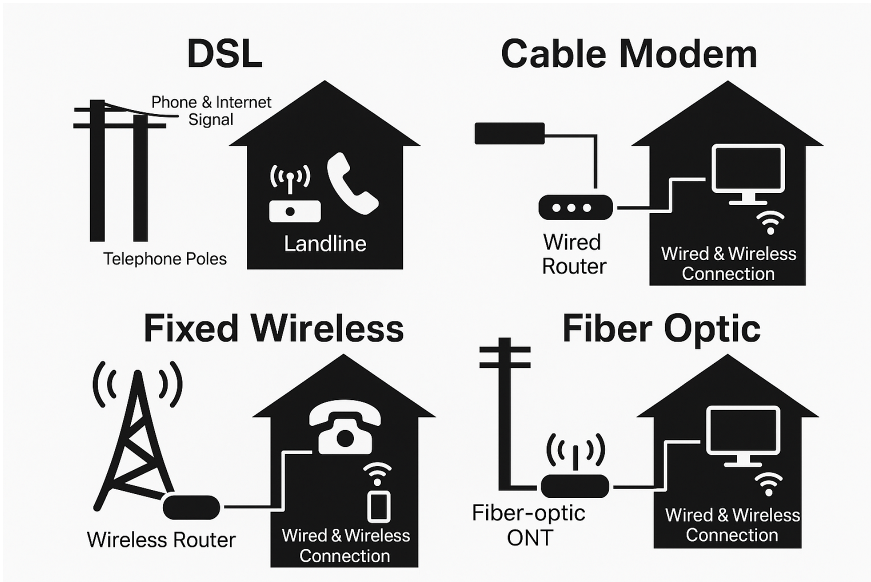


Figure 8: Broadband Products



C Proofs

Proposition 1

Proof: Let $\Delta_j r_{fi}\left(Y_{-ji}\right) = r_{fi}\left(Y_{ji}=1, Y_{-ji}\right) - r_{fi}\left(Y_{ji}=0, Y_{-ji}\right)$ be the difference in the firm f' variable profit when the product Y_{ji} turns from $Y_{ji}=1$ to $Y_{ji}=0$, where $\Delta_j r_{fi}\left(Y_{-ji}\right) = r_{fi}\left(Y_{ji}=1, Y_{-ji}\right) - r_{fi}\left(Y_{ji}=0, Y_{-ji}\right)$, and Y_{-ji} represents the observed decision in market i of other products, except for firm f's product j.

Under Assumption 2, the necessary conditions for the observed decision Y_i to be an equilibrium can be written as follows

$$Y_{ji} = 1 \implies \Delta_j \pi_{if}\left(X_{ji}\right) > 0 \tag{30}$$

If $Y_{ji} = 1$, then (30) implies that

$$\zeta < \frac{\Delta_j r_{fi}\left(Y_{-ji}\right) - W_i \theta}{\sigma_\zeta} \tag{31}$$

$$Y_{ji} = 0 \implies \Delta_j \pi_{if}\left(X_{ji}\right) \leq 0 \tag{32}$$

If $Y_{ji} = 0$, then (32) implies that

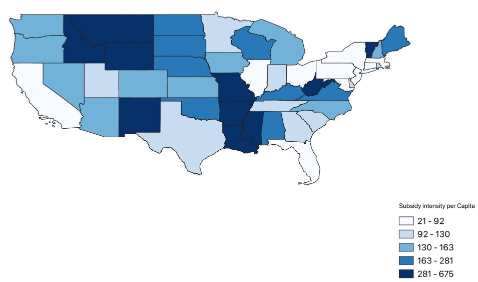
$$\zeta \geq \frac{\Delta_j r_{fi}\left(Y_{-ji}\right) - W_i\theta}{\sigma_\zeta} \tag{33}$$

$\square$

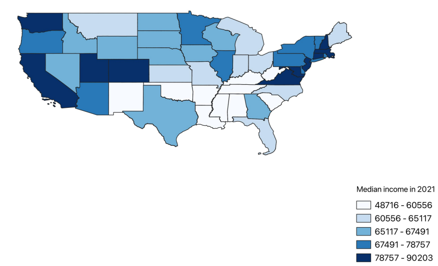
D Difference-in-Differences Design with Continuous Treatment

Figure 9: Spatial distribution of key state-level characteristics in 2020 (pre-intervention)

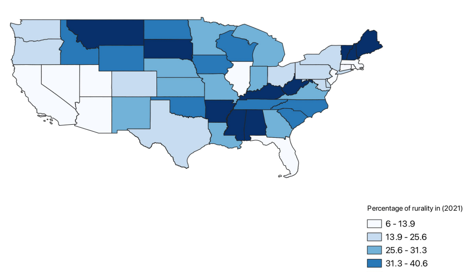
(a) Panel A: Subsidy per capita (2021)



(b) Panel B: Housing units per km^2 (2020)



(c) Panel C: Median income (2020)



(d) Panel D: Percentage of Rurality (2020)

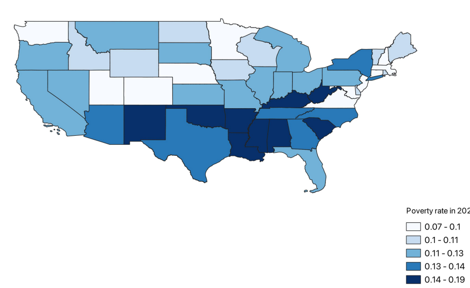
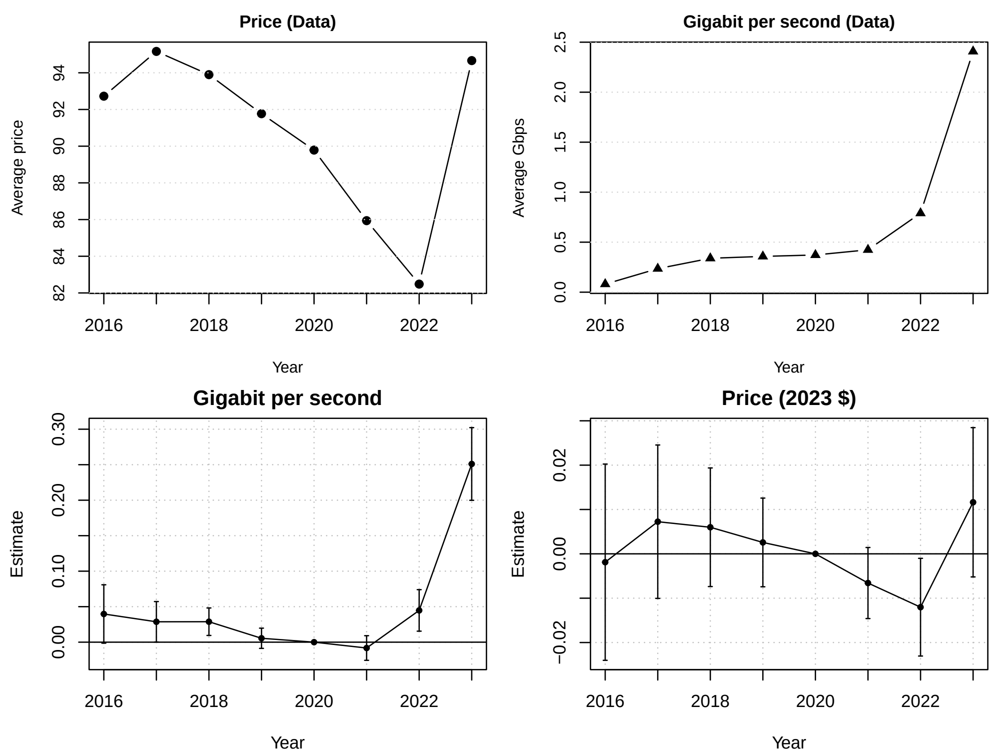
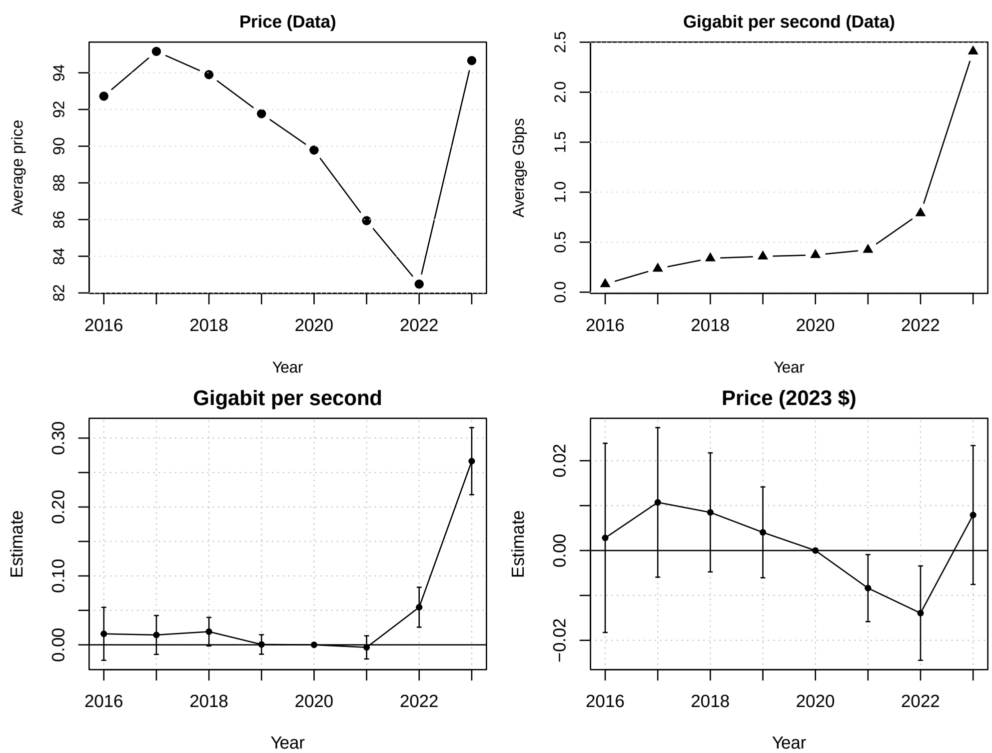


Figure 10: DiD with Continuous Treatment without covariates



Note: The first two rows of the figure display the data: the average price (in 2023 dollars) and average speed (in gigabits per second). The last row shows the corresponding estimates generated by the model in (1) without X_i.

Figure 11: DiD with Continuous Treatment and excluding for the number of underserved areas



Note: The first two rows of the figure display the data: the average price (in 2023 dollars) and average speed (in gigabits per second). The last row shows the corresponding estimates generated by the model in (1) excluding for the number of underserved areas as covariate.

E Demand and Supply

E.1 First-stage IV regression (demand)

Table 12: First-Stage IV Regressions for Demand Estimation

	Nest $(\log(s_{j/g}))$	**Price** (p_{ij})
Upstream (in Gbps)	-2.509^{***}	-0.085
	(0.299)	(0.077)
Upstream^2	0.082^{***}	-0.002
	(0.015)	(0.003)
Downstream (in Gbps)	2.812^{***}	0.396^{***}
	(0.302)	(0.080)
Downstream^2	-0.112^{***}	-0.018^{***}
	(0.012)	(0.003)
With Allowance	-0.415^{***}	-0.030
	(0.088)	(0.019)
High Speed	0.318^{**}	0.105^{***}
	(0.094)	(0.014)
z1	0.064	0.015
	(0.045)	(0.010)
z2	$-0.081^{\cdot}$	-0.023^{*}
	(0.043)	(0.010)
z3	0.036^{**}	-0.007^{**}
	(0.011)	(0.002)
z5	-0.258^{***}	-
	(0.029)	
Observations	$2,595$	$2,595$
Adjusted R^2	0.608	0.476
Within R^2	0.218	0.343
State Fixed Effects	Yes	Yes
Provider Fixed Effects	Yes	Yes
Wald Test (Instruments)	$F(4,2514) = 40.9$, $p < 0.001$	$F(3,2515) = 28.2$, $p < 0.001$

Note: (1) z1, z2, z3, and z4 are the BLP instruments defined in Section 4.1. These instruments are constructed from, respectively, the Upstream, Downstream, and High-Speed indicators, and the average number of competing products. (2) This table reports the first-stage results for the endogenous variables p_{ij} and $\log(s_{j/g})$. Instruments include rival product characteristics (upstream, downstream, and high-speed indicators) and the average number of competing products, and the total number of products (excluding j) for $\log(s_{j/g})$. The F-statistics for joint instrument significance are 40.9 (nest equation) and 28.2 (price equation), both significant at $p < 0.001$, well above the usual weak-instrument threshold of 10. Given that the average number of products per market is relatively small ($J_i \approx 9$), these results suggest that BLP-type instruments are strong and appropriate for this setting.

E.2 Empirical Distributions

Figure 12: Predicted and Observed Market Shares

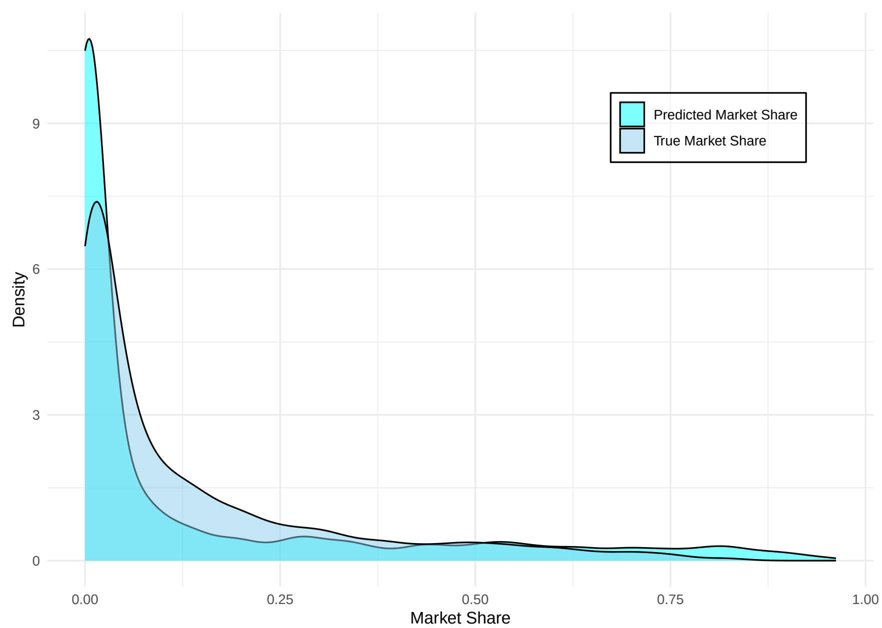


Figure 13: Density of Own Price Elasticities and Markup

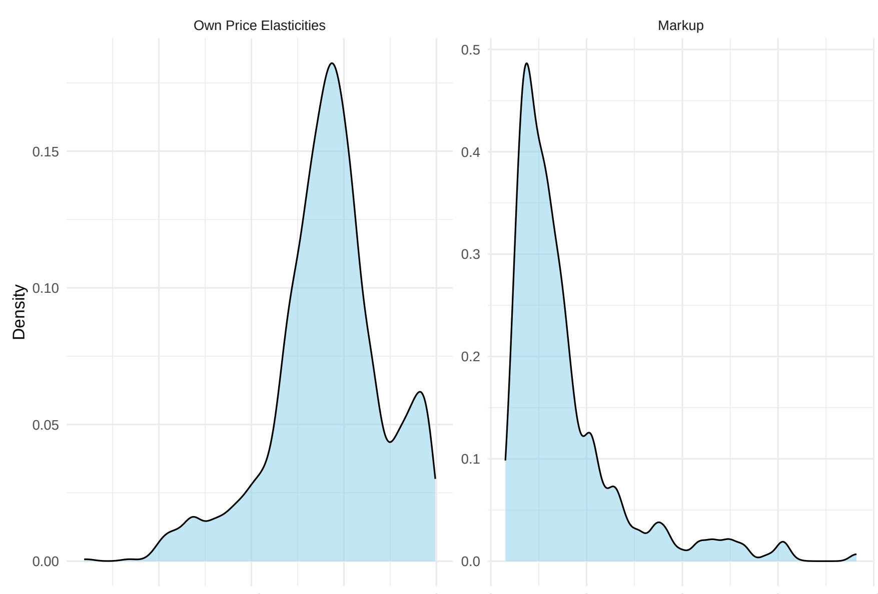
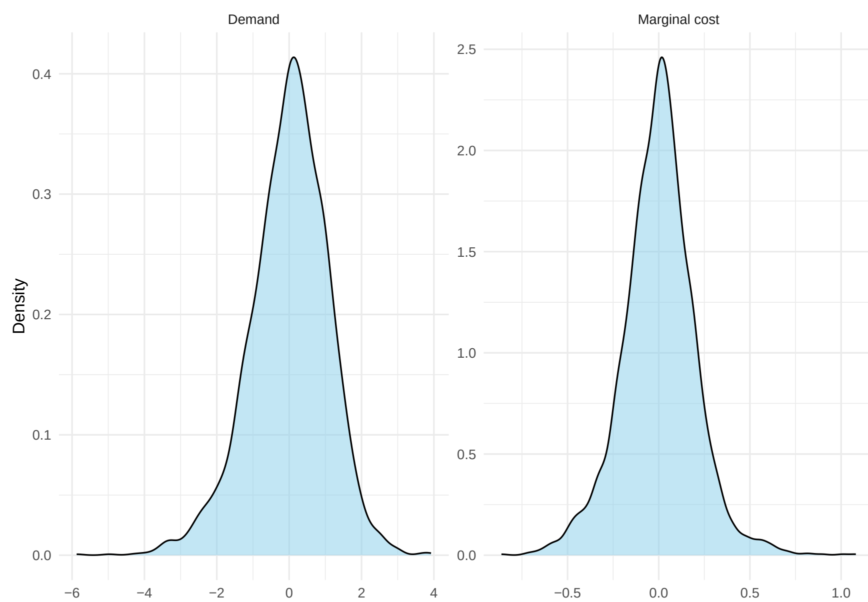


Figure 14: Distribution of Demand and Marginal Cost Shocks



F Product Offerings

F.1 Algorithm

Consider a product portfolio $Y_i \in \{0,1\}^{J_i}$

- **Step 1:** For each product j offered in market i i.e $Y_{ji} = 1$, draw $B = 100$ values from the empirical distribution of $\hat{\xi}_{ji}$ and $\hat{\eta}_{ji}$. Denote the values by $\{\hat{\xi}_{ji}^{(b)}, 1 \leq b \leq B\}$ and $\{\hat{\eta}_{ji}^{(b)}, 1 \leq b \leq B\}$.

- **Step 2:** For each b and for each j, compute the marginal costs, optimal prices, and market shares[44].

  (i) Compute the marginal cost $\hat{mc}_{ji}^{(b)}$ using (15).

  (ii) Compute the optimal prices $\hat{p}_i^{(b)}$ by solving the non linear (13)

[44] According to Nocke and Schutz (2018), a nonlinear pricing equation has a unique solution in the nested logit framework. To solve for the optimal price, I employed a fixed-point algorithm with a precision threshold of $\varepsilon = 10^{-12}$ and a maximum of 200 iterations. It is important to note that, for a single-product monopoly, the computation of the expected variable profit does not require this algorithm because the optimal price and corresponding market share can be directly determined.

(iii) Finally, compute the shares $\hat{s}_{ji}^{(b)}$ as follows

$$\hat{s}_{ji}^{(b)} = \frac{\exp\left(\hat{\delta}_{ji}^{(b)}/(1-\hat{\rho})\right)}{\left(D_g^{(b)}\right)^{\hat{\rho}}\left(\sum_{g'}\left(D_{g'}^{(b)}\right)^{1-\hat{\rho}}\right)}$$

where $D_g^{(b)} = \sum_{j\in\mathscr{J}_g}\exp\left(\hat{\delta}_{ji}^{(b)}/(1-\hat{\rho})\right)$, $\hat{\delta}_{ji}^{(b)} = X_{ji}\hat{\beta} + \hat{\alpha}\hat{p}_{ji}^{(b)} + \hat{\xi}_{ji}^{(b)}$ and $\mathscr{J}_g$ is the set of products belonging to group g.

- **Step 3:** Compute the variable profit for each firm f

$$\hat{r}_{if}(Y_i) = \frac{1}{B}\sum_{b=1}^{B}\sum_{j\in\mathscr{J}_{fi}} M_i Y_{ji}\left(\hat{p}_{ji}^{(b)} - \hat{cm}_{ji}^{(b)}\right)\hat{s}_{ji}^{(b)}$$

G Counterfactual

G.1 Fixed Cost Draw

- **Step 1:** For each product j of firm f, compute the change in its expected variable profit when product j enters market i

$$\Delta_j\left(Y_{-ji}, X_{ji}\right) = r_{fi}\left(Y_{ji}=1, Y_{-ji}, X_{ji}\right) - r_{fi}\left(Y_{ji}=0, Y_{-ji}, X_{ji}\right),$$

where,

Y_{-ji} is the observed decision, but product j. If $Y_{ji}=1$, define a range of $\left(-\infty, \Delta_j\left(Y_{-ji}, X_{ji}\right)\right)$.

Otherwise, $\left(\Delta_j\left(Y_{-ji}, X_{ji}\right), \infty\right)$

- **Step 2:** Simulate the draws of fixed costs for firm f from a truncated normal distribution with mean $W_{ji}\hat{\theta}$ and variance $\hat{\sigma}_{\zeta}^2$. The support for the truncated normal distribution is defined in Step 1. The draws satisfy necessary conditions for the observed Y_i to be an equilibrium

- **Step 3:** Compute $r_{fi}\left(Y_{fi}, Y_{-fi}\right)$, and the variable profit of firm f for each possible combination, $2^{|\mathscr{J}_{fi}|}-1$ (excluding the case where firm f offers no products), using Algorithm F.1, holding the observed decision Y_{-fi} of the other players fixed.

- **Step 4:** For each draw from Step 2, check whether the firm f's best response to Y_{-fi} is Y_{fi}. If so, keep the set of draws for firm f. Otherwise, return to Step 2 and redraw the fixed costs.
- **Step 5:** Repeat the process for every firm

G.2 Simulation

Consider a product portfolio $Y_i \in \{0,1\}^{J_i}$

- **Step 1:** Compute the expected equilibrium variable profits for each firm $f \in \mathscr{F}$ and for each $Y_i \in \mathscr{Y}_i$. This requires using Algorithm F.1 for all possible $2^{|\mathscr{J}_i|} - 1$ market structure combinations, excluding the case in which there is no player in the market. Store the relevant equilibrium outcomes, such as variable profit, welfare, prices, and shares.

- **Step 2:** Use the simulated fixed cost draws from Algorithm G.1 and find the market structure where the following entry decision holds for every firm $f \in \mathscr{F}$

$$r_{fi}(Y_i) - \sum_{j \in \mathscr{J}_{fi}} Y_{ji} \cdot \mathrm{FC}_{ji}(\theta) \geq 0 \tag{34}$$

  Denote the set of market structure for which (34) holds as $\mathscr{Y}_i^2 \subseteq \mathscr{Y}_i$

- **Step 3:** For each firm f and for each $Y_i = \left(Y_{fi}, Y_{-fi}\right) \in \mathscr{Y}_i^2$, find the most profitable product assortment Y_{fi} while holding competitors' Y_{-fi} fixed. Denote the set of product assortments as $\mathscr{Y}_i^3 \subseteq \mathscr{Y}_i^2$. The set of product assortments $\mathscr{Y}_i^3$ contains all Nash equilibria in which any deviation is not profitable.

  This set typically includes the observed decision, as the fixed cost draws are made to ensure that the observed decision is a Nash equilibrium.

- **Step 4:** Construct the bound of the equilibrium object of interest by finding min and max across the $\mathscr{Y}_i^3$

H Two-step Inference Procedure

The following two-step procedure allows for the computation of the critical value, as proposed in Section 4.1.2. on page 1880 Chernozhukov et al. (2019).

- **Step 1:** Let $1 < \beta < \alpha/2$ be a tuning parameter and $\Phi(\cdot)$ be the cumulative distribution function of the standard normal distribution. Define

$$\hat{k}_n = \sum_{l=1}^{k} \mathrm{I}\left\{ \frac{\sqrt{n}\bar{m}_{n,l}\left(\theta, \sigma_\zeta\right)}{\hat{\sigma}_{n,l}\left(\theta, \sigma\right)} > -2\hat{c}_{n,k}\left(1-\beta; \theta, \sigma_\zeta\right) \right\}, \tag{35}$$

  where

$$\hat{c}_{n,k}\left(1-\beta; \theta, \sigma_\zeta\right) = \left(\frac{\Phi^{-1}\left(1-\beta/k\right)}{\sqrt{1-\Phi^{-1}\left(1-\beta/k\right)^2/n}} \right). \tag{36}$$

- **Step 2:** Define the critical value of the test as

$$\hat{c}_n\left(1-\alpha; \theta, \sigma_\zeta\right) = \left(\frac{\Phi^{-1}\left(1-\left(\alpha-2\beta\right)/\hat{k}_n\right)}{\sqrt{1-\Phi^{-1}\left(1-\left(\alpha-2\beta\right)/\hat{k}_n\right)^2/n}} \right). \tag{37}$$

Following the recommendation in Chernozhukov et al. (2019), I set the tuning parameter to $\beta = \alpha/50$ with $\alpha = 0.05$ (see Section 6.1 in Chernozhukov et al. (2019)).

Once the critical value $\hat{c}n\left(1-\alpha; \theta, \sigma\zeta\right)$ is obtained, I begin by considering a wide range of possible values for the parameter pair $\left(\theta, \sigma_\zeta\right)$. This initial set is then refined by excluding inconsistent values, that is, points rejected by the test statistic. From the remaining admissible region, I construct a fine grid of 10,000 points for $\left(\theta, \sigma_\zeta\right)$, with each parameter taking 100 evenly spaced values. Finally, I identify the grid points that satisfy (29) corresponding to the parameter combinations that are not rejected under the null hypothesis.

I Sensibility for Cost-Benefit Analysis

Table 13: Cost-Benefit Analysis of BEAD Program under Alternative Discount Rates (25-Year Horizon)

		ΔSocial Welfare (Billion $)		Program Cost (Billion $)		CBR	
Discount rate	Program	LB	UB	LB	UB	LB	UB
BEAD at 25% fixed-cost subsidy							
$\delta = 0.02$		12.339	37.251	1.643	3.104	7.509	12.001
$\delta = 0.03$		11.005	33.224	1.643	3.104	6.697	10.704
$\delta = 0.05$		8.907	26.891	1.643	3.104	5.421	8.664
$\delta = 0.07$		7.365	22.235	1.643	3.104	4.482	7.164
BEAD at 50% fixed-cost subsidy							
$\delta = 0.02$		27.040	57.770	3.287	6.208	8.227	9.306
$\delta = 0.03$		24.117	51.526	3.287	6.208	7.338	8.300
$\delta = 0.05$		19.520	41.704	3.287	6.208	5.939	6.718
$\delta = 0.07$		16.140	34.483	3.287	6.208	4.911	5.555
BEAD at 75% fixed-cost subsidy							
$\delta = 0.02$		45.919	81.784	4.930	9.312	9.315	8.783
$\delta = 0.03$		40.956	72.944	4.930	9.312	8.308	7.834
$\delta = 0.05$		33.149	59.040	4.930	9.312	6.724	6.340
$\delta = 0.07$		27.409	48.817	4.930	9.312	5.243	5.560

Notes: (1) LB and UB denote lower and upper bounds, respectively. (2) Annual welfare gains are $0.632–1.908 (25%), $1.385–2.959 (50%), and $2.352–4.189 (75%) billion. (3) Welfare gains are discounted over a 25-year horizon, while program costs are incurred upfront. (4) Discount rates follow OMB Circular A-4 (2023). (5) The Benefit–Cost Ratio (BCR) is computed as discounted benefits divided by discounted costs at each rate.

Table 14: Cost-Benefit Analysis of BEAD Program under Alternative Discount Rates (30-Year Horizon)

		ΔSocial Welfare (Billion $)		Program Cost (Billion $)		CBR	
Discount rate	Program	LB	UB	LB	UB	LB	UB
BEAD at 25% fixed-cost subsidy							
$\delta = 0.02$		14.155	42.732	1.643	3.104	8.614	13.767
$\delta = 0.03$		12.387	37.398	1.643	3.104	7.538	12.049
$\delta = 0.05$		9.715	29.331	1.643	3.104	5.912	9.450
$\delta = 0.07$		7.843	23.676	1.643	3.104	4.772	7.628
BEAD at 50% fixed-cost subsidy							
$\delta = 0.02$		31.019	66.271	3.287	6.208	9.438	10.676
$\delta = 0.03$		27.147	57.998	3.287	6.208	8.260	9.343
$\delta = 0.05$		21.291	45.487	3.287	6.208	6.478	7.327
$\delta = 0.07$		17.187	36.718	3.287	6.208	5.229	5.915
BEAD at 75% fixed-cost subsidy							
$\delta = 0.02$		52.676	93.819	4.930	9.312	10.685	10.075
$\delta = 0.03$		46.100	82.106	4.930	9.312	9.351	8.818
$\delta = 0.05$		36.156	64.395	4.930	9.312	7.334	6.916
$\delta = 0.07$		29.186	51.981	4.930	9.312	5.582	5.920

Notes: (1) LB and UB denote lower and upper bounds, respectively. (2) Annual welfare gains are \$0.632–1.908 (25%), \$1.385–2.959 (50%), and \$2.352–4.189 (75%) billion. (3) Welfare gains are discounted over a 30-year horizon, whereas program costs are incurred upfront. (4) Discount rates follow OMB Circular A-4 (2023). (5) The Benefit–Cost Ratio (BCR) is the ratio of discounted benefits to discounted costs at each rate.

Table 15: Cost-Benefit Analysis of BEAD Program under Alternative Discount Rates (50-Year Horizon)

		ΔSocial Welfare (Billion $)		Program Cost (Billion $)		CBR	
Discount rate	Program	LB	UB	LB	UB	LB	UB
BEAD at 25% fixed-cost subsidy							
$\delta = 0.02$		19.860	59.956	1.643	3.104	12.085	19.317
$\delta = 0.03$		16.261	49.092	1.643	3.104	9.896	15.817
$\delta = 0.05$		11.538	34.832	1.643	3.104	7.021	11.222
$\delta = 0.07$		8.722	26.332	1.643	3.104	5.308	8.484
BEAD at 50% fixed-cost subsidy							
$\delta = 0.02$		43.522	92.982	3.287	6.208	13.242	14.978
$\delta = 0.03$		35.636	76.134	3.287	6.208	10.843	12.264
$\delta = 0.05$		25.284	54.019	3.287	6.208	7.693	8.702
$\delta = 0.07$		19.114	40.836	3.287	6.208	5.816	6.578
BEAD at 75% fixed-cost subsidy							
$\delta = 0.02$		73.908	131.633	4.930	9.312	14.992	14.136
$\delta = 0.03$		60.516	107.782	4.930	9.312	12.276	11.575
$\delta = 0.05$		42.938	76.474	4.930	9.312	8.710	8.213
$\delta = 0.07$		32.459	57.811	4.930	9.312	6.209	6.584

Notes: (1) LB and UB denote lower and upper bounds, respectively. (2) Annual welfare gains are \$0.632–1.908 (25%), \$1.385–2.959 (50%), and \$2.352–4.189 (75%) billion. (3) Welfare gains are discounted over a 50-year horizon, whereas program costs are incurred upfront. (4) Discount rates follow OMB Circular A-4 (2023). (5) The Benefit–Cost Ratio (BCR) is computed as discounted benefits divided by discounted costs at each rate.