# Broadband Deployment in Equilibrium: Subsidy Design for the Digital Divide*

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**Abstract**

Broadband access has become a near necessity, yet many U.S. households remain without high-speed access or significant choice among Internet service providers. This article examines the potential effects of policies that have been proposed to ameliorate the digital divide. Combining data from a survey of Seattle households' broadband subscriptions and broadband deployment data from the FCC, I estimate a dynamic structural model of Seattle's broadband market, which allows me to quantify the effect of competition on broadband availability and quality in equilibrium. I find that, of recent policies proposed to address the digital divide, a demand-side subsidy program increasing broadband affordability for low-income households is significantly more cost effective than a supply-side policy that subsidizes increased broadband deployment.

**Keywords:** broadband, digital divide, dynamic games, subsidies, infrastructure investment, policy analysis

**JEL Classification:** L13, L52, L96, D22, D61

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# 1 Introduction

The current structure of the broadband industry is such that improvements in quality are enormously costly for Internet service providers (ISPs), because state-of-the-art technology that supports high-speed data transmission requires substantial sunk cost investments. As a result, many American households have few choices of broadband providers, and broadband subscriptions are relatively expensive (Nuechterlein and Weiser 2013).[1] Limited, expensive, and uneven access to high-speed broadband is particularly acute in the U.S., in part, due to large geographic variation in population density. ISPs choose to collocate in dense urban markets where they can expect to recoup their capital investments, while sparsely populated rural markets have relatively limited access to broadband both in terms of number of providers and quality of service—a problem dubbed the "digital divide" (Greenstein and Prince 2006). However, concern about the digital divide is not only limited to rural communities. Due to the scale of upfront capital necessary to deploy broadband, lack of access to high-speed Internet service may exist even in urban centers where relatively high prices, as a result of a lack of competition, may restrict the supply of broadband subscriptions—particularly for low-income households.

The Federal Communications Commission (FCC) has pursued several different policies to tackle the digital divide including both supply- and demand-side policies. Despite these interventions policymakers, industry commentators, and affected consumers continue to be concerned about limited access and choice in the residential broadband market—a concern reflected in the recently passed Investment Infrastructure and Jobs Act (IIJA), which includes a $65 billion carve out for broadband expansion.[2]

This article investigates whether increasing high-speed broadband through a supply-side expansion policy that subsidizes providers' cost of deployment would be a cost-effective solution to the digital divide, relative to an alternative demand-side subsidy program that increases the affordability of broadband for low-income households. On the one hand, subsidizing providers' deployment may increase the choices available to consumers and increase competition among providers along the dimensions of price and product quality, resulting in more favorable market outcomes for consumers. On the other hand, due to the substantial cost of broadband infrastructure, in practice the cost of such a policy may dwarf the cost of alternative demand-side subsidy programs.

In order to answer this question, I develop and estimate a dynamic structural model of equilibrium behavior in the broadband industry that endogenizes providers' entry and product quality investment decisions along with consumer demand. The model

[1] "The typical American has a choice of only two fixed-line broadband providers: the local telephone company and the local cable company."

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

allows me to quantify the effects of various policy interventions on equilibrium market outcomes, including those most relevant to the digital divide. In the model, households choose among the set of available broadband plans offered by providers in their area based upon price and quality. Given consumer demand, providers choose when, where, and what quality of broadband to deploy based upon their beliefs about their rivals' future deployment.

I estimate the model using data from Seattle's broadband market during the 2014–2018 period. This dataset includes information about the evolution of broadband providers' coverage, their product offerings and prices, as well as novel data on individual households' broadband subscription choices from a survey conducted by the city of Seattle. This rich household-level microdata enables me to flexibly model and estimate households' demand for the three main wireline providers in the Seattle area: CenturyLink, Comcast, and Wave. Then, using households' demand as an input along with census block-level deployment data from the FCC, I estimate a dynamic game of CenturyLink and Comcast's investment decisions to recover their sunk costs of broadband deployment. The per household deployment costs I recover from the model, a key empirical object in my policy analysis, are commensurate with industry estimates.

With estimates of the model in hand, I conduct a series of counterfactuals to measure the impact of digital divide policies on broadband availability, subscribership, and consumer welfare, and ultimately to compare their cost-effectiveness. Specifically, I estimate the cumulative costs and benefits of two primary policies that have been proposed to address the digital divide: (1) demand-side subsidies to increase the affordability of broadband and (2) supply-side subsidies to increase access to high-speed broadband. In the analysis, I assume policymakers' have a fixed budget which they can choose to invest in the following options:

1. entirely in demand subsidy program;
2. entirely in supply expansion program;
3. in an approximately 50-50 split between both programs.

I find that a demand subsidy of $10 per month to low-income households, increases the overall share of broadband subscribers by 4.6 percentage points (% pt.) to 86.5% and generates consumer surplus of $241 million at a cost of $70 million. While a supply-side subsidy costing an equivalent amount increases access to high-speed broadband, generating $44 million in consumer surplus, but does not meaningfully increase the overall share of subscribers. Under the same budget constraint, a mixed policy increases the share of subscribers by 3.4% pt. to 85.3% and increases consumer surplus by $195 million.

Expanding policymakers' budget from $70 million to $560 million, I find that a demand subsidy of $30 per month to low-income households increases the share of broadband subscribers by 12.1% pt. to 94% and generates consumer surplus of $1,287 million. A supply-side subsidy, again does not have a meaningful impact on the overall share of broadband subscribers but increases consumer surplus by $153 million. And a mixed policy increases the share of subscribers by 8.9% pt. to 90.8%, generating $700 million in consumer surplus.

Overall, based on these results, in my empirical setting I find that demand-side subsidies aimed at increasing the affordability of broadband for low-income households more or less dominate supply-side subsidies aimed at expanding providers' coverage in terms of their cost-effectiveness.

Most closely related to this article are Espin and Rojas (2024) and Wilson (2024). Espin and Rojas (2024) analyze the effects of digital divide policies on broadband subscribership in the U.S. and also find that targeted demand-side subsidies are likely to be more cost effective than network expansion. However, unlike this paper, they do not model the supply-side of the broadband market, nor the equilibrium behavior of providers and households in the market. Wilson (2024) investigates whether public provision of broadband induces or crowds out private investment. He estimates a dynamic game in which private and municipal broadband providers make endogenous entry and investment decisions given consumer demand and finds that public competition increases private investment in fiber. The primary contribution of this article is that, like Wilson (2024), I model both supply and demand for broadband, which allows me to measure the effects of digital divide policies in equilibrium.

To model broadband providers' equilibrium behavior, I build upon Igami (2017)'s approach to estimating dynamic games, also applied by Yang (2020), Wilson (2024), and others. First, I estimate demand for broadband for the three main wireline providers in Seattle, CenturyLink, Comcast, and Wave, using a novel dataset that includes rich data on households' broadband subscription choices. Crucially, I observe individual households' choice of broadband provider along with an estimate of their monthly bill, as well as demographic data. This data enables me to link households' choices to information about the menu of subscriptions offered by each broadband provider and allows me to estimate a discrete-choice demand model that includes demographic-characteristic interactions along the lines of Berry et al. (2004), Petrin (2002), and Goolsbee and Petrin (2004).

Unlike prior studies that have estimated demand for broadband, I observe individual subscription choices among the primary set of providers offering service in Seattle. Previous studies have relied upon stated-preference data (Goolsbee 2006, Rosston et al. 2010, Varian 2002), national or city-level aggregate data (Dutz et al. 2009, Goetz 2019,

Wilson 2024), or individual choice data from a single provider (Lambrecht et al. 2007, Nevo et al. 2016). A key contribution of this paper is that I estimate household demand for broadband under competitive conditions—that is the data allows me to measure substitution both within and across providers at the household-level.

Second, I estimate providers' sunk costs of broadband deployment within a dynamic game using deployment data from the FCC. In the data, I observe providers' entry and product quality investment decisions in the Seattle area, at the census block-level, on a biannual basis during the period December, 2014 to June, 2018. With estimates from my demand model, I construct providers' period profits in each location under each possible counterfactual market structure. Then, I recover the sunk costs that rationalize providers' observed deployment decisions across locations, over time. With empirical estimates of households' demand preferences and providers' deployment costs I am able to implement my policy counterfactuals.

This article contributes to several existing literatures. First, this article adds to work analyzing the digital divide. Greenstein and Prince (2006) give an overview of the early literature and describe the economic forces driving the urban, rural digital divide during the initial waves of Internet diffusion. Goldfarb and Prince (2008) find that high-income, more educated individuals were more likely to have adopted the Internet by 2001, but conditional on adoption low-income, less educated individuals spend more time online. Prieger (2003) investigates whether there is unequal access to broadband across income and minority groups combining census and FCC data. After controlling for cost conditions, demand factors, and local competition, he finds that differences in broadband access across these groups largely disappear. In a similar more recent study, Martin (2019) finds that variation in supply alone is insufficient to explain the digital divide and that correlations with demographic factors point to digital literacy as an important and under-explored determinant of the divide. I add to this work by developing an underlying model of ISPs' deployment decisions, which can not only explain the supply-side of the digital divide but can also be used to investigate which policies would be most effective at closing the divide (including demand-side policies) by predicting equilibrium outcomes.

This article also contributes to the literature examining the relationship between market structure and entry and investment decisions in the broadband industry. Augereau and Greenstein (2001), perhaps the earliest empirical study to model ISPs' technology investment decisions, find that ISPs are more likely to adopt high-speed technologies in urban areas with high levels of infrastructure, placing some (but less) weight on competitive conditions and demographics, foreshadowing the disparity in broadband access between high- and low-density areas. Building upon this work, Augereau et al. (2006) show how standard setting also played a role in ISPs' early technology adop-

tion decisions. Consistent with economics of broadband deployment, Xiao and Orazem (2011) provide empirical evidence that sunk costs are a major determinant of ISPs' entry patterns. Wallsten and Mallahan (2013) and Molnar and Savage (2017) examine the relationship between number of providers and broadband speeds and find that markets with two or more providers have higher speeds than monopoly markets. More recently, Wilson et al. (2021) find that the threat of potential entry delays entry into local broadband markets by an average of two years, leading to an 11% decrease in future download speeds for every year of delay.

More broadly, this article is related to studies of entry and investment in other network industries including telecommunications and cable television. Greenstein and Mazzeo (2006), Economedies et al. (2008), Seim and Vivard (2011), Goldfarb and Xiao (2011), and Fan and Xiao (2015) study the consequences of entry into local telephone markets in the wake of the 1996 Telecommunications Act including its effects on product differentiation, market structure, and consumer welfare. Goolsbee and Petrin (2004) and Chu (2010) examine the entry of direct broadcast satellite into local television markets. Similar to this paper, Elliott et al. (2025) develop and estimate a model of endogenous infrastructure investment and competition among mobile telephone providers.

Finally, I contribute to previous empirical work in industrial organization examining the relationship between competition and innovation in oligopoly markets. Understanding how competition affects market outcomes other than price, including entry, product differentiation (including quality), and innovation, has become an increasing focus of research in industrial organization and antitrust policy.[3] Several other papers including Goettler and Gordon (2011), Igami (2017), Igami and Uetake (2020), Yang (2020), and Wilson (2024) have investigated the effects of competition on innovation in various industries.

# 2 Industry Background

## 2.1 The Residential Broadband Industry

Most U.S. households today access the Internet via fixed wireline broadband providers that deploy DSL, fiber, or cable technologies (see figure 1). Households subscribe to residential ISPs on a monthly basis for Internet plans that are primarily differentiated by downstream and upstream bandwidth (speed) and price, where the maximum bandwidth a provider is capable of delivering to customers is limited by the transmission technology it deploys. The dominant fixed wireline providers today are typically local

[3] 2010 Horizontal Merger Guidelines, U.S. Department of Justice and the Federal Trade Commission, ftc.gov/system/files/documents/public_statements/804291/100819hmg.pdf

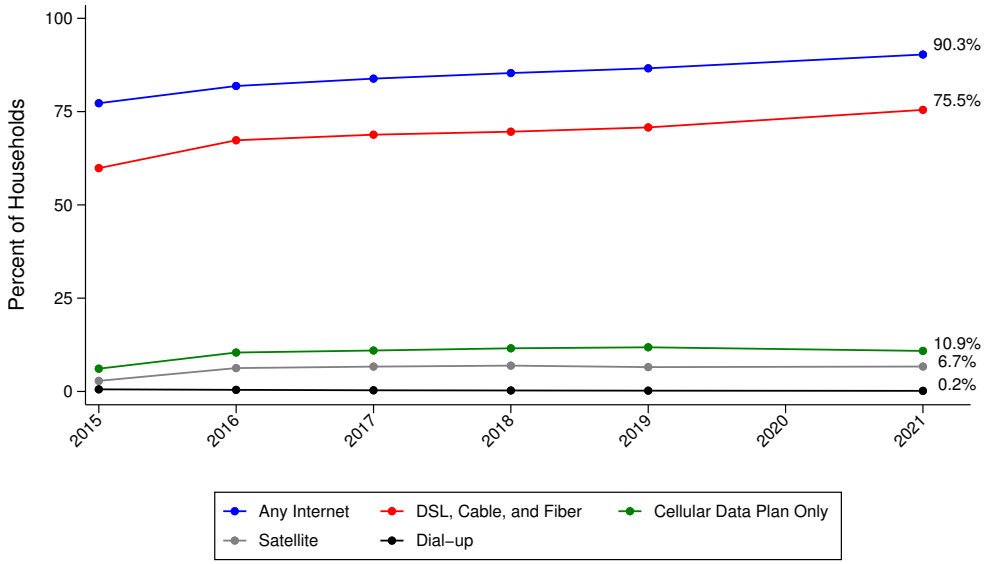
telephone or cable companies, including AT&T, Charter, Comcast, and Verizon, which began distributing Internet service over their existing network infrastructure (alongside their telephone and television services) as the Internet became widely adopted and digitization eliminated the technological barriers separating the distribution of these services (Nuechterlein and Weiser 2013).

The provision of wireline Internet service can be described relatively simply. ISPs provide customers with access to their networks through a physical connection, which allows users to transmit and receive information (or data) across the network. Information sent at one end is converted into discrete digital packets that traverse separately across the network and are reassembled at the receiving end, for example, to navigate a website, stream video content, or participate in a video conference call.

Traditionally, local telephone providers transmit broadband over copper telephone lines, commonly known as digital subscriber line (or DSL) service, while cable companies transmit broadband over coaxial cables previously used to distribute video services. Because the transmission of video requires more bandwidth than telephone service, coaxial cable is capable of supporting higher capacity service than telephone lines, and therefore cable companies have generally been able to deliver higher speeds. However, increasingly telephone providers have been replacing DSL service with high speed fiber service by deploying fiber-optic cable. Fiber-optic cable is essentially a thin glass tube that transmits light and, unlike copper wire for which bandwidth varies inversely (and increasingly-so) with length, can support very high bandwidths with little degradation over long distances. Fiber technology has dramatically increased the bandwidths providers are able to offer consumers, and as a result, where profitable, ISPs are investing to upgrade portions of their networks with fiber.

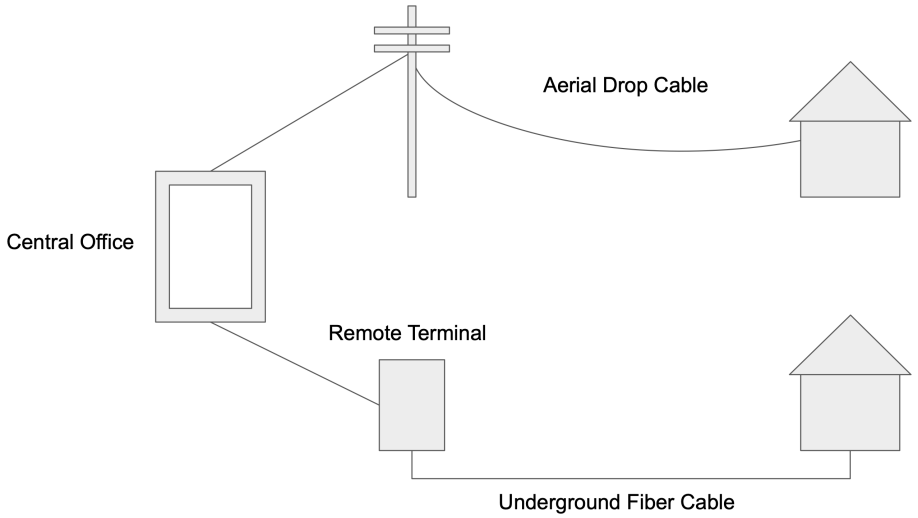
While many U.S. households have access to ISPs that deploy other transmission technologies including satellite, and increasingly mobile providers, where available the majority of households continue to rely upon fixed wireline as their primary source of broadband (see figure 1). This is because wireline connections are generally faster and more reliable than wireless alternatives. However, fixed wireline broadband is more costly to deploy, because unlike wireless technologies, fixed wireline requires a direct physical connection to each customer location. In order to deploy new or upgraded service, providers must extend the so-called "last mile" of their existing network infrastructure to reach the premises of new customers. To do so, providers install new cable either underground, by digging trenches, or aerially, by mounting it to utility poles (see figure 2). The last mile is connected to the rest of the network via central offices or data centers, which manage the distribution of data across the network.

**Figure 1. Internet Subscriptions by Technology (return)**




*Notes*: ACS 1-year estimates. Subscriptions broken down by ACS response categories.

**Figure 2. Network Diagram (return)**




The cost of broadband deployment varies considerably by the number and density of customer connections, terrain, and local regulatory and labor market conditions. By some estimates, laying fiber-optic cable can cost $60,000–$80,000 per mile. One industry estimate puts the cost of deploying fiber service at $700–$1,500 per household in urban areas and $3,000–$6,000 per household in rural areas (Cartesian 2019). Another estimates that fiber costs $13,900 per household on average (Tarana 2023). The city of Seattle conducted a study to assess the feasibility of stating a municipal broadband provider from scratch. They estimated that it would cost between $440–$850 million to

serve 246,635 locations, an implied per location cost of between $1,784–$3,446, which the city ultimately determined was prohibitively expensive.[4] The barrier to entry created by these high sunk cost explains the relative lack of competition and new entry in residential broadband and why, in addition to concerns about basic Internet access, policymakers are concerned about affordability and the potential exercise of market power in local broadband markets.

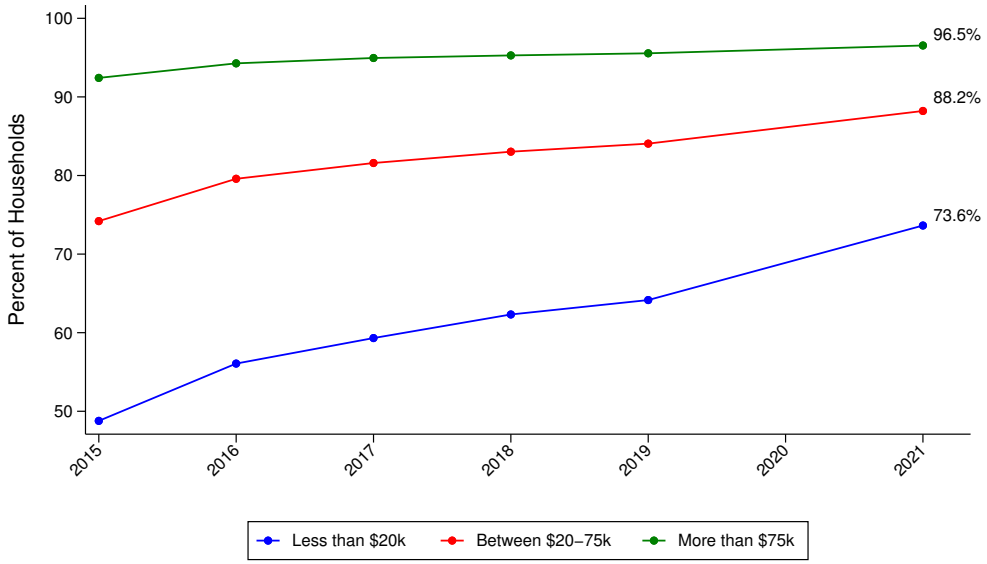
## 2.2 The Digital Divide

The structural barriers to competition in broadband, and in telecommunications more broadly, have long been recognized, dating back at least to the instantiation of the FCC in 1934. One of the primary objectives of the 1934 Communications Act was to achieve "universal service" in the provision of telephone service "to make available, so far as possible, [...] world-wide wire and radio communication service with adequate facilities at reasonable charges."[5] The 1996 Telecommunications Act extended this principle to other services: "[q]uality services should be available at just, reasonable, and affordable rates" and "[a]ccess to advanced telecommunications and information services should be provided in all regions of the Nation."[6]

With the advent of the Internet, the importance of access to broadband for the success of both individuals and businesses in the modern economy has become increasingly apparent. Despite progress in increasing coverage and subscription rates (see figure 1), however, there is still a substantial gap in broadband subscription rates across income groups (see figure 3) and other demographics groups including minorities and rural and tribal communities.

[4] https://www.seattle.gov/tech/initiatives/broadband/studies-and-history
[5] Communications Act of 1934, 47 U.S.C. §151.
[6] *Id.*, 47 U.S.C. §254.

**Figure 3. Broadband Subscriptions by Income (return)**




*Notes*: ACS 1-year estimates. Broadband subscriptions include "DSL, cable, and fiber", "cellular data plans", and "satellite" subscriptions as categorized by ACS.

In recent years, the FCC has made closing the digital divide, particularly in rural and tribal areas, a policy priority. According to the Commission's 2018 broadband deployment report, "[f]ar too many Americans remain unable to access high-speed broadband Internet access, and we have much work to do if we are going to continue to encourage the deployment of broadband to all Americans, including those in rural areas, those on Tribal lands, and those in schools and classrooms."[7] The FCC has put in place both supply- and demand-side policies in attempts to address these gaps. On the supply-side, starting in 2011 the FCC introduced the Connect America Fund,[8] a reverse auction program designed to subsidize the deployment of broadband to particularly high-cost areas. On the demand-side, the FCC has implemented several low-income subsidy programs including the Lifeline Program[9] and, more recently during the COVID-19 pandemic, the Affordable Connectivity Program.[10]

The impact of the COVID-19 pandemic, which forced a substantial portion of economic activity online, further highlighted the importance of widespread equal access to broadband, and several papers have documented how various inequities stemming from the digital divide were exacerbated during the pandemic. Chiou and Tucker (2020) find that high-speed internet access was a main determinant of individuals' ability to stay at home during the pandemic. Sen and Tucker (2020) find that children from low-income or

[7] https://docs.fcc.gov/public/attachments/FCC-18-10A1.pdf
[8] https://www.fcc.gov/general/connect-america-fund-caf
[9] https://www.fcc.gov/general/lifeline-program-low-income-consumers
[10] https://www.fcc.gov/acp

minority backgrounds were less likely to have internet connections, and therefore, were less prepared to navigate the transition from in-person to online instruction. Barrero et al. (2021) estimate large economic gains from universal broadband access allowing workers to work from home.

Relatedly, an earlier literature has documented various benefits resulting from the diffusion and adoption of broadband in several domains including productivity, labor markets, and education. Greenstein and McDevitt (2011) quantify new economic growth and consumer surplus generated by the diffusion of broadband. LoPiccalo (2022) finds that the adoption of broadband in rural areas increases agricultural productivity. Dettling (2017) finds that internet access increases the labor force participation of married women. Zuo (2021) finds that a broadband discount program offered by Comcast to low-income households increased the employment rate and earnings of eligible participants. Dettling et al. (2018) find that broadband access increased students' SAT scores and expanded their set of college applications. Campbell (2024) finds that broadband access improves students' reading and math test scores and employment outcomes.

## 2.3 Seattle's Broadband Market

In this article, I focus on Seattle's broadband market, an urban market, which is served by three fixed wireline ISPs: (1) CenturyLink, (2) Comcast, and (3) Wave. Although my data come from a single market, Seattle is more or less a representative urban broadband market, primarily dominated by two large providers, therefore, I view my empirical results as more broadly applicable to the broadband industry.

CenturyLink (now Lumen Technologies, previously Century Telephone) is Seattle's legacy local telephone provider. It deploys and operates both DSL and fiber technologies across its coverage area in the city and the broader region (see figure 5). Like other national telcos (e.g. AT&T, Frontier, and Verizon), CenturyLink has been gradually upgrading its network from DSL to fiber (see figure 6). Comcast and Wave are both local cable providers also operating in Seattle and broader region. Comcast's coverage area is much larger than Wave's, and therefore, it exerts a greater competitive constraint on CenturyLink. Other wireline providers operating in the region, though not within the Seattle MSA, include local telephone provider Frontier. Because I only observe demand for Seattle households, I exclude these other providers from my primary analysis.

Each provider offers households a similar menu of monthly broadband subscriptions, differentiated by downstream and upstream bandwidth, price, and in some instances, usage allowance. One unique feature of the broadband market is that providers appear to set plan prices uniformly across their local coverage areas and perhaps as widely as at the national level (Wilson 2024). As discussed in more detail later on, in my empirical

model I assume that providers set uniform prices across geography.

# 3 Data

I construct a dataset that combines households' broadband subscription choices and ISPs' deployment decisions in the city of Seattle and surrounding urban areas. To compile this dataset, I combine data from four different sources.

First, I rely upon survey data from the 2018 Seattle Technology Access and Adoption Study for household-level broadband subscription choices. Second, I use the FCC's Broadband Urban Rate Survey to identify the plans and prices offered by ISPs operating in Seattle. Third, I obtain household demographic data from the American Community Survey (ACS) to estimate the number of households in each census block, for block group level demographic estimates including household income weights, and for the overall share of households with broadband subscriptions. Fourth, I use census block level data from FCC Form 477 to identify providers' broadband deployment decisions over the 2014–2018 period. I discuss each data source, as well as the integration of these data in more detail below.

## 3.1 Household Subscription Data

Comprehensive provider-level data on broadband subscriptions is not publicly available. Although highly aggregated subscription data is available from some broadband providers' public filings, it is a challenge to estimate a realistic model of demand with these data, because ISPs' do not report broadband subscriptions for different geographic markets nor do they segment subscriptions by plans in their financials. Ideally a researcher studying the broadband market would rely upon microdata reported by providers with detailed information about households' subscription choices including the quality and price of different plans across various geographic markets. In the absence of such data, I rely upon a 2018 survey of Seattle households conducted by Pacific Market Research on behalf of the City of Seattle. This survey provides a unique opportunity to study demand for broadband in a major U.S. city, because it includes information about individual households' broadband subscription choices and demographic characteristics. I use this data to estimate households' probabilities of subscribing to the set of broadband plans offered by the three major fixed wireline ISPs that serve Seattle: CenturyLink, Comcast, and Wave.

The survey data consists of responses from 4,315 households of which 1,999 were used in my analysis after excluding responses with missing data.[11] Each respondent

[11]Households were excluded on the basis of not providing demographic information and/or infor-

answered 38 questions about their household's internet access and usage, use of other technologies such as computers and mobile phones, as well as about the household's demographics. Most importantly each respondent was asked whether the household had Internet access, whether the household subscribed to a fixed wireline broadband provider, to which provider it subscribed, and was asked to estimate the monthly cost of the household's Internet subscription (see figure A1). Respondents were also asked to report their zip code of residence, household income, household size, education level, and other demographic information. Table 1 reports the overall number of respondents in my sample by ISP including respondents who indicated that they did not subscribe to any of the three fixed wireline providers in Seattle.

**Table 1. Subscribers' Provider Choices and Demographics (return)**

| Provider | CenturyLink | Comcast | Wave | None | Total |
|---|---|---|---|---|---|
| Subscriber Count | 597 | 892 | 159 | 351 | 1,999 |
| Income [0k, 50k) | 0.24 | 0.25 | 0.23 | 0.72 | 0.33 |
| Income [50k, 100k) | 0.25 | 0.27 | 0.25 | 0.18 | 0.25 |
| Income [100k, 200k+) | 0.50 | 0.48 | 0.53 | 0.10 | 0.42 |
| Less than HS Grad | 0.01 | 0.01 | 0.03 | 0.06 | 0.02 |
| HS Grad and Some College | 0.20 | 0.19 | 0.17 | 0.50 | 0.24 |
| Bachelor's Degree or Higher | 0.79 | 0.81 | 0.80 | 0.44 | 0.74 |
| Household Size (1–3) | 0.74 | 0.78 | 0.90 | 0.93 | 0.80 |
| Household Size (4+) | 0.26 | 0.22 | 0.10 | 0.07 | 0.20 |

*Notes*: Seattle Technology Adoption Survey 2018. This table summarizes the demographic characteristics of households included in my estimation sample by choice of broadband provider including "None". Statistics represent the percent of households in each demographic category.

While I *do* observe households' choice of provider, I *do not* observe their choice of specific broadband plan. In order to estimate the probability that a household subscribes to a particular broadband plan, I match survey respondents' to broadband plans based on price and self-reported estimates of respondents' monthly subscription bills. While this method of matching survey responses to broadband subscriptions is imperfect, respondents' estimates of their monthly bills at the very least represent a measure of households' willingness-to-pay for broadband, which is a reasonable approximation of demand (tethered to information about households' actual provider choices, this data is arguably more informative than standard stated-preference data). However, measurement error in prices and product characteristics may lead to attenuation in my demand estimates.

I match households' survey responses to ISPs' plans based on price information

mation about their Internet service provider including estimates of their monthly bill.

collected from the FCC's 2018 Broadband Urban Rate Survey. The Urban Rate Survey is published annually by the FCC to track changes in Internet subscription prices over time and across geography. The data consists of the prices and attributes of ISPs' plans across different urban areas (aggregated up to the state level). I use plans and prices for Washington state in 2018 as the basis of the subscriptions households choose among in the demand model, reported in table 2.

**Table 2. Plan Summary Statistics (return)**

| Plan | Subscriber Count | Monthly Charge | Download Speed (mbps) | Upload Speed (mbps) | Usage Allowance (GB) |
|---|---|---|---|---|---|
| CenturyLink: plan 1 | 294 | 56.99 | 12 | 0.875 | 1,000 |
| CenturyLink: plan 2 | 43 | 61.99 | 12 | 5 | 1,000 |
| CenturyLink: plan 3 | 39 | 66.99 | 20 | 0.875 | 1,000 |
| CenturyLink: plan 4 | 21 | 71.99 | 20 | 5 | 1,000 |
| CenturyLink: plan 5 | 31 | 76.99 | 40 | 5 | 1,000 |
| CenturyLink: plan 6 | 62 | 81.99 | 40 | 20 | 1,000 |
| CenturyLink: plan 7 | 79 | 96.99 | 100 | 50 | 1,000 |
| CenturyLink: plan 8 | 28 | 156.94 | 1,000 | 1,000 | . |
| Comcast: plan 1 | 290 | 49.95 | 10 | 2 | 1,024 |
| Comcast: plan 2 | 190 | 64.95 | 55 | 5 | 1,024 |
| Comcast: plan 3 | 152 | 79.95 | 100 | 5 | 1,024 |
| Comcast: plan 4 | 173 | 94.95 | 200 | 10 | 1,024 |
| Comcast: plan 5 | 42 | 149.95 | 250 | 25 | 1,024 |
| Comcast: plan 6 | 45 | 159.95 | 987 | 35 | 1,024 |
| Wave: plan 1 | 43 | 45.10 | 10 | 1 | 100 |
| Wave: plan 2 | 66 | 73.45 | 100 | 5 | 400 |
| Wave: plan 3 | 50 | 81.55 | 250 | 10 | 500 |

*Notes*: Seattle Technology Adoption Survey 2018, FCC Urban Rate Survey 2018. This table summarizes the primary characteristics of providers' broadband plans as reported by the FCC Urban Rate Survey.

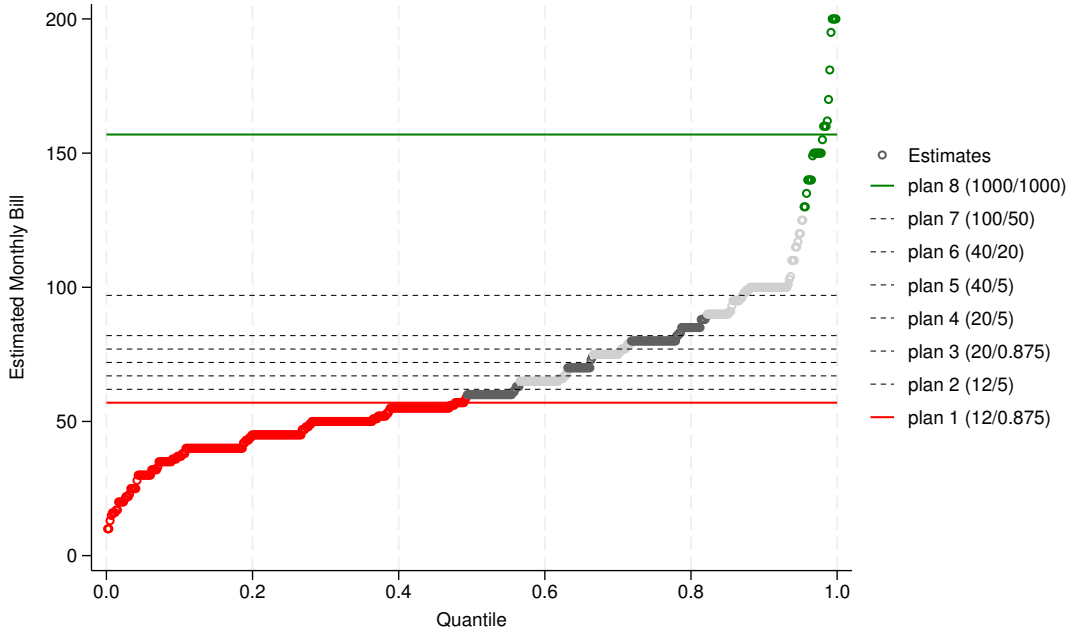
As discussed above, I match households to broadband plans based on their estimated monthly subscription bills. Because the prices of subscriptions offered by each provider increase monotonically with downstream and upstream bandwidth, I devise price bands for each subscription and assign households to plans according to these bands. In

general, I use the following interpolation rule,

$$j_i(\hat{p}_i) = \begin{cases} 1, & \text{if } \hat{p}_i \in [0, \frac{p_1+p_2}{2}) \\ 2, & \text{if } \hat{p}_i \in [\frac{p_1+p_2}{2}, \frac{p_2+p_3}{2}) \\ \vdots & \\ n-1, & \text{if } \hat{p}_i \in [\frac{p_{n-2}+p_{n-1}}{2}, \frac{p_{n-1}+p_n}{2}) \\ n, & \text{if } \hat{p}_i \in [\frac{p_{n-1}+p_n}{2}, \infty) \end{cases},$$

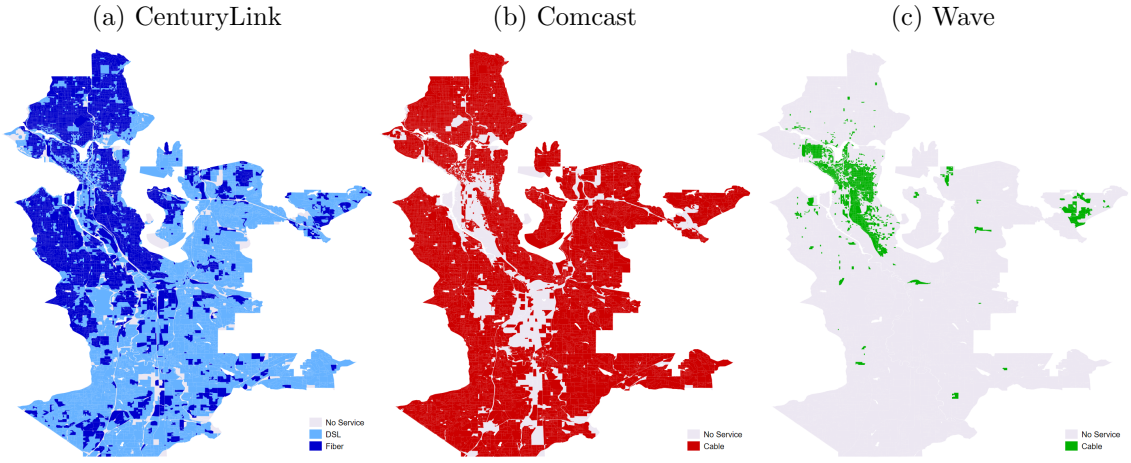
where $j_i(\hat{p}_i)$ is household $i$'s choice of subscription, which depends on its estimated monthly bill $\hat{p}_i$. If the household's estimated bill is greater than zero but less than the average of the price of the lowest and second to lowest cost plan, then I assume household $i$ subscribes to the lowest cost plan, and so on. Figure 4 displays the distribution of estimated monthly bills for CenturyLink subscribers, as well as the share of subscribers assigned to each plan following the interpolation rule above. When it comes to estimating demand, I test the robustness of my estimates to this matching procedure (discussed in detail in appendix B).

**Figure 4. Distribution of Households' Monthly Bills**
**CenturyLink Subscribers (return)**




*Notes*: Seattle Technology Adoption Survey 2018, FCC Urban Rate Survey 2018. This figure shows the distribution of CenturyLink subscribers' estimated monthly bills with CenturyLink's menu of subscriptions overlayed. The lowest priced plan (in red) is 12/0.875 mbps download/upload speed. The highest priced plan (in green) is 1,000/1,000 mbps download/upload speed. The alternating dark and light shaded points in the distribution denote households assigned in "intermediate" plans that lie in between the lowest and highest priced plans.

**Figure 5. Provider Footprints (return)**




*Notes*: FCC Form 477 data. Providers' 2018 coverage areas within the Seattle MSA and surrounding urban census blocks.

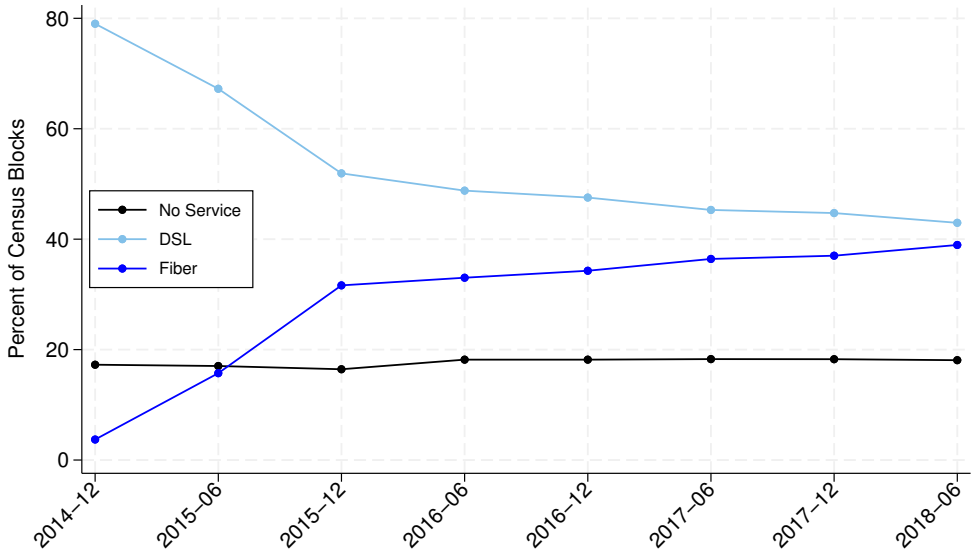
## 3.2 Provider Deployment Data

I collect data on providers' deployment decisions across census blocks in the Seattle MSA and surrounding urban area where CenturyLink, Comcast, and Wave operate during the period December, 2014 to June, 2018 from the FCC's Form 477 broadband deployment data. FCC Form 477 requires broadband providers to report information about their broadband deployment including transmission technology and maximum download and upload speeds at the census block-level every six months. I collect deployment data for the major fixed wireline broadband providers that serve Seattle. While other ISPs, including satellite and wireless providers serve the city, as is evident from the 2018 Seattle Technology Access and Adoption Study data, most Seattle subscribers purchase service from one of the major fixed wireline providers.

Figure 5 displays CenturyLink, Comcast, and Wave's 2018 service footprints in the geographic area I analyze. My sample is comprised of all urban census blocks surrounding the Seattle MSA within King county, excluding territory served by competing provider Frontier, which operates on the outskirts of the city (see figures A2–A5 in appendix A for further information about sample selection).

Figure 6 plots CenturyLink's broadband deployment over time in terms of the percentage of census blocks with DSL and fiber service.

**Figure 6. CenturyLink Deployment (return)**




*Notes*: FCC Form 477 data. CenturyLink's broadband deployment over time within the Seattle MSA and surrounding urban census blocks.

# 4 Empirical Model

I model broadband providers' deployment decisions within a geographic market over time, which depend upon household demand, the sunk costs associated with deploying broadband technologies, and the strategic behavior of competing providers.

In the model, given households' demand for broadband in different geographic locations (census blocks) within the market, each period each provider chooses whether to be deployed in each location, and which technology to deploy given its current state, the states of its rivals, and its expectation of the future evolution of the market. Given realized deployment decisions, providers set plan prices uniformly across their coverage areas to maximize profits.

Following the approach of other studies in the dynamic games literature including Aguirregabiria and Ho (2012), Igami (2017), Yang (2020), and Wilson (2024), I estimate the model in two steps. First, I recover households' preferences for broadband plans using microdata on individual household choices supplemented with other demand-relevant data. With these estimates, I construct providers' period profits across locations under counterfactual deployment. Second, given estimates of their period profits, I recover providers' sunk costs of deployment using data on their deployment decisions across locations, over time.

I begin by describing the demand model and its estimation, followed by the deployment model and its estimation.

## 4.1 Household Demand for Broadband

I model households' demand for broadband using a discrete choice model, where each household $i$ residing in census block $\ell$ chooses among $j \in J_\ell$ broadband plans offered by the providers that serve census block $\ell$.

The outside option $j = 0$ represents the household's decision not to subscribe to fixed wireline broadband (the outside option therefore encompasses several alternative choices including choosing no form of Internet access, as well as Internet access via satellite or mobile providers or via public institutions such as schools and libraries).

Household $i$'s monthly indirect utility from subscribing to plan $j$ is,

$$u_{i,j} = x_j(\bar{\beta} + \beta_i z_i) - (\bar{\alpha} + \alpha_i z_i)\log(p_j) + \lambda_i z_i + \xi_j + \epsilon_{i,j}, \tag{1}$$

where $x_j$ is a vector of broadband plan characteristics excluding price, $p_j$ is price, and $z_i$ is a vector of household $i$'s demographic characteristics. The parameters $\bar{\beta}$ and $\bar{\alpha}$ represent households' baseline preferences for plan characteristics, which in my empirical specification include downstream bandwidth, upstream bandwidth, and provider fixed effects. The parameters $\beta_i, \alpha_i$, and $\lambda_i$ capture heterogeneity in households' preferences given their demographics characteristics, which include household income, household size, and educational attainment. Further, $\xi_j$ is an econometric error term, which I argue is uncorrelated with price—I unpack this assumption in a later section. Finally, $\epsilon_{i,j}$ is the household's idiosyncratic taste for product $j$, which is assumed to be i.i.d. extreme value type 1, and households' indirect utility from the outside option is normalized to zero, $u_{i,0} = 0 + \epsilon_{i,0}$.

For estimation it is useful to decompose $u_{i,j}$ into two parts:

$$\begin{aligned}\delta_j &= x_j\bar{\beta} - \bar{\alpha}\log(p_j) + \xi_j,\\ \mu_{i,j} &= x_j(\beta_i z_i) - \alpha_i z_i \log(p_j) + \lambda_i z_i,\end{aligned}$$

where, as in Berry (1994), $\delta_j$ represents households' baseline utility from plan $j$, and $\mu_{i,j}$ represents the observable component of utility which varies across households. I denote the parameters associated with each component as $\bar{\theta} = (\bar{\beta}, \bar{\alpha})$ and $\tilde{\theta} = (\beta_i, \alpha_i, \lambda_i)$, respectively.

Because of the distributional assumption on $\epsilon_{i,j}$, the probability that household $i$ subscribes to plan $j$ in census block $\ell$ is given by the multinomial logit function,

$$s_{i,j,\ell} = \frac{\exp\left(\delta_j + \mu_{i,j}\right)}{1 + \sum_{k \in J_\ell} \exp\left(\delta_k + \mu_{i,k}\right)}. \tag{2}$$

It follows that the aggregate market share of product $j$ in census block $\ell$ is given by,

$$S_{j,\ell} = \int \frac{\exp\left(\delta_j + \mu_{i,j}\right)}{1 + \sum_{k \in J_\ell} \exp\left(\delta_k + \mu_{i,k}\right)} dG_\ell(z_i),$$

where $G_\ell(z_i)$ is the distribution of demographic characteristics over households residing in census block $\ell$.

## 4.2 Aggregate Broadband Shares

When it comes to estimating the model, in some specifications I rely on aggregate share data—specifically, the share of households subscribing to any fixed wireline broadband provider at the census block group level (aggregate "broadband shares"). To compute the empirical analog of these shares with my model, I specify a discrete distribution of household types corresponding to their demographic characteristics each with weight $\omega_{i,\ell}$. These weights come from ACS estimates of the share of households with different demographic characteristics at the census block group level.

Using these weights, the aggregate market share of product $j$ in census block $\ell$ is given by,

$$S_{j,\ell} = \sum_{i \in I_\ell} \frac{\exp\left(\delta_j + \mu_{i,j}\right)}{1 + \sum_{k \in J_\ell} \exp\left(\delta_k + \mu_{i,k}\right)} \omega_{i,\ell},$$

where the aggregate plan shares vary across census blocks given differences in households' choice set $J_\ell$ and in the distribution of household demographics $\omega_{i,\ell}$.

Similarly, the aggregate share of households subscribing to any broadband provider in census block group $g$ is given by,

$$S_{b,g} = \sum_{\ell \in g} \sum_{i \in I_\ell} H_\ell \frac{\sum_{k \in J_\ell} \exp\left(\delta_k + \mu_{i,k}\right)}{1 + \sum_{k \in J_\ell} \exp\left(\delta_k + \mu_{i,k}\right)} \omega_{i,\ell},$$

where the aggregate share at the census block group level comes from summing over the households residing in each census block $\ell$ within block group $g$. These aggregate "broadband shares" provide an additional source of identification in estimation.

## 4.3 Providers' Pricing Behavior

I assume that providers set uniform prices for their plans across their coverage areas according to Nash-Bertrand behavior. Specifically, given the current set of plans a provider offers $J_{F,\ell}$ (and competes against $J_{-F,\ell}$) in each census block $\ell$, the provider sets $J_F$ prices to maximize its profit across all the census blocks in its geographic

footprint,

$$\max_{p_j, j \in J_F} \sum_{\ell \in \mathcal{M}_F} \sum_{j \in J_{F,\ell}} H_\ell S_{j,\ell}(p_j - c_j),$$

where $H_\ell$ is the number of households in census block $\ell$, $c_j$ is product $j$'s marginal cost, and $\mathcal{M}_F \subset \mathcal{M}$ is the subset of census blocks in which firm $F$ is deployed.

Equilibrium prices satisfy the following first-order conditions,

$$\sum_{\ell \in \mathcal{M}_F} \left( H_\ell S_{j,\ell} + \sum_{k \in J_{F,\ell}} H_\ell \frac{\partial S_{k,\ell}}{\partial p_j}(p_k - c_k) \right) = 0, \forall j \in J_F.$$

Stacking together all providers' FOCs, in appendix D, I show that the system of equations that characterizes equilibrium price setting is essentially a household-weighted version of the supply-side pricing relationship in Nevo (2000),

$$\tilde{\mathbf{S}} + \tilde{\mathbf{\Delta}}(\mathbf{p} - \mathbf{c}) = \mathbf{0}.$$

This equation can be rearranged to represent providers' markups in terms of objects that can be recovered directly from my demand system,

$$\mathbf{p} - \mathbf{c} = \underbrace{-\tilde{\mathbf{\Delta}}^{-1}\tilde{\mathbf{S}}}_{\mathbf{\Psi}}.$$

Following Gentzkow (2007), I use this relationship to construct product level supply-side moments that aid in the identification of certain demand parameters:

$$p_j - c_j = \psi_j(\bar{\theta}, \tilde{\theta}) + \zeta_j, \tag{3}$$

where $(p_j - c_j)$ is the observed markup for product $j$, $\psi_j(.)$ is the markup implied by the demand parameters, and $\zeta_j$ is an econometric error term. These moments are particularly helpful for identifying $\bar{\alpha}$ and $\alpha_i$'s in my setting where prices don't vary across geography. Gentzkow (2007) uses this identification strategy in his study of demand for print and online newspapers where price variation is similarly limited.

Like Gentzkow (2007), I directly incorporate information about firms' costs into estimation, which enables me to connect observed markups to demand parameters. Specifically, in my preferred specification I assume that providers' marginal costs are zero ($c_j = 0, \forall j \in J$), which is consistent with conventional wisdom in the telecommunications industry that marginal costs are near zero. As a robustness check, in an alternative specification I assume $c_j = 10, \forall j \in J$, based on industry cost estimates by Greenstein and McDevitt (2011).

## 4.4 Estimation

To estimate households' utility parameters in equation (1), I rely on three different types of demand-side data. First, "micro" data that includes information about individual households' broadband subscription choices, $d_{i,j}$, and their demographic characteristics, $z_i$. Second, product level data that includes information about broadband providers' plan characteristics, $x_j$ and $p_j$. Third, aggregate "broadband share" data that gives the share of households subscribing to any fixed wireline broadband provider at the census block group level, $S_{b,g}$. Additionally, I incorporate supply-side restrictions imposed by firms' pricing behavior as another source of identification.

I integrate these four different types of data and estimate the model using an estimator similar to Grieco et al. (2025)'s CLEER.[12] The primary differences between my estimator and theirs' are: (1) I observe aggregate "broadband shares" that are not product level shares but are a function of aggregate product shares, and (2) I incorporate supply-side restrictions. I discuss the formulation of each component of my estimator below.

First, the likelihood contribution of individual households' broadband subscription choices, the "microdata" is given by,

$$\mathcal{L}_1(\delta, \tilde{\theta}) = \sum_{c=1}^{\mathcal{C}} \sum_{j=0}^{J_c} \sum_{i=1}^{I_c} d_{i,j,c} \log \hat{s}_{i,j,c}(\delta, \tilde{\theta}),$$

where $d_{i,j,c}$ is a dummy variable indicating whether household $i$ subscribes to broadband plan $j$ given its choice set $c$. This function depends upon the mean utility of each plan, $\delta_j$'s, and the parameters that capture variation in utility across households' demographic characteristics $\tilde{\theta} = (\alpha_i, \beta_i, \lambda_i)$.

Second, I form product level moments by projecting the matrix of product characteristics onto the estimates of $\delta_j$'s,

$$m_1(\delta, \bar{\theta}) = \sum_{c=1}^{\mathcal{C}} \sum_{j=1}^{J_c} \Big(x_j, \log(p_j)\Big) \Big(\delta_{j,c} - x_j\bar{\beta} + \bar{\alpha} \log(p_j)\Big),$$

from which I recover the parameters associated with households' baseline utilities for product characteristics and price $\bar{\theta} = (\bar{\alpha}, \bar{\beta})$. The corresponding GMM objective function is, $\Lambda_1(\delta, \bar{\theta}) = \frac{1}{2} m_1(\delta, \bar{\theta})' W_1 m_1(\delta, \bar{\theta})$, where $W_1$ is the optimal GMM weighting matrix.

[12] Conformant Likelihood Estimator with Exogeneity Restrictions.

Next, the likelihood contribution of the aggregate "broadband shares" is given by,

$$\mathcal{L}_2(\bar{\theta}, \tilde{\theta}) = \sum_{g \in \mathcal{M}} H_g S_{b,g} \log \hat{\mathcal{S}}_{b,g}(\bar{\theta}, \tilde{\theta}) + H_g(1 - S_{b,g}) \log(1 - \hat{\mathcal{S}}_{b,g}(\bar{\theta}, \tilde{\theta})),$$

where $S_{b,g}$ is the share of households, $H_g$, in census block group $g$ that subscribe to any broadband provider, which I observe in the data, and $\hat{\mathcal{S}}_{b,g}(\bar{\theta}, \tilde{\theta})$ is the share predicted by the model.

Finally, I form supply-side moments by comparing firms' observed markups to those predicted by the model,

$$m_2(\bar{\theta}, \tilde{\theta}) = \Big( p_j - c_j - \psi_j(\bar{\theta}, \tilde{\theta}) \Big),$$

where $\psi_j(\bar{\theta}, \tilde{\theta})$ is product $j$'s markup implied by the demand parameters. The corresponding GMM objective function is, $\Lambda_2(\bar{\theta}, \tilde{\theta}) = \frac{1}{2} m_2(\bar{\theta}, \tilde{\theta})' W_2 m_2(\bar{\theta}, \tilde{\theta})$, where I use the identity matrix as the weighting matrix $W_2$.

Combining terms, I estimate the model by searching for the set of parameters that minimizes the following objective function,

$$(\delta^*, \bar{\theta}^*, \tilde{\theta}^*) = \arg\min_{\delta, \bar{\theta}, \tilde{\theta}} - \underbrace{\mathcal{L}_1(\delta, \tilde{\theta})}_{\text{micro}} + \underbrace{\Lambda_1(\delta, \bar{\theta})}_{\text{products}} - \underbrace{\mathcal{L}_2(\bar{\theta}, \tilde{\theta})}_{\text{shares}} + \underbrace{\Lambda_2(\bar{\theta}, \tilde{\theta})}_{\text{supply}}.$$

Notice that the microdata and product level moments together are sufficient to identify all of the model's parameters. This allows me to assess how the inclusion of the "broadband share" data and supply-side restrictions affects my estimates.

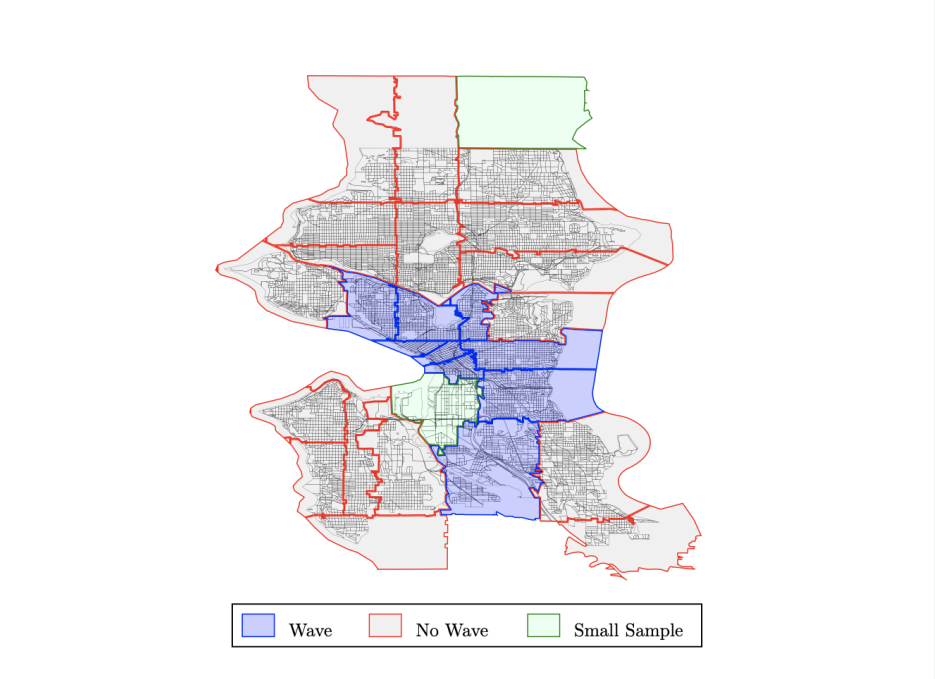
## 4.5 Identification

The demand parameters are identified by several sources of variation in my data. First, the alternative-specific constants (or baseline utilities) $\delta_j$'s and product characteristic-demographic interactions $\tilde{\theta}$ are identified by variation in households' demographics correlated with their broadband subscription choices. For example, higher income households generally purchase higher quality, more expensive subscriptions, which is reflected in the estimates of $\alpha_i$.

Second, mean product characteristic parameters $\bar{\theta}$ are identified by variation in characteristics $x_j$ and prices $p_j$ across products, which vary widely across products because providers offer households wide ranging menus of plans in terms of bandwidth and price (see table 2). Additionally, to mitigate potential concerns that identifying $\bar{\alpha}$ may be challenging in settings where prices don't vary across geographic markets, as discussed above, I construct supply-side moments from the relationship between prices,

costs, and markups under profit-maximizing behavior which also identify $\bar{\alpha}$. Because $\bar{\alpha}$ is overidentified when both the demand and supply-side moments are included, in the results section I compare the sensitivity of my estimates to the inclusion of each.

**Figure 7. Households' Choice Sets (return)**




*Notes*: This figure overlays Seattle zip codes onto census blocks. Wave is available in the blue shaded areas. Wave is unavailable in gray shaded areas. Green shaded areas do not have enough survey respondents to determine which providers are generally available.

Third, differences in households' choice sets across the Seattle MSA help pin down the parameters—specifically Wave's coverage area is more limited than CenturyLink and Comcast's as shown in figure 5. To take advantage of this variation in product availability, I partition zip codes (observed in the household survey data) into two groups—(1) those with access to all three providers and (2) those without access to Wave—based on my analysis of survey responses and the FCC 477 deployment data. Figure 7 overlays zip codes within the Seattle MSA onto census blocks and identifies zip codes that fall into these two groups.

Fourth, the aggregate "broadband share" data also aids with identification by exploiting variation in the share of households that take up broadband from any provider across census block groups, which is correlated with households' location-specific demographics and choice sets. For example, I generally observe higher shares in census block groups with relatively more high income households (see figure A6).

## 4.6 Price Endogeneity

A standard concern in demand estimation is that if firms set prices in response to unobservable local demand shocks (in my model, represented by unobservable plan quality $\xi_j$), then estimates of consumers' price sensitivity, $\bar{\alpha}$, will tend to be attenuated without valid price instruments. However, as described above, in my empirical setting broadband providers set plan prices uniformly across broad geographic areas (perhaps as widely as at the national level as documented by Wilson (2024)). As a result, local demand shocks should not be correlated with price, obviating the need for instruments.

To see this clearly, suppose one component of unobservable plan quality that varies across geography is network quality, because some areas are more prone to network outages than others. If providers engaged in geographic price discrimination by varying their prices in response to local differences in demand driven by network quality, this would generate a correlation between $p_j$ and $\xi_j$. However, because providers set uniform prices, these prices are not responsive to local demand shocks by definition, and therefore, the two should be uncorrelated.

Given the above, credibly identifying $\bar{\alpha}$ in equation (1) primarily rests upon reasonably controlling for differences in plan quality, which I argue should be captured by download and upload speeds, as well as by provider fixed effects to soak up any unobserved differences in quality across providers.

## 4.7 Demand Results

Table 3 presents the main demand estimation results. Column (1) displays a baseline specification that relies only on microdata and product level moments. Moving from left to right, columns (2–5) incorporate additional data and moments to identify households' demand parameters. Column (2) adds aggregate "broadband shares"; column (3) adds supply-side restrictions, excluding the price moment from the demand-side; column (4) combines the additions to (2) and (3); and finally, column (5), my preferred specification, uses all available information including both demand and supply-side price moments.

All five specifications allow for heterogeneity in households' price sensitivity across income groups, which I find to be the primary source of variation in households' preferences (see table B1 for other demographic interactions). Comparing price coefficients across models, I find including aggregate share data has little impact on households' price sensitivity, while incorporating the supply-side restrictions has significant bite. With supply-side restrictions, households appear to be less price sensitive, and generally, the model parameters are more precisely estimated. Including both together in columns (4) and (5) results in very similar estimates to column (3). Figure 8 summa-

rizes this visually and includes comparisons with alternative specifications described in appendix B.

Across models, in general, households' price sensitivity decreases monotonically with income. Also, the baseline plan characteristic parameters are economically intuitive, where utility is increasing in download and upload speeds, with download speed being relatively more important. Based upon these criteria, the precision of the estimates and the fact that it takes advantage of all available information, I use specification (5) as my preferred demand estimates going forward. I summarize the model fit in appendix B.

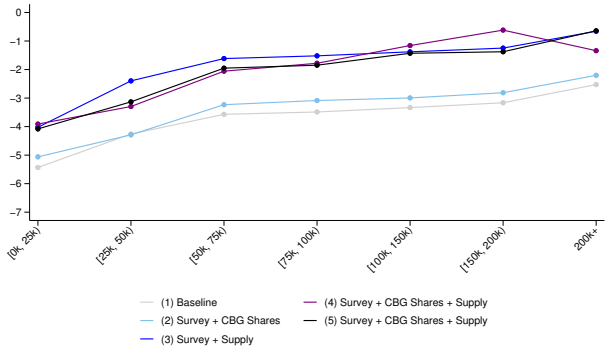
**Table 3. Demand Estimates: Main (return)**

| Parameters | (1) | | (2) | | (3) | | (4) | | (5) | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Baseline Utility:** $(\bar{\alpha}, \bar{\beta})$ | | | | | | | | | | |
| Log Price | -5.434 | (1.793) | -5.060 | (1.923) | -4.024 | (0.164) | -3.911 | (0.217) | -4.081 | (0.231) |
| Log Download Speed | 0.487 | (0.487) | 1.091 | (0.490) | 0.093 | (0.252) | 0.123 | (0.077) | 0.115 | (0.077) |
| Log Upload Speed | 0.044 | (0.229) | -0.297 | (0.149) | -0.181 | (0.158) | 0.059 | (0.047) | 0.067 | (0.046) |
| Comcast | 0.746 | (0.529) | -0.020 | (0.363) | 0.288 | (0.220) | 0.314 | (0.079) | 0.322 | (0.079) |
| Wave | 0.155 | (0.886) | -3.412 | (0.689) | 1.252 | (0.189) | -7.543 | (0.146) | -7.409 | (0.140) |
| Constant | 17.910 | (6.362) | 15.516 | (6.899) | 13.653 | (0.945) | 13.265 | (0.881) | 13.979 | (0.940) |
| **Log Price × Income:** $(\alpha_i)$ | | | | | | | | | | |
| Income [25k, 50k) | 1.175 | (0.405) | 0.771 | (0.421) | 1.627 | (0.334) | 0.615 | (0.434) | 0.949 | (0.491) |
| Income [50k, 75k) | 1.864 | (0.395) | 1.829 | (0.374) | 2.409 | (0.248) | 1.853 | (0.441) | 2.130 | (0.328) |
| Income [75k, 100k) | 1.946 | (0.396) | 1.975 | (0.374) | 2.504 | (0.255) | 2.131 | (0.478) | 2.233 | (0.345) |
| Income [100k, 150k) | 2.099 | (0.369) | 2.065 | (0.348) | 2.645 | (0.201) | 2.752 | (0.304) | 2.652 | (0.217) |
| Income [150k, 200k) | 2.269 | (0.400) | 2.248 | (0.382) | 2.776 | (0.251) | 3.293 | (0.327) | 2.705 | (0.315) |
| Income 200k+ | 2.907 | (0.377) | 2.858 | (0.358) | 3.368 | (0.196) | 2.572 | (0.210) | 3.438 | (0.263) |
| **Demographics:** $(\lambda_i)$ | | | | | | | | | | |
| Income [25k, 50k) | -3.656 | (1.688) | -2.861 | (1.771) | -5.512 | (1.394) | -2.013 | (1.803) | -3.424 | (2.043) |
| Income [50k, 75k) | -5.926 | (1.659) | -5.569 | (1.595) | -8.182 | (1.052) | -5.475 | (1.867) | -6.678 | (1.388) |
| Income [75k, 100k) | -6.142 | (1.667) | -6.165 | (1.605) | -8.458 | (1.086) | -6.625 | (2.034) | -7.066 | (1.460) |
| Income [100k, 150k) | -5.749 | (1.556) | -5.040 | (1.498) | -8.024 | (0.864) | -8.032 | (1.311) | -0.742 | (0.910) |
| Income [150k, 200k) | -6.476 | (1.708) | -6.230 | (1.659) | -8.586 | (1.102) | -11.023 | (1.415) | -8.064 | (1.358) |
| Income 200k+ | -8.868 | (1.614) | -8.830 | (1.540) | -10.794 | (0.871) | -0.026 | (0.912) | -11.063 | (1.115) |
| **Price Coefficients:** $(\bar{\alpha} + \alpha_i)$ | | | | | | | | | | |
| Income [0k, 25k) | -5.434 | (1.793) | -5.060 | (1.923) | -4.024 | (0.164) | -3.911 | (0.217) | -4.081 | (0.231) |
| Income [25k, 50k) | -4.259 | (1.778) | -4.289 | (1.787) | -2.397 | (0.213) | -3.296 | (0.247) | -3.132 | (0.281) |
| Income [50k, 75k) | -3.570 | (1.774) | -3.232 | (1.856) | -1.615 | (0.203) | -2.057 | (0.375) | -1.951 | (0.254) |
| Income [75k, 100k) | -3.488 | (1.774) | -3.085 | (1.871) | -1.519 | (0.215) | -1.780 | (0.433) | -1.848 | (0.275) |
| Income [100k, 150k) | -3.335 | (1.767) | -2.995 | (1.846) | -1.379 | (0.153) | -1.159 | (0.240) | -1.429 | (0.069) |
| Income [150k, 200k) | -3.164 | (1.773) | -2.812 | (1.844) | -1.248 | (0.211) | -0.617 | (0.201) | -1.376 | (0.235) |
| Income 200k+ | -2.527 | (1.766) | -2.202 | (1.831) | -0.655 | (0.063) | -1.339 | (0.070) | -0.643 | (0.061) |
| Av. Own-price Elasticity | -3.302 | | -3.086 | | -1.480 | | -1.707 | | -1.713 | |
| Micro Data | x | | x | | x | | x | | x | |
| Broadband Shares | | | x | | | | x | | x | |
| Supply-side Restrictions | | | | | x | | x | | x | |
| Price Moments | Demand | | Demand | | Supply | | Supply | | Both | |
| Household Survey Respondents | 1,977 | | 1,977 | | 1,977 | | 1,977 | | 1,977 | |
| Households w/ Wave Access (Choice Set 1) | 618 | | 618 | | 618 | | 618 | | 618 | |
| Households w/o Wave Access (Choice Set 2) | 1,359 | | 1,359 | | 1,359 | | 1,359 | | 1,359 | |
| Census Block Groups (Broadband Share Obs.) | | | 476 | | | | 476 | | 476 | |
| Census Blocks (Provider Deployment Obs.) | | | 9,298 | | | | 9,298 | | 9,298 | |
| Objective Value | 4,540 | | 153,752 | | 4,548 | | 153,952 | | 153,963 | |

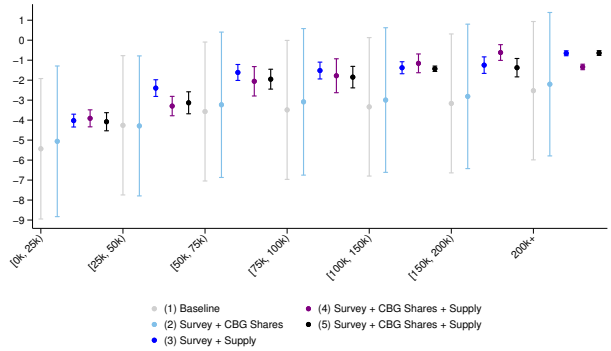
*Notes*: This table presents households' estimated preferences for broadband subscriptions. The primary unit of observation is a household × plan coming from microdata on individual households' subscription choices. Additional moments are included in specifications (2–5) as described in the main text and denoted by "x". Estimation closely follows Grieco et al.'s (2025) CLEER. Standard errors reported in parentheses. See appendix B for alternative specifications and robustness checks.

**Figure 8. Demand Estimates:**
**Price Sensitivity by Income Group (return)**

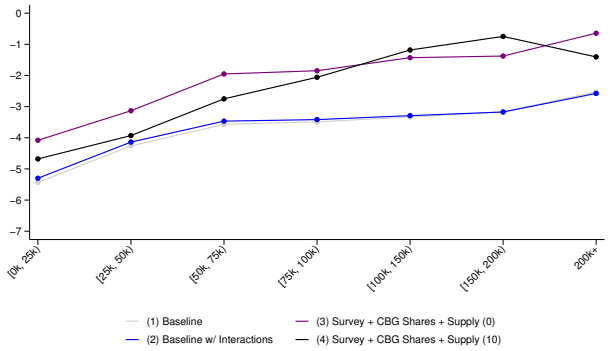
(a) Main Estimates



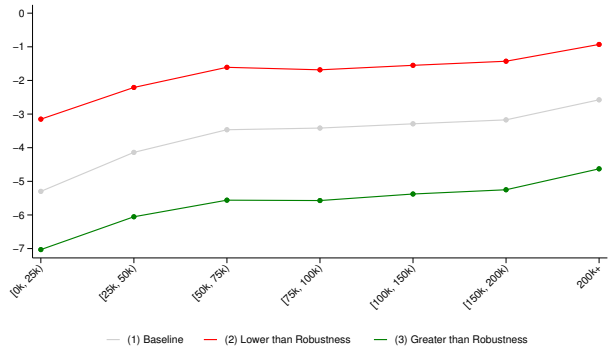

(b) Main Confidence Intervals




(c) Alternative Specifications




(d) Plan Matching Robustness




*Notes*: This figure displays households' estimated price sensitivity by income group based on various demand specifications. Panel (a) plots the point estimates of households' price parameters for the specifications displayed in table 3. Panel (b) plots both point estimates and 95% confidence intervals for the same set of specifications. Panel (c) plots corresponding point estimates for the alternative demand specifications displayed in table B1. Panel (d) plots corresponding point estimates for demand specifications that investigate the robustness of my results to the procedure I use to match households to broadband plans, displayed in table B2.

## 4.8 Deployment Model

I model providers' broadband deployment decisions as a dynamic game in which firms make discrete entry and investment decisions. In the model, time is discrete with finite horizon $t = 0, 1, 2, ..., T$, providers, CenturyLink and Comcast, are indexed by $F \in \{L, M\}$, and locations are indexed by $\ell = 1, ..., \mathcal{M}$.

In each location $\ell$ and in any period $t$, CenturyLink can be in one of three technological states, $x_{L,\ell,t} \in \{$potential entrant, DSL incumbent, fiber incumbent$\}$. Similarly, Comcast can be in one of two technological states, $x_{M,\ell,t} \in \{$potential entrant, cable incumbent$\}$. When a firm is a potential entrant, it chooses either to remain out of the location or enter as a DSL, fiber, or cable provider (depending on the firm's technological capabilities). When the firm is an incumbent, it chooses either to exit the location forever, or remain as an active provider. When CenturyLink is a DSL incumbent, in addition to exiting or remaining as a DSL provider, it also has the option to upgrade from a DSL provider to a fiber provider.

If providers' deployment decisions are interdependent across locations, the combination of possible deployment configurations is *enormous*. For example, in my empirical application, the space of possible market outcomes is $(3 \times 2)^{\mathcal{M}}$ each period, making the problem computationally intractable. Following Aguirregabiria and Ho (2012), I simplify the problem and instead assume that a provider's deployment decision in one location is independent of its decisions in all other locations. This assumption significantly shrinks the space of outcomes that providers' consider ($3 \times 2$ in each location) and is also econometrically convenient in that it permits a likelihood-based approach to estimation.

In each location, each period $t$ starts with competition between the current set of active firms, where each firm earns period profits $\pi_{F,\ell,t}(x_{\ell,t})$ given the location's current aggregate state $x_{\ell,t}$. This aggregate state,

$$x_{\ell,t} = (x_{L,\ell,t}, x_{M,\ell,t}, \mathcal{H}_{\ell,t}, \mathcal{D}_{\ell,t}),$$

is comprised of firms' states, the current number of households residing in the location $\mathcal{H}_{\ell,t}$ (or "market size"), and demand conditions of the location $\mathcal{D}_{\ell,t}$ (discussed in more detail below).

The timing of the game is as follows. In each location, each period,

1. Competition occurs, and firms earn profits $\pi_{L,\ell,t}(x_{\ell,t}), \pi_{M,\ell,t}(x_{\ell,t})$.
2. Comcast observes the location's state $x_{\ell,t}$, forms rational expectations about its future evolution, and draws i.i.d. shocks $\epsilon(a_{M,\ell,t})$, which represent random components of sunk costs. Depending upon whether Comcast is a potential entrant

or incumbent, these shocks are denoted as $\epsilon^e(a^e_{M,\ell,t})$ or $\epsilon^c(a^c_{M,\ell,t})$, respectively.

3. Comcast takes an action $a_{M,\ell,t} \in A_M$ and incurs the associated sunk cost $\phi + \epsilon(a_{M,\ell,t})$.
4. CenturyLink observes Comcast's action and the location's state, forms rational expectations about its future evolution, and draws i.i.d. cost shocks $\epsilon(a_{L,\ell,t})$. Depending upon whether CenturyLink is a potential entrant, DSL incumbent, or fiber incumbent, these shocks are denoted as $\epsilon^e(a^e_{L,\ell,t})$, $\epsilon^d(a^d_{L,\ell,t})$, or $\epsilon^f(a^f_{L,\ell,t})$, respectively.
5. CenturyLink takes an action $a_{L,t} \in A_L$ and incurs the associated sunk cost $\phi + \epsilon(a_{L,\ell,t})$.
6. The location's state evolves from $x_{\ell,t}$ to $x_{\ell,t+1}$ based upon firms' actions and the exogenous evolution of market size and demand conditions.

In the final period $T$, each firm earns a terminal value $V_{F,\ell,T}(x_{\ell,T}) = \frac{\pi_{F,\ell,T}(x_{\ell,T})}{(1-\rho)}$.

## 4.9 Period Profits

In each location, each period firms' technological states, market size $\mathcal{H}_{\ell,t}$, and demand conditions $\mathcal{D}_{\ell,t}$ together determine each firm's period profits:

$$\pi_{F,\ell,t}(x_{F,\ell,t}, x_{-F,\ell,t}, \mathcal{H}_{\ell,t}, \mathcal{D}_{\ell,t}) = \mathcal{H}_{\ell,t} \sum_{j \in J_F} S_{j,\ell,t}(x_{-F,\ell,t}, \mathcal{D}_{\ell,t}) p_j,$$

where $J_F$ is the firm's menu of broadband plans given its current technological state. $S_{j,\ell,t}(.)$ is the market share of product $j$, which depends upon rival firms' technological states, as well as local demand conditions, $\mathcal{D}_{\ell,t}$, which characterize household heterogeneity within a location. As discussed in section 4.3, marginal costs in broadband are likely de minimus, therefore, I assume providers' period profits are equivalent to their period revenues.

When CenturyLink deploys either DSL or fiber in a location, it offers households a specific menu of plans associated with that technology. These menus, reported in table A1, come from the FCC's Urban Rate Survey. When Comcast deploys cable in a location, it offers households the menu of plans reported in table 2.

## 4.10 Dynamic Optimization

Providers make their broadband deployment decisions in each location weighing the future stream of profits they expect to earn against the sunk cost of deployment. Their objective is to choose the series of actions $a_{\ell,t} \in A_F$ that maximizes the NPV of their

expected profits. Providers discount their future streams of profits by a factor $\rho \in (0,1)$ with rational expectations about the endogenous evolution of competitors' deployment decisions and the exogenous evolution of market size.[13]

CenturyLink's dynamic programming problem as a potential entrant is characterized by the following Bellman equation:

$$V^e_{L,\ell,t}(x_{\ell,t},\epsilon_{L,\ell,t}) = \max\Big\{\rho E\big[V^e_{L,\ell,t+1}(x_{\ell,t+1},\epsilon_{L,\ell,t+1})|x_{\ell,t},\epsilon_{L,\ell,t}\big] + \epsilon^e_{L,\ell,t,0},$$
$$\rho E\big[V^d_{L,\ell,t+1}(x_{\ell,t+1},\epsilon_{L,\ell,t+1})|x_{\ell,t},\epsilon_{L,\ell,t}\big] - \phi_d + \epsilon^e_{L,\ell,t,d},$$
$$\rho E\big[V^f_{L,\ell,t+1}(x_{\ell,t+1},\epsilon_{L,\ell,t+1})|x_{\ell,t},\epsilon_{L,\ell,t}\big] - \phi_f + \epsilon^e_{L,\ell,t,f}\Big\},$$

and as a DSL or fiber incumbent, respectively:

$$V^d_{L,\ell,t}(x_{\ell,t},\epsilon_{L,\ell,t}) = \pi^d_{L,\ell,t}(x_{\ell,t}) + \max\Big\{\epsilon^d_{L,\ell,t,0},\ \rho E\big[V^d_{L,\ell,t+1}(x_{\ell,t+1},\epsilon_{L,\ell,t+1})|x_{\ell,t},\epsilon_{L,\ell,t}\big] + \epsilon^d_{L,\ell,t,d},$$
$$\rho E\big[V^f_{L,\ell,t+1}(x_{\ell,t+1},\epsilon_{L,\ell,t+1})|x_{\ell,t},\epsilon_{L,\ell,t}\big] - \phi_u + \epsilon^d_{L,\ell,t,f}\Big\},$$

$$V^f_{L,\ell,t}(x_{\ell,t},\epsilon_{L,\ell,t}) = \pi^f_{L,\ell,t}(x_{\ell,t}) + \max\Big\{\epsilon^f_{L,\ell,t,0},\ \rho E\big[V^f_{L,\ell,t+1}(x_{\ell,t+1},\epsilon_{L,\ell,t+1})|x_{\ell,t},\epsilon_{L,\ell,t}\big] + \epsilon^f_{L,\ell,t,f}\Big\}.$$

Similarly, Comcast's dynamic programming problem as a potential entrant is characterized by the following Bellman equation:

$$V^e_{M,\ell,t}(x_{\ell,t},\epsilon_{M,\ell,t}) = \max\Big\{\rho E\big[V^e_{M,\ell,t+1}(x_{\ell,t+1},\epsilon_{M,\ell,t+1})|x_{\ell,t},\epsilon_{M,\ell,t}\big] + \epsilon^e_{M,\ell,t,0},$$
$$\rho E\big[V^c_{M,\ell,t+1}(x_{\ell,t+1},\epsilon_{M,\ell,t+1})|x_{\ell,t},\epsilon_{M,\ell,t}\big] - \phi_c + \epsilon^e_{M,\ell,t,c}\Big\},$$

and as a cable incumbent:

$$V^c_{M,\ell,t}(x_{\ell,t},\epsilon_{M,\ell,t}) = \pi^c_{M,\ell,t}(x_{\ell,t}) + \max\Big\{\epsilon^c_{M,\ell,t,0},\ \rho E[V^c_{M,\ell,t+1}(x_{\ell,t+1},\epsilon_{M,\ell,t+1})|x_{\ell,t},\epsilon_{M,\ell,t}] + \epsilon^c_{M,\ell,t,c}\Big\}.$$

Besides firms' period profit functions, the key parameters of this game are firms' sunk costs of deployment, $\phi$. CenturyLink's sunk costs of deploying DSL and fiber service are $\phi_d$ and $\phi_f$, respectively, and its cost of upgrading from DSL to fiber is $\phi_u$. Comcast's cost of deploying cable service is $\phi_c$.[14]

[13] I assume firms have perfect foresight about the future evolution of market size, $\mathcal{H}_{\ell,t}$, and that location demand conditions are invariant over time $\mathcal{D}_{\ell,t} \equiv \mathcal{D}_\ell$.

[14] I assume that firms' fixed operating costs are zero, as are their scrap values upon exiting.

## 4.11 Equilibrium

As in Igami (2017), for a given set of parameter values $\phi = (\phi_d, \phi_f, \phi_u, \phi_c)$, there exists a unique Perfect Bayesian Equilibrium. Three features of the game guarantee a unique equilibrium: (1) i.i.d. cost shocks, (2) the sequential order of firms' actions, and (3) the finite horizon.

First, because firms' private information are i.i.d. cost shocks, firms' payoffs are only affected by their rivals' cost shocks through their actual choices, not the specific realizations of $\epsilon$'s. Second, the sequential order of actions means that each firm effectively solves a single-agent dynamic programming problem based upon its expectation over the future evolution of the state space, avoiding issues with multiple equilibria that arise in simultaneous-move games. Third, the finite horizon enables me to solve the model by backwards induction for a unique PBE, starting with firms' terminal values in period $T$ and computing their value functions in earlier periods by iterating backwards.

Firms' terminal values in each technological state are,

$$\Big(V^e_{L,\ell,T}(x_{\ell,T}), V^d_{L,\ell,T}(x_{\ell,T}), V^f_{L,\ell,T}(x_{\ell,T}), V^e_{M,\ell,T}(x_{\ell,T}), V^c_{M,\ell,T}(x_{\ell,T})\Big) =$$

$$\Big(0,\ \frac{\pi^d_{L,\ell,T}(x_{\ell,T})}{(1-\rho)},\ \frac{\pi^f_{L,\ell,T}(x_{\ell,T})}{(1-\rho)},\ 0,\ \frac{\pi^c_{M,\ell,T}(x_{\ell,T})}{(1-\rho)}\Big).$$

In period $T-1$, CenturyLink's problem as a DSL incumbent is,

$$\max\Big\{\epsilon^d_{L,\ell,T-1,0},\ \rho E\big[V^d_{L,\ell,T}(x_{\ell,T})|x_{\ell,T-1}\big]+\epsilon^d_{L,\ell,T-1,d},\ \rho E\big[V^f_{L,\ell,T}(x_{\ell,T})|x_{\ell,T-1}\big]-\phi_u+\epsilon^d_{L,\ell,T-1,f}\Big\}.$$

Assuming firms' cost shocks are distributed extreme value, the expected value of a firm's decision in each state, before its cost shocks are realized, is given by a closed-form expression. For example, the expected value of CenturyLink using DSL in period $T-1$ is,

$$E\big[V^d_{L,\ell,T-1}(x_{\ell,T-1},\epsilon_{L,\ell,T-1})|x_{\ell,T-1}\big] = \pi^d_{L,\ell,T-1}(x_{\ell,T-1})+$$
$$\lambda\Big\{\gamma+\log\Big[\exp(0)+\exp\Big(\frac{\rho E\big[V^d_{L,\ell,T}(x_{\ell,T})|x_{\ell,T-1}\big]}{\lambda}\Big)+\exp\Big(\frac{\rho E\big[V^f_{L,\ell,T}(x_{\ell,T})|x_{\ell,T-1}\big]-\phi_u}{\lambda}\Big)\Big]\Big\},$$

where $\gamma$, Euler's constant, is the mean of the extreme value distribution, and $\lambda$ is its scale. Similar expressions hold for all of CenturyLink and Comcast's technological states. Using these expressions I can derive firms' value functions from period $T$ back to period 0, as well as form choice probabilities associated with firms' actions in each period and state. For example, the probability of CenturyLink exiting as a DSL incumbent is

given by,

$$P^d_{L,\ell,t,0}(x_{\ell,t}) = \frac{\exp(0)}{\exp(0) + \exp\left(\frac{\rho E[V^d_{L,\ell,t+1}(x_{\ell,t+1})]}{\lambda}\right) + \exp\left(\frac{\rho E[V^f_{L,\ell,t+1}(x_{\ell,t+1})] - \phi_u}{\lambda}\right)}.$$

With these choice probabilities, I can estimate the model by maximizing the following log-likelihood function:

$$Q(\phi) = \sum_{\ell} \sum_{t=0}^{T-1} \Big( \sum_{a' \in A_L} a_{L,\ell,t,a'} \log(P_{L,\ell,t,a'}(x_{\ell,t})) + \sum_{a' \in A_M} a_{M,\ell,t,a'} \log(P_{M,\ell,t,a'}(x_{\ell,t})) \Big).$$

## 4.12 Estimation and Identification

To estimate providers' sunk cost parameters, I rely on a panel of providers' broadband deployment decisions, $a_{F,\ell,t}$, coupled with estimates of providers' period profits recovered from my demand system, $\pi_{F,\ell,t}(x_{\ell,t})$. My sample consists of CenturyLink and Comcast's biannual deployment decisions across 23,115 census blocks over the period Dec., 2014–Jun., 2018, for a sample size of 115,575 census block-periods.

To facilitate estimation, I smooth the data by interpolating providers' deployment decisions and period profits over a grid of potential deployment locations (see figure A7). For robustness, I test the sensitivity of my results to grid size using a coarser grid of 1,164 locations and a finer grid of 4,002 and obtain comparable parameter estimates.

The sunk cost parameters, $\phi$, are identified by variation in period profits and other location characteristics together with providers' observed deployment decisions across locations, over time (see figure 6). For example, if I observe a relatively high proportion of locations where CenturyLink upgrades its service from DSL to fiber, this would imply a relatively low sunk cost of upgrading its service, whereas a relatively low proportion would imply a relatively high sunk cost (illustrated in figure 9a).

The logit scale parameter, $\lambda$, is identified by providers' sensitivity to profits in their payoff functions relative to the sunk cost parameters, which affects their predicted deployment decisions as illustrated in figure 9b.

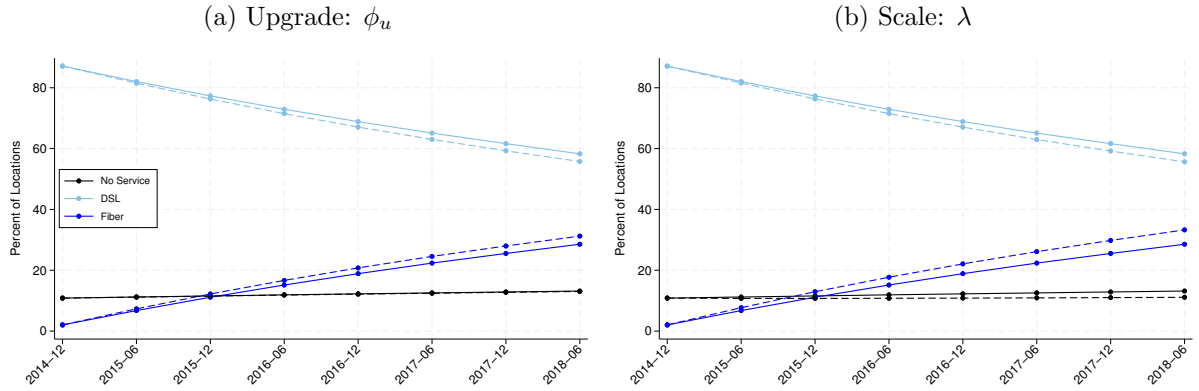
Finally, I set providers' discount factor $\rho$ to 0.95, corresponding to an annual interest rate of 10.8%.[15]

## 4.13 Sunk Cost Results

Table 4 displays sunk cost estimates (in hundreds of thousands of dollars) from two different model specifications for two different gird sizes. Columns (1) and (2) present

[15] $r = \left(\frac{1}{0.95^2}\right) - 1 \approx 0.108$

**Figure 9. Supply Model Identification (return)**




*Notes*: The solid lines in panels (a) and (b) display CenturyLink's predicted deployment given the sunk cost estimates of specification (3) displayed in table 4. The dotted lines in panel (a) show the model's predicted deployment reducing $\phi_u$ by 5%, holding other parameters fixed. Similarly, the dotted lines in panel (b) show the model's predicted deployment increasing $\lambda$ by 5%, holding other parameters fixed. Both "experiments" demonstrate how providers' actual deployment decisions identify their sunk cost parameters in the model.

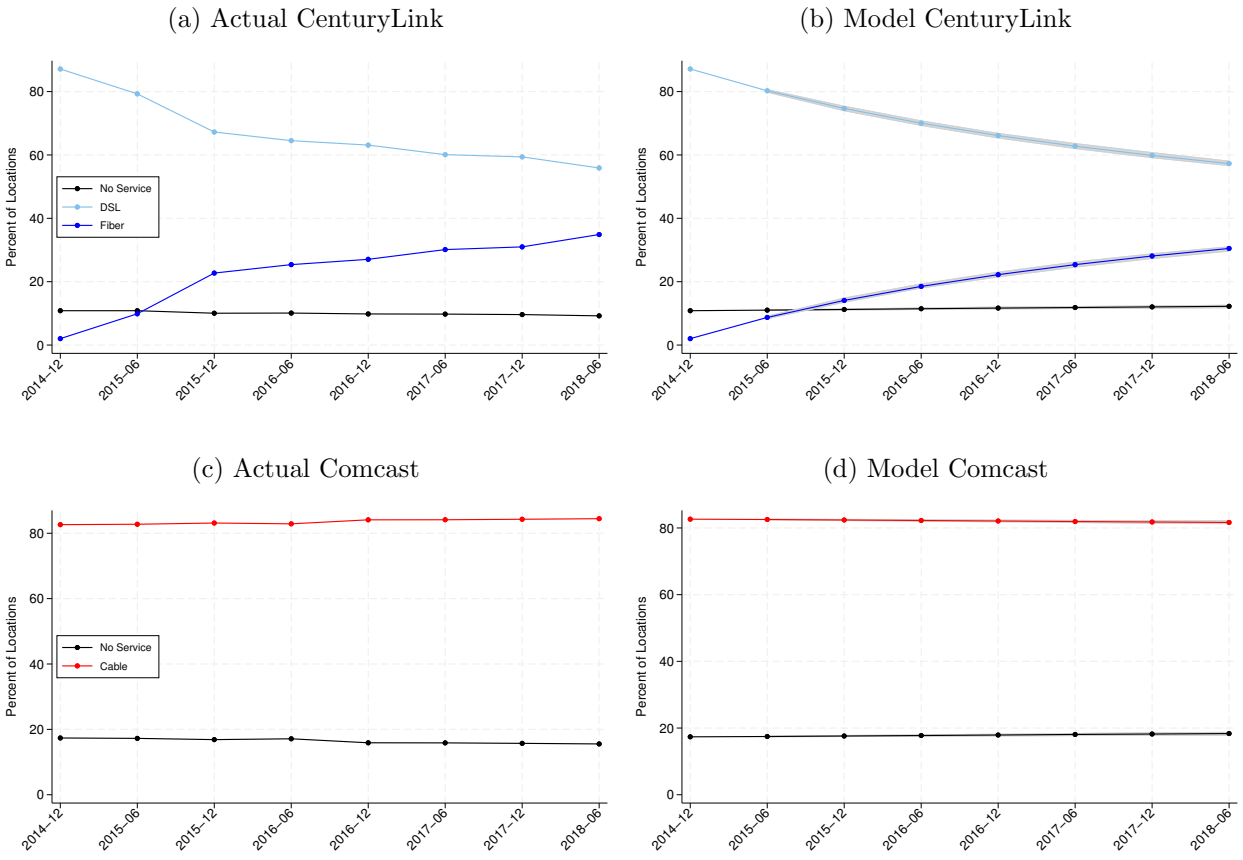
results using data interpolated over a coarse grid, while columns (3) and (4) present estimates using a fine grid. Columns (1) and (3) present results from a baseline specification where sunk costs are constant across locations, while columns (2) and (4) present results from an alternative specification that allows CenturyLink's sunk costs to vary across locations based on their distance from the origin of its fiber network in Seattle (see figure A7). This parameterization allows locations further away from CenturyLink's fiber network in period $t = 1$ to have higher sunk costs than locations that are closer, capturing the economics of broadband deployment in a parsimonious way. Figure 10 shows the fit of specification (4) compared to providers' observed deployment decisions over time.

In column (3), the sunk cost parameters can be interpreted as the mean cost of deployment per location. These results indicate that per location it costs approximately \$560,000, \$630,000, and \$770,000 to deploy DSL, cable, and fiber, respectively. CenturyLink's cost to upgrade from DSL to fiber is of a similar magnitude, \$280,000, but approximately one third the cost of de novo fiber deployment.

As discussed, the specification in column (4) allows sunk costs to vary across locations by distance from the origin of CenturyLink's fiber network. The results show that deployment costs are increasing in distance, which is economically intuitive. On their face, these estimates are more difficult to interpret, than those in column (3). For ease of interpretation, in table A2, I present summary statistics on the distribution of the sunk costs per household implied by the model over my sample (see also figures A8 and A9). Conditional on location characteristics, for the average location in my sample, it

costs \$3,100, \$3,900, and \$4,500 per household to deploy DSL, cable, and fiber, respectively. Similarly, on average it costs \$1,600 per household for CenturyLink to upgrade from DSL to fiber. Also, notice that the distribution of sunk costs per household across locations is left-skewed, with a relatively small proportion of relatively "high" cost locations. Overall, the deployment cost estimates I recover from the model are in the range of those reported by industry sources (on the order of \$700–\$6,000 per household).

**Figure 10. Deployment Model Fit (return)**




*Notes*: This figure displays providers' actual and predicted deployment according to the estimates of specification (4) in table 4. The average predicted paths (solid lines in panels (b) and (d)) are generated from 200 simulations of the model taking into account variance in households' preferences and the stochastic nature of firms' cost shocks. 95% confidence intervals are represented by the gray shaded areas. Simulations are described in more detail in appendix C.

## Table 4. Sunk Cost Estimates (return)

| Parameters | Coarse Grid | | Fine Grid | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | |
| **Deploy DSL:** ($\phi_d$) | | | | | |
| Constant | 5.687 | 5.671 | 5.619 | 5.150 | [5.116, 5.185] |
| | (0.349) | (0.351) | (0.159) | (0.138) | |
| **Deploy Fiber:** ($\phi_f$) | | | | | |
| Constant | 9.024 | 5.288 | 7.725 | 2.587 | [2.547, 2.618] |
| | (0.971) | (1.811) | (0.274) | (0.282) | |
| Distance | | 0.303 | | 0.326 | [0.324, 0.328] |
| | | (0.194) | | (0.030) | |
| **Upgrade DSL to Fiber:** ($\phi_u$) | | | | | |
| Constant | 3.074 | 1.032 | 2.787 | 0.789 | [0.703, 0.867] |
| | (0.066) | (0.169) | (0.036) | (0.087) | |
| Distance | | 0.116 | | 0.117 | [0.117, 0.119] |
| | | (0.009) | | (0.004) | |
| **Deploy Cable:** ($\phi_c$) | | | | | |
| Constant | 6.564 | 6.542 | 6.281 | 6.618 | [6.595, 6.647] |
| | (0.292) | (0.292) | (0.141) | (0.152) | |
| Scale ($\lambda$) | 0.659 | 0.657 | 0.838 | 0.847 | [0.843, 0.851] |
| | (0.006) | (0.006) | (0.003) | (0.004) | |
| Discount Factor ($\rho$) | 0.95 | 0.95 | 0.95 | 0.95 | |
| Log-likelihood | -2,303 | -2,211 | -8,168 | -7,701 | |
| Locations | 1,164 | 1,164 | 4,002 | 4,002 | |
| Periods | 7 | 7 | 7 | 7 | |
| Locations × Periods × Providers (Obs.) | 16,296 | 16,296 | 56,028 | 56,028 | |

*Notes*: This table displays providers' estimated sunk costs of deployment for broadband technologies. The unit of observation is a location × period × provider. As described in the main text, specifications (1) and (2) are estimated using data from a coarse grid of locations, 1,164. Specifications (3) and (4) are estimated using data from a fine grid of locations, 4,002. See figure A7 for maps of grid locations. Standard errors reported in parentheses are computed from the observed information matrix—these estimates do not take into account the variance in households' estimated demand parameters. To account for the variance in households' preferences, for specification (4) I compute bootstrapped standard errors by taking 200 random draws of demand parameters from the estimated variance-covariance matrix of my demand model. For each draw, I predict providers' period profits and estimate providers' sunk cost parameters. 95% confidence intervals for these bootstrapped sunk cost estimates are reported in brackets.

# 5 Digital Divide Policy Counterfactuals

In this section, I compare the costs and benefits of different subsidy policies designed to address the digital divide. To do this, I use the estimates from my structural model to perform a series of counterfactuals and compare outcomes across policies. I focus my analysis on the two primary policies that have been proposed to reduce the digital divide: (1) demand-side subsidies to increase the affordability of broadband and (2) supply-side subsidies to increase access to high-speed broadband.

First, I estimate the costs and benefits (in terms of consumer surplus) of a "demand subsidy" program that reduces the cost of broadband subscriptions for low-income households. Second, I estimate the costs and benefits of a "supply expansion" policy in which CenturyLink deploys fiber and Comcast deploys cable to all underserved households in the Seattle area. Finally, I compare the cost and benefits of both policies on an equal footing assuming that policymakers face a budget constraint and may choose to invest in a combination of demand and supply subsidies.[16]

I use the latest period in my data, June 2018, to estimate the annual cost and benefits of each policy. However, since the supply expansion policy is a one time lump sum investment, whereas demand subsidies must be paid out on an annual basis, in order to "normalize" the comparison I also calculate the cumulative costs and benefits of each policy over an infinite horizon using an annual discount factor of 5%.[17]

I briefly discuss the implementation of these counterfactuals below but describe them in more detail in appendix C.

## 5.1 Demand Subsidies

To quantify the costs and benefits of a demand-side subsidy program in a realistic manner, I consider two levels of subsidies for low-income households modeled after programs implemented by the FCC. Under the FCC's Lifeline Program, eligible households received a $10 credit towards their preferred broadband subscription on a monthly basis, and under the Affordable Connectivity Program (ACP), eligible households received an analogous $30 credit. Using my demand estimates, I estimate households' counterfactual subscription choices where households with income less than $50,000 receive either a $10 or $30 credit towards whichever subscription they choose. To recover the total cost of each program, I multiply the per household cost by the number of households that take-up the program.

As displayed in table 5, I estimate that a demand subsidy of $10 would cost $3.5

[16] In appendix E, I describe in detail how I calculate lower and upper bounds of changes in consumer surplus attributable to policy changes.

[17] This calculation simply amounts to multiplying annual costs and benefits by a factor of $\left(\frac{1}{0.05}\right)$.

million on an annual basis, generate $12 million in consumer surplus (lower bound), and raise the overall broadband subscription rate by 4.5 percentage points (% pt.) to 86.5%. In terms of cumulative costs and benefits, this would amount to costs of $70.4 million and consumer surplus (lower bound) of $241 million. A $30 subsidy program would cost $28 million annually, generate $64 million in consumer surplus (lower bound), and raise the overall broadband subscription rate by 12% pt. to 94%. Cumulatively, a $30 subsidy would result in costs $560 million and consumer surplus (lower bound) of $1,287 million.

## 5.2 Supply Expansion

To quantify the costs and benefits of a supply expansion policy, I consider a supply-side subsidy to providers that incentivizes them to deploy service to underserved locations. Specifically, using CenturyLink's sunk cost estimates, in each location where households reside without access to fiber service, I determine the minimum payment CenturyLink would require to deploy fiber. Similarly, using Comcast's sunk cost estimates, in each location where households reside without access to cable service, I determine the minimum payment Comcast would require to deploy cable. Then, I sum over these payments to determine the total cost of the policy (discussed further in appendix C).

In column (4) of table 5, I estimate that deploying fiber and cable to all underserved households in the Seattle area would cost $1,219 million. On an annual basis this expansion would generate $15 million in consumer surplus (lower bound) and raise the overall broadband subscription rate by 0.4% pt. to 82.3%. Cumulatively, this would result in an increase in consumer surplus (lower bound) of $295 million.

## 5.3 Budget Constrained Policy Analysis

The preceding counterfactual results suggest that a demand subsidy program would likely be a more cost-effective policy in terms of increasing consumers' access to broadband service. However, to explicitly determine which policy is more cost effective, I evaluate their benefits assuming that policymakers face a budget constraint. Specifically, I assume policymakers have a fixed budget which they can invest in one of the following policy options:

1. entirely in a demand subsidy program;
2. entirely in a supply expansion program;
3. in an approximately 50-50 split between both programs.[18]

[18]Incorporating a mix of demand and supply subsidies into policymakers' choice set not only adds a realistic policy option but also enables me to evaluate the extent to which the programs are comple-

## Table 5. Policy Counterfactual Summary (return)

| | | Demand Subsidy | | Supply Expansion | | | Demand + Supply Subsidies | |
|---|---|---|---|---|---|---|---|---|
| | Baseline | \$10, BC1 | \$30, BC2 | All | BC1 | BC2 | BC1 | BC2 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Broadband Share | 81.9 [81.8, 82.1] | 86.5 [86.2, 86.7] | 94.0 [93.6, 94.3] | 82.3 [82.2, 82.5] | 81.9 [81.7, 82.1] | 81.9 [81.8, 82.1] | 85.3 [85.1, 85.5] | 90.8 [90.5, 91.1] |
| **Provider Coverage** | | | | | | | | |
| CenturyLink DSL | 51.2 [49.5, 53.0] | 51.2 [49.5, 53.0] | 51.2 [49.5, 53.0] | 0.0 [0.0, 0.0] | 38.0 [36.4, 39.4] | 10.6 [9.5, 11.7] | 42.9 [41.4, 44.5] | 22.7 [21.4, 24.1] |
| CenturyLink Fiber | 45.6 [43.9, 47.3] | 45.6 [43.9, 47.3] | 45.6 [43.9, 47.3] | 99.9 [99.7, 100.0] | 59.1 [57.8, 60.5] | 87.2 [86.2, 88.3] | 54.1 [52.6, 55.4] | 74.7 [73.5, 76.1] |
| Comcast | 94.1 [93.5, 94.8] | 94.1 [93.5, 94.8] | 94.1 [93.5, 94.8] | 99.6 [99.4, 99.8] | 95.0 [94.3, 95.5] | 97.2 [96.6, 97.7] | 94.6 [94.0, 95.3] | 96.1 [95.5, 96.6] |
| **Annual Benefits and Costs (\$ MM)** | | | | | | | | |
| Consumer Surplus (Lower Bound) | – | 12.0 [11.7, 12.4] | 64.3 [62.6, 66.1] | 14.7 [12.4, 17.2] | 2.2 [1.3, 3.0] | 7.6 [5.6, 9.6] | 9.7 [9.1, 10.5] | 35.0 [33.6, 36.6] |
| Consumer Surplus (Upper Bound) | – | 42.8 [41.7, 44.0] | 228.8 [222.6, 235.1] | 52.4 [43.9, 61.3] | 7.8 [4.7, 10.8] | 27.2 [19.8, 34.1] | 34.7 [32.4, 37.2] | 124.4 [119.6, 130.3] |
| Cost | – | 3.5 [3.4, 3.6] | 28.0 [27.2, 28.8] | 1,219.4 [1,201.4, 1,238.1] | 70.4 [68.0, 72.8] | 559.8 [544.0, 575.3] | 33.0 [31.9, 34.2] | 297.2 [287.8, 305.5] |
| **Cumulative Benefits and Costs (\$ MM)** | | | | | | | | |
| Consumer Surplus (Lower Bound) | – | 240.6 [234.7, 247.7] | 1,286.8 [1,252.0, 1,322.4] | 294.5 [247.1, 344.8] | 43.8 [26.3, 60.7] | 152.9 [111.5, 191.6] | 195.0 [182.3, 209.2] | 699.8 [672.8, 732.9] |
| Consumer Surplus (Upper Bound) | – | 855.3 [834.4, 880.6] | 4,575.3 [4,451.4, 4,701.8] | 1,047.0 [878.6, 1,225.8] | 155.8 [93.7, 215.7] | 543.7 [396.6, 681.2] | 693.2 [648.1, 743.8] | 2,488.2 [2,392.1, 2,606.0] |
| Cost | – | 70.4 [68.1, 72.9] | 560.0 [544.3, 575.4] | 1,219.4 [1,201.4, 1,238.1] | 70.4 [68.0, 72.8] | 559.8 [544.0, 575.3] | 70.4 [68.0, 72.8] | 559.9 [542.6, 576.8] |

*Notes*: This table summarizes the results of my policy counterfactuals. From left to right, column (1) displays the baseline overall share of households with broadband subscriptions and provider coverage (the number of households with broadband access), columns (2–3) display the effects of demand subsidies, columns (4–6) display the effects of supply subsidies, and columns (7–8) display the effects of mixed subsidies. Cumulative benefits and costs are computed by valuing annual benefits and costs over an infinite horizon using an annual discount factor of 5%. Annual and cumulative costs are equivalent for supply subsides, since they are a one-time lump sum investment. The computation of the lower and upper bounds of changes in consumer surplus is described in detail in appendix E. Point estimates are averages over 200 model simulations. 95% confidence intervals reported in brackets. Simulations are described in detail in appendix C.

Then, I compare outcomes across these policy options. I perform these simulations using a smaller budget constraint and a larger budget constraint (BC1 and BC2) to assess the effect of relaxing policymakers' budget constraint. Table 5 and figure 11 present these results. Figure 11 depicts the smaller and larger budget constraints represented by the dashed and solid lines, where the numbers in parentheses represent the estimated gains in consumer surplus (lower bound) attributable to each policy.

In the first set of budget constrained counterfactuals (BC1), I assume that policymakers' budget is enough to fund a demand subsidy of $10 (corresponding to column (2) of table 5), or $70.4 million. When investing in the supply expansion program, providers expand their coverage sequentially from least costly to most costly location until policymakers' budget is exhausted (discussed further in appendix C). As shown in column (5), under this budget constraint, CenturyLink's fiber coverage increases from 46% of households to 59% of households, while Comcast's coverage increases from 94% to 95%. This expansion leads to a $44 million increase in consumer surplus compared to the $241 million in consumer surplus generated by an equivalent investment in demand subsidies (lower bound).

Under the same budget constraint, when policymakers invest roughly equally in both demand and supply subsidies, their investment covers the cost of a $7.5 per household subsidy to low-income households plus a supply-side expansion that increases CenturyLink's fiber coverage from 46% of 54% and Comcast's coverage from 94.1% to 94.6%. This mixed investment results in a gain of $195 million in consumer surplus (lower bound).

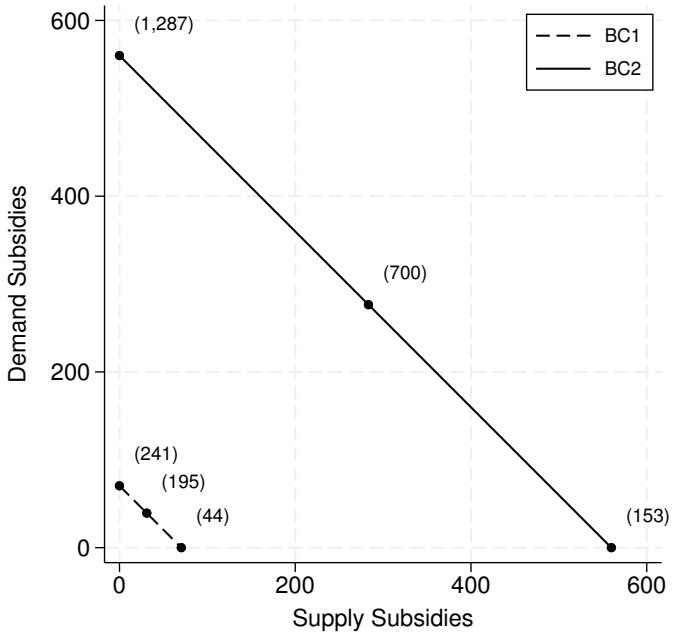
In the second set of budget constrained counterfactuals (BC2), I assume that policymakers' budget expands enough to fund a demand subsidy of $30 (corresponding to column (3) of table 5), or $560 million. As displayed in column (6), under this budget constraint, a supply-side expansion increases CenturyLink's fiber coverage from 46% to 87% and Comcast's coverage from 94% to 97%. This expansion leads to an $153 million increase in consumer surplus compared to the $1,287 million in consumer surplus generated by an equivalent investment in demand subsidies (lower bound).

Under this expanded budget constraint, when policymakers invest roughly equally in both demand and supply subsidies, their investment covers the cost of a $20 per household subsidy to low-income households plus a supply-side expansion that increases CenturyLink's fiber coverage from 46% of 75% and Comcast's coverage from 94% to 96%. This mixed investment results in a gain of $700 million in consumer surplus (lower bound).

Overall, in my empirical setting, I find that demand subsidies targeted towards low-income households are significantly more cost effective than supply-side subsidies

mentary in my setting.

**Figure 11. Budget Constrained Policy Comparisons (return)**




*Notes*: This figure summarizes the results of my policy counterfactuals in terms of policymakers' budget constraint. The dashed line represents a smaller budget constraint of $70.4 million (BC1). The solid line represents a larger budget constraint of $560 million (BC2). The plotted points represent policymakers' potential policy choices in my counterfactual analysis. The numbers in parentheses represent the cumulative consumer surplus (lower bound) generated by each policy choice.

to broadband providers in terms of increasing the share of households that subscribe to broadband and generating consumer surplus—arguably two primary goals of digital divide policy. When policymakers are faced with a fixed budget, investment in demand-side subsidies more or less dominates investment in supply-side subsidies in terms of maximizing consumer welfare, as well as the overall share of broadband subscribers. These results are potentially informative for policymakers trying to design effective digital divide policy with limited resources.

# 6 Conclusion

In this article I develop and estimate a dynamic model of broadband deployment to assess the costs and benefits of digital divide policies in equilibrium. I find that targeted demand-side subsidies for low-income households are more cost effective than supply-side subsidies in terms of increasing the overall share of broadband subscribers and consumer surplus in my empirical setting. This article contributes to existing evidence on the efficacy of digital divide policies and offers the first empirical estimates of equilibrium effects. By explicitly modeling providers' behavior, unlike previous work, I am able to directly estimate providers' sunk deployment costs, as well as conduct policy analysis that considers supply-side responses. My empirical results are potentially useful to policymakers seeking to design effective policies to tackle the digital divide.

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# 7 Appendix A: Additional Tables and Figures

This section includes additional tables and figures referenced throughout this article.

**Table A1. CenturyLink Plans by Technology (return)**

| Plan | Monthly Charge | Download Speed (mbps) | Upload Speed (mbps) | Usage Allowance (GB) |
|---|---|---|---|---|
| CenturyLink (DSL): plan 1 | 46.99 | 1.5 | .875 | 1,000 |
| CenturyLink (DSL): plan 2 | 51.99 | 7 | .875 | 1,000 |
| CenturyLink (DSL): plan 3 | 56.99 | 12 | .875 | 1,000 |
| CenturyLink (DSL): plan 4 | 66.99 | 20 | .875 | 1,000 |
| CenturyLink (DSL): plan 5 | 71.99 | 20 | 2 | 1,000 |
| CenturyLink (DSL): plan 6 | 76.99 | 40 | 5 | 1,000 |
| CenturyLink (DSL): plan 7 | 101.98 | 60 | 5 | 1,000 |
| CenturyLink (DSL): plan 8 | 126.98 | 100 | 12 | 1,000 |
| CenturyLink (Fiber): plan 1 | 56.99 | 12 | .875 | 1,000 |
| CenturyLink (Fiber): plan 2 | 61.99 | 12 | 5 | 1,000 |
| CenturyLink (Fiber): plan 3 | 66.99 | 20 | .875 | 1,000 |
| CenturyLink (Fiber): plan 4 | 71.99 | 20 | 5 | 1,000 |
| CenturyLink (Fiber): plan 5 | 76.99 | 40 | 5 | 1,000 |
| CenturyLink (Fiber): plan 6 | 81.99 | 40 | 20 | 1,000 |
| CenturyLink (Fiber): plan 7 | 96.99 | 100 | 50 | 1,000 |
| CenturyLink (Fiber): plan 8 | 156.94 | 1,000 | 1,000 | . |

*Notes*: FCC Urban Rate Survey 2018. This table summarizes the primary characteristics of CenturyLink's broadband plans by technology as reported by the FCC Urban Rate Survey.

## Table A2. Sunk Costs per Household (return)

| | | Percentiles | | | | |
|---|---|---|---|---|---|---|
| Sunk Costs | Mean | 5th | 25th | 50th | 75th | 95th |
| DSL Deployment | 3,085 | 471 | 1,094 | 1,831 | 3,010 | 7,627 |
| Fiber Deployment | 4,583 | 344 | 998 | 2,294 | 4,572 | 12,511 |
| Upgrade | 1,592 | 108 | 324 | 785 | 1,592 | 4,405 |
| Cable Deployment | 3,935 | 601 | 1,395 | 2,335 | 3,840 | 9,727 |

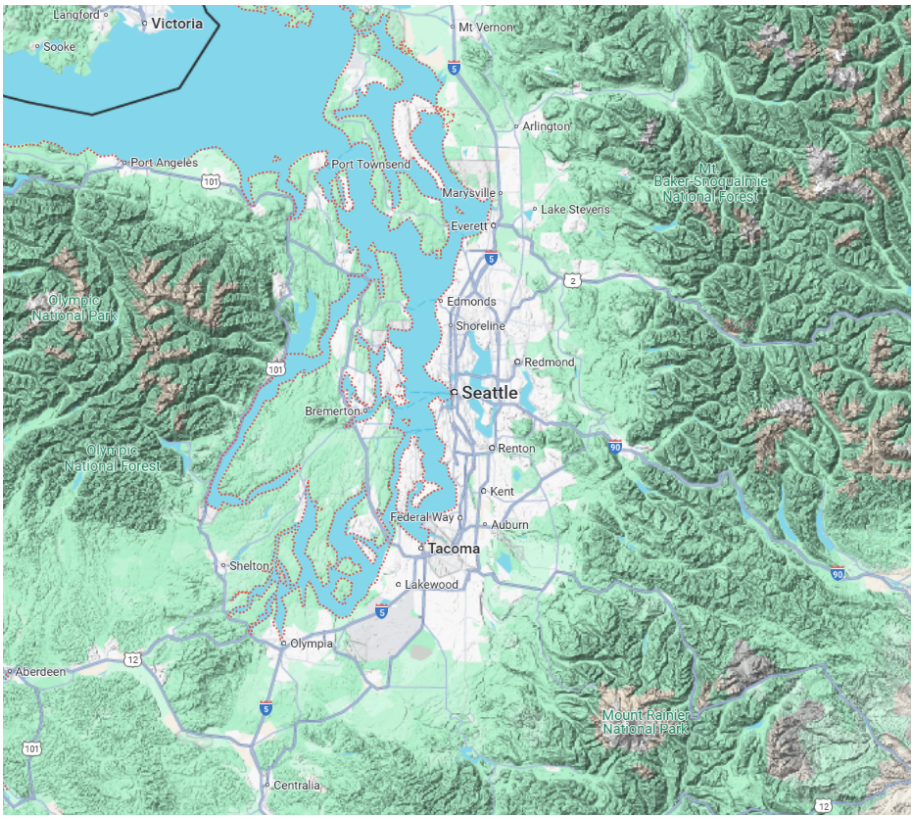
*Notes*: This table displays the distribution of providers' sunk costs of deployment by broadband technology, on a per household basis, across locations. These estimates are recovered from specification (4) of table 4.

## Figure A1. Seattle Technology Access and Adoption Survey (return)

**Q5.** **For each of the ways you get internet where you live, please tell us approximately how much each internet service costs per month to your household. If the cost is included as part of your rent or homeowner's dues, please check the box provided. If it is part of a bundled service that also includes other services (such as cable TV, calling and/or text, home security, etc.) please tell us the total cost per month for all bundled services:**
**Please check all that apply.**

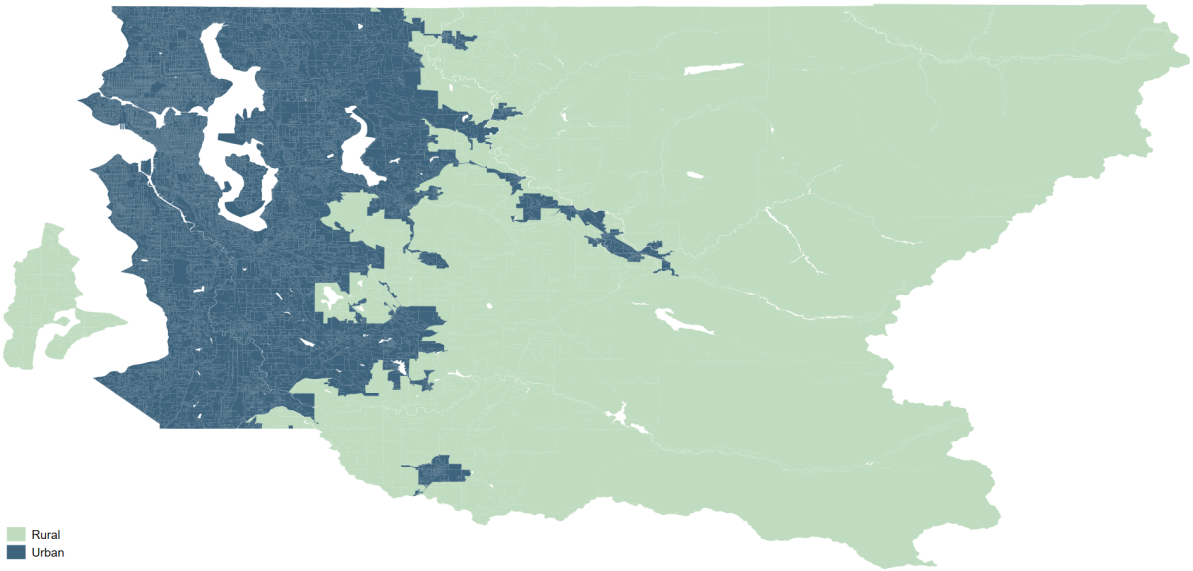
| | Have This Service Where I Live | Answer for Separately Charged Services | | | Answer for Bundled Services | |
|---|---|---|---|---|---|---|
| | | Included with My Rent or Homeowner Dues | Pay for Each Service Individually | Approx. Monthly Cost for Each Service | Pay as Part of Bundled Service | Approx. Monthly Cost for Bundled Services |
| Century Link (DSL or fiber internet) | ❑ | ❑ | ❑ | $_____ | ❑ | $_____ |
| Wave cable internet | ❑ | ❑ | ❑ | $_____ | ❑ | $_____ |
| Comcast cable internet | ❑ | ❑ | ❑ | $_____ | ❑ | $_____ |
| Cellular data plan | ❑ | | ❑ | $_____ | ❑ | $_____ |
| Other specify: _____ | ❑ | ❑ | ❑ | $_____ | ❑ | $_____ |

**Figure A2. Seattle Area**




*Notes*: Google Maps. Seattle and surrounding areas.

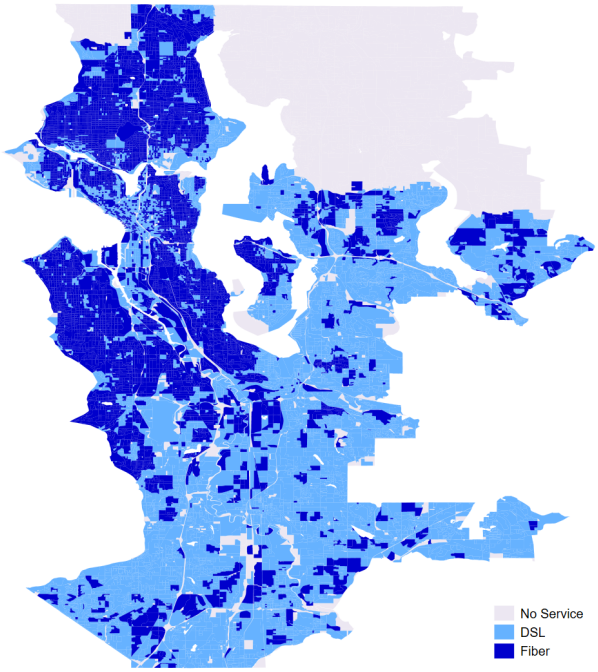
**Figure A3. King County Rural/Urban Census Blocks**



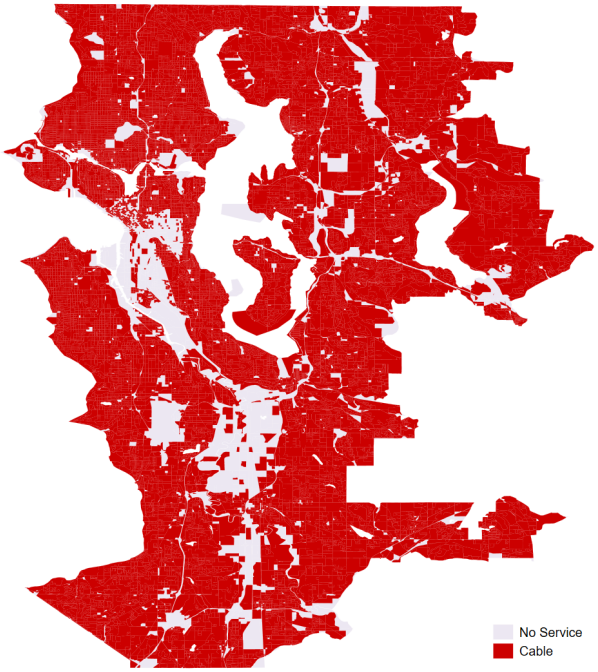

*Notes*: Census TIGER/Line data 2018. King County, Washington census blocks rural/urban classification.

**Figure A4. Provider Footprints**

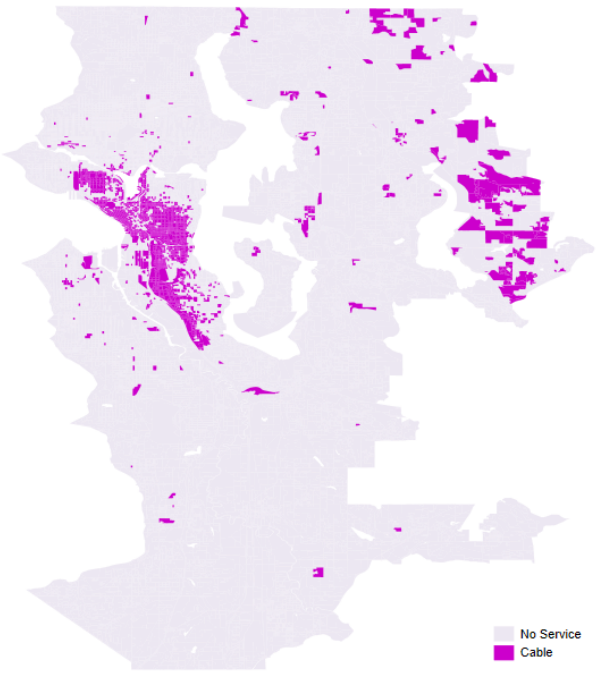
(a) CenturyLink



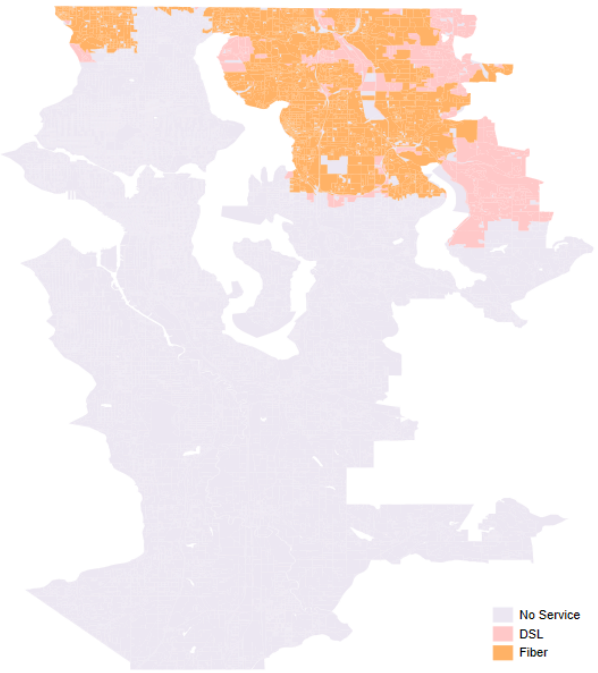

(b) Comcast




(c) Wave

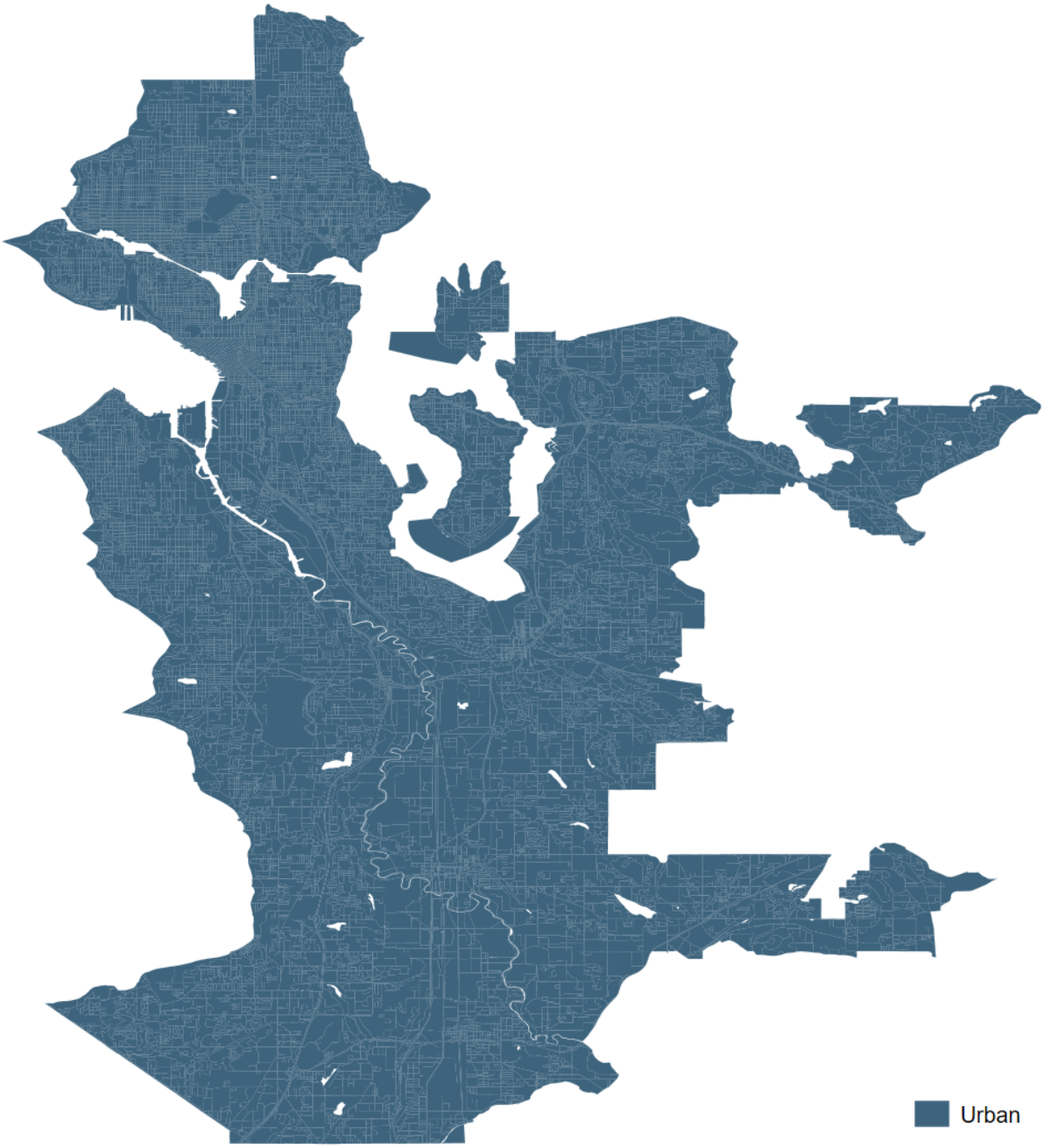



(d) Frontier



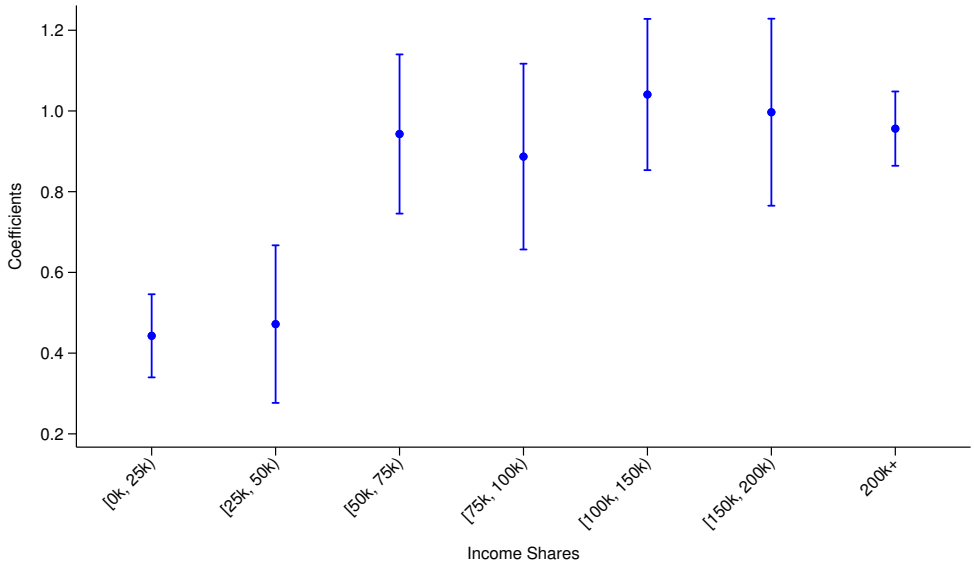

*Notes*: FCC Form 477 data 2018. This figure depicts the coverage areas of the four main wireline broadband providers within the Seattle MSA and surrounding urban census blocks. Frontier's footprint is primarily concentrated to the Northeast of the Seattle MSA.

**Figure A5. Analysis Area**



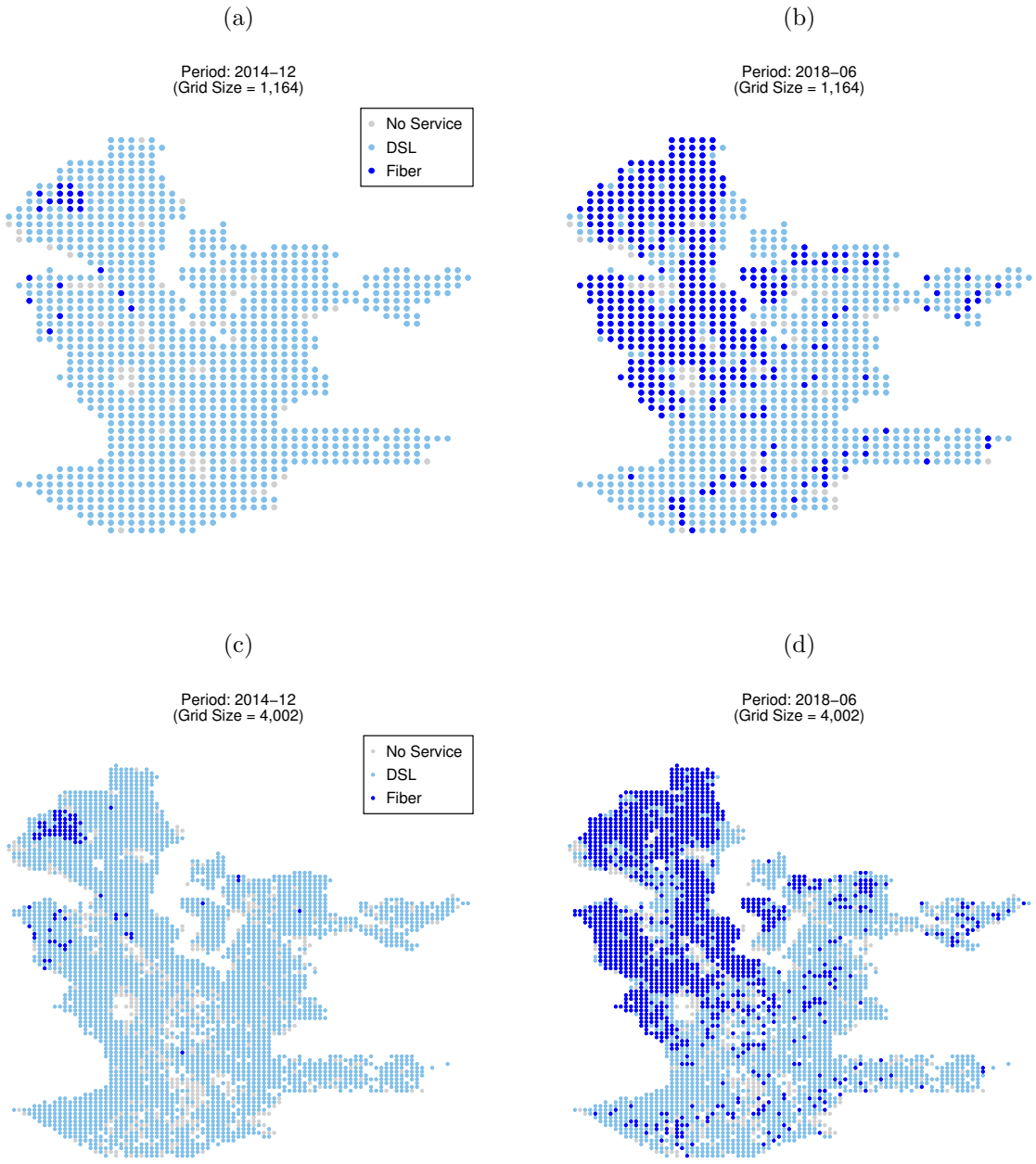

*Notes*: The area of analysis that makes up my final dataset consists of urban census blocks within King County nearby the Seattle MSA, excluding census block groups in which Frontier operates.

**Figure A6. Reduced-form Regression Coefficients: Broadband Shares on Income Shares (return)**



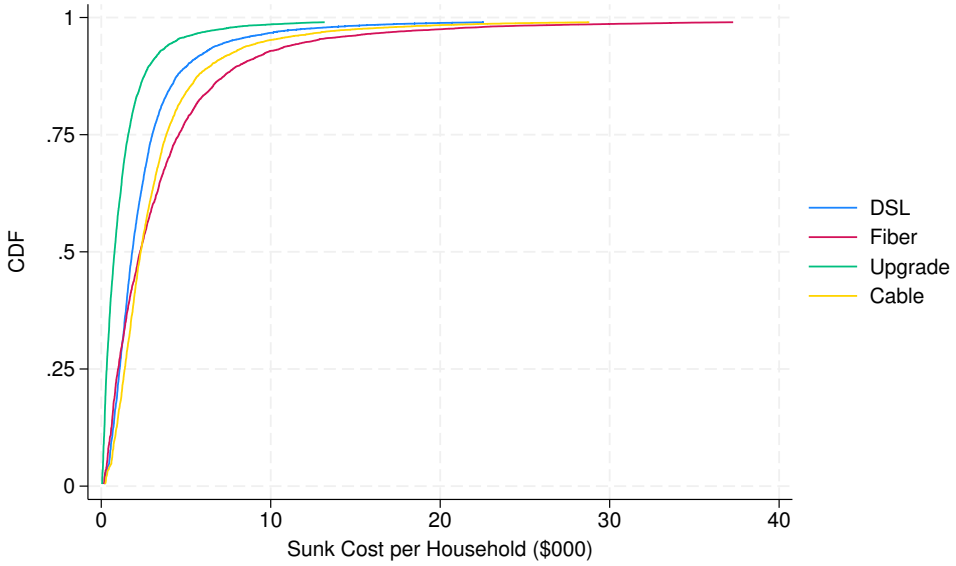

*Notes*: This figure displays regression coefficients and 95% confidence intervals from a regression of census block group-level broadband shares on the shares of households within each income bracket ($\omega_i$'s). Notice generally that increases in the shares of higher income households are associated with larger increases in the overall share of broadband subscribers.

**Figure A7. CenturyLink Deployment Interpolated over Grids (return)**




*Notes*: This figure depicts the interpolation of CenturyLink's broadband deployment decisions over a coarser grid of 1,164 locations and over a finer grid of 4,002 locations in the earliest and latest periods in my dataset. The "x" marks the "origin" of CenturyLink's fiber network in Seattle.

**Figure A8. CDFs of Sunk Costs per Household (return)**

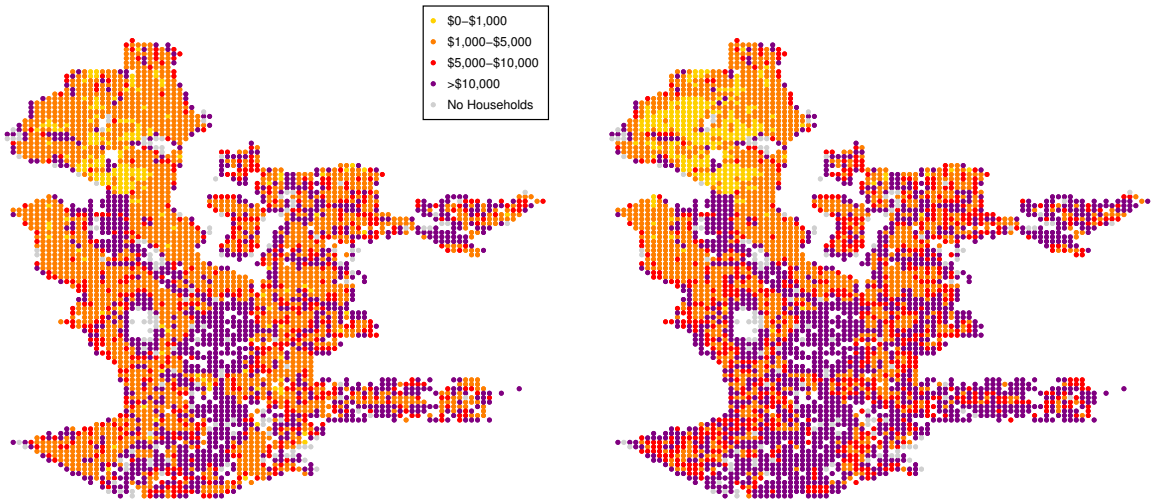



*Notes*: This figure displays the distribution of providers' sunk costs per household across locations by broadband technology. For scaling, I censor the top 1% of each distribution.

**Figure A9. Sunk Costs per Household (return)**

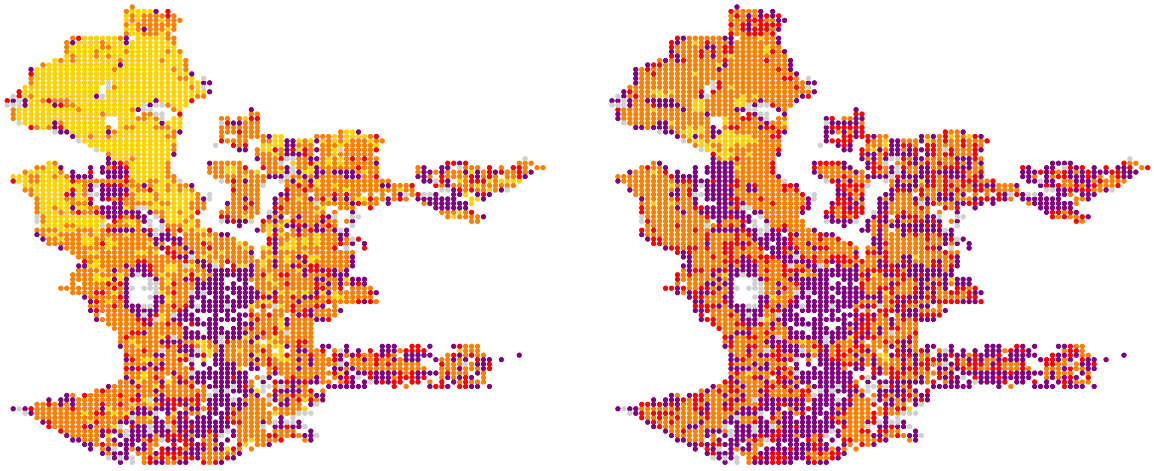
(a) Deploy DSL

(b) Deploy Fiber




(c) Upgrade to Fiber

(d) Deploy Cable



*Notes*: This figure displays geographic variation in providers' sunk costs of deployment, on a per household basis, across locations. Estimated sunk costs per household are binned into four discrete categories: (1) \$0–\$1,000, (2) \$1,000–\$5,000, (3) \$5,000–\$10,000, (4) >\$10,000. Locations with no households are represented in gray. The sunk cost estimates depicted here come from a single simulation of the model—these simulations are described in detail in appendix C.

# 8 Appendix B: Demand Robustness and Model Fit

## 8.1 Alternative Specifications

In table B1, I compare specifications from my main demand results to two alternative specifications. First, in columns (1) and (2) I compare my baseline specification to one that includes additional interactions between plan characteristics and household demographics. Specifically, I allow households' preferences to vary based on their education and household size. Overall, I find the inclusion of these additional interactions has a relatively minor effect on the primary parameters of interest—households' price sensitivity and baseline utility for plan characteristics—likely because household income is correlated with these other characteristics and because households have relatively homogeneous preferences for broadband speed. Second, in columns (3) and (4) I test the robustness of my preferred specification to the magnitude of providers' marginal costs embedded in the supply-side restrictions. In column (4) I increase providers' marginal costs from $c_j = 0$ to $c_j = 10$. Overall, perturbing the marginal cost estimates has a modest affect on the estimates, decreasing the average own-price elasticity from -1.71 to -1.98.

## 8.2 Plan Matching Robustness

In table B2, I test the robustness of my baseline demand specification to the interpolation rule I use to match households to broadband plans based on their survey responses. As described in section 3, I match each household to a broadband plan based upon how close the household's estimated monthly bill is to the list price of the plan. My preferred rule (the "Midpoint Rule") matches a household to plan $n$ when the household's monthly bill lies between the midpoint of the prices of plan $n$ and plan $n-1$ and the midpoint of the prices of plan $n$ and plan $n+1$, where plans $n-1$ and $n+1$ are closest in price to plan $n$ from below and above, respectively. In order to test the sensitivity of my demand estimates to this matching method, I match households to plans using two alternative rules that perturb my preferred method in opposite directions, at opposite extremes. Then, I re-estimate my demand model using these different methods and compare results. Below I describe these alternative matching rules.

Using the "Less than Rule", I match household $i$ to plan $n$ when the household's monthly bill, $\hat{p}_i$, lies between the prices of plan $n-1$ and plan $n$. Or more specifically,

## Table B1. Demand Estimates: Alternative Specifications (return)

| Parameters | (1) | | (2) | | (3) | | (4) | |
|---|---|---|---|---|---|---|---|---|
| **Baseline Utility:** $(\bar{\alpha}, \bar{\beta})$ | | | | | | | | |
| Log Price | -5.434 | (1.793) | -5.298 | (1.796) | -4.081 | (0.231) | -4.679 | (0.233) |
| Log Download Speed | 0.487 | (0.487) | 0.489 | (0.492) | 0.115 | (0.077) | 0.136 | (0.075) |
| Log Upload Speed | 0.044 | (0.229) | -0.010 | (0.240) | 0.067 | (0.046) | 0.109 | (0.048) |
| Comcast | 0.746 | (0.529) | 0.764 | (0.529) | 0.322 | (0.079) | 0.312 | (0.076) |
| Wave | 0.155 | (0.886) | 0.198 | (0.886) | -7.409 | (0.140) | -7.528 | (0.157) |
| Constant | 17.910 | (6.362) | 17.139 | (6.371) | 13.979 | (0.940) | 16.343 | (0.934) |
| **Log Price × Income:** $(\alpha_i)$ | | | | | | | | |
| Income [25k, 50k) | 1.175 | (0.405) | 1.159 | (0.410) | 0.949 | (0.491) | 0.749 | (0.440) |
| Income [50k, 75k) | 1.864 | (0.395) | 1.832 | (0.407) | 2.130 | (0.328) | 1.928 | (0.507) |
| Income [75k, 100k) | 1.946 | (0.396) | 1.882 | (0.411) | 2.233 | (0.345) | 2.621 | (0.527) |
| Income [100k, 150k) | 2.099 | (0.369) | 2.009 | (0.389) | 2.652 | (0.217) | 3.496 | (0.299) |
| Income [150k, 200k) | 2.269 | (0.400) | 2.126 | (0.420) | 2.705 | (0.315) | 3.933 | (0.355) |
| Income 200k+ | 2.907 | (0.377) | 2.722 | (0.403) | 3.438 | (0.263) | 3.275 | (0.223) |
| **Log Download Speed × Demographics:** $(\beta_i)$ | | | | | | | | |
| Bachelors Degree or Higher | | | -0.006 | (0.087) | | | | |
| Household Size (4+) | | | -0.036 | (0.077) | | | | |
| **Log Upload Speed × Demographics:** $(\beta_i)$ | | | | | | | | |
| Bachelors Degree or Higher | | | 0.010 | (0.085) | | | | |
| Household Size (4+) | | | 0.181 | (0.072) | | | | |
| **Demographics:** $(\lambda_i)$ | | | | | | | | |
| Income [25k, 50k) | -3.656 | (1.688) | -3.775 | (1.710) | -3.424 | (2.043) | -2.552 | (1.821) |
| Income [50k, 75k) | -5.926 | (1.659) | -6.105 | (1.709) | -6.678 | (1.388) | -5.747 | (2.124) |
| Income [75k, 100k) | -6.142 | (1.667) | -6.255 | (1.728) | -7.066 | (1.460) | -8.634 | (2.242) |
| Income [100k, 150k) | -5.749 | (1.556) | -5.817 | (1.641) | -0.742 | (0.910) | -11.140 | (1.285) |
| Income [150k, 200k) | -6.476 | (1.708) | -6.383 | (1.792) | -8.064 | (1.358) | -13.697 | (1.532) |
| Income 200k+ | -8.868 | (1.614) | -8.673 | (1.725) | -11.063 | (1.115) | -3.096 | (0.967) |
| Bachelors Degree or Higher | | | 0.686 | (0.271) | | | | |
| Household Size (4+) | | | 0.554 | (0.321) | | | | |
| **Price Coefficients:** $(\bar{\alpha} + \alpha_i)$ | | | | | | | | |
| Income [0k, 25k) | -5.434 | (1.793) | -5.298 | (1.796) | -4.081 | (0.231) | -4.679 | (0.233) |
| Income [25k, 50k) | -4.259 | (1.778) | -4.139 | (1.779) | -3.132 | (0.281) | -3.930 | (0.260) |
| Income [50k, 75k) | -3.570 | (1.774) | -3.466 | (1.774) | -1.951 | (0.254) | -2.750 | (0.418) |
| Income [75k, 100k) | -3.488 | (1.774) | -3.416 | (1.774) | -1.848 | (0.275) | -2.058 | (0.496) |
| Income [100k, 150k) | -3.335 | (1.767) | -3.289 | (1.767) | -1.429 | (0.069) | -1.182 | (0.208) |
| Income [150k, 200k) | -3.164 | (1.773) | -3.172 | (1.774) | -1.376 | (0.235) | -0.745 | (0.218) |
| Income 200k+ | -2.527 | (1.766) | -2.576 | (1.767) | -0.643 | (0.061) | -1.404 | (0.088) |
| Av. Own-price Elasticity | -3.302 | | | | -1.713 | | -1.977 | |
| Micro Data | x | | x | | x | | x | |
| Broadband Shares | | | | | x | | x | |
| Supply-side Restrictions | | | | | x | | x | |
| Price Moments | Demand | | Demand | | Both | | Both | |
| Household Survey Respondents | 1,977 | | 1,977 | | 1,977 | | 1,977 | |
| Households w/ Wave Access (Choice Set 1) | 618 | | 618 | | 618 | | 618 | |
| Households w/o Wave Access (Choice Set 2) | 1,359 | | 1,359 | | 1,359 | | 1,359 | |
| Census Block Groups (Broadband Share Obs.) | | | | | 476 | | 476 | |
| Census Blocks (Provider Deployment Obs.) | | | | | 9,298 | | 9,298 | |
| Objective Value | 4,540 | | 4,519 | | 153,963 | | 153,975 | |

*Notes*: This table presents households' estimated preferences for broadband subscriptions. The primary unit of observation is a household × plan coming from microdata on individual households' subscription choices. Additional moments are included in specifications (3–4) denoted by "x". Standard errors reported in parentheses.

household $i$'s plan $j_i$ is given by,

$$j_i(\hat{p}_i) = \begin{cases} 1, & \text{if } \hat{p}_i \in [0, p_1) \\ 2, & \text{if } \hat{p}_i \in [p_1, p_2) \\ & \vdots \\ n-1, & \text{if } \hat{p}_i \in [p_{n-2}, p_{n-1}) \\ n, & \text{if } \hat{p}_i \in [p_{n-1}, \infty) \end{cases}.$$

Using the "Greater than Rule", I match household $i$ to plan $n$ when the household's monthly bill, $\hat{p}_i$, lies between the prices of plan $n$ and plan $n+1$. Or more specifically, household $i$'s plan $j_i$ is given by,

$$j_i(\hat{p}_i) = \begin{cases} 1, & \text{if } \hat{p}_i \in [0, p_2) \\ 2, & \text{if } \hat{p}_i \in [p_2, p_3) \\ & \vdots \\ n-1, & \text{if } \hat{p}_i \in [p_{n-1}, p_n) \\ n, & \text{if } \hat{p}_i \in [p_n, \infty) \end{cases}.$$

Figures B1–B3, show how these alternative matching rules affect the assignment of households to broadband plans for each provider.

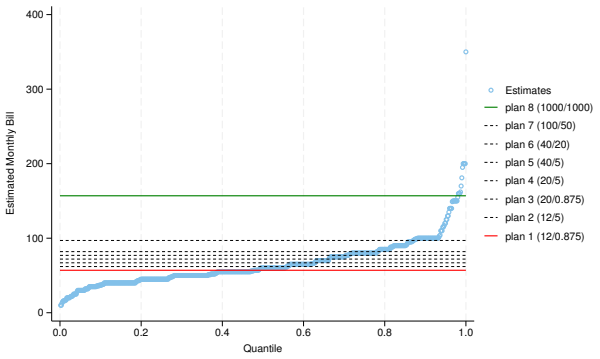
Table B2 displays estimates for the baseline demand model that includes additional interactions between plan characteristics and household demographics. Columns (1–3) present estimates based on the "Midpoint Rule", "Less than Rule", and "Greater than Rule", respectively. I find that estimates derived from these alternative matching rules bound estimates from my preferred method, and these bounds are approximately symmetric. For example, using my preferred matching method I find an own-price elasticity for households earning between $50,000–$75,000 of approximately -3.47 with an upper bound from the "Less than Rule" of -1.61 and a lower bound from the "Greater than Rule" of -5.56. Although these bounds are relatively wide, my preferred method yields own-price elasticities that are similar to other estimates in the literature.

## 8.3 Model Fit

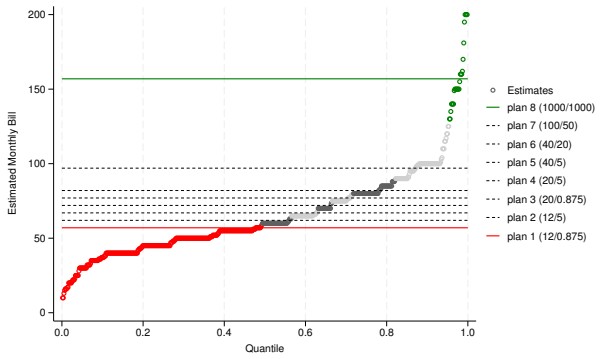
To demonstrate the fit of my demand model, I compute aggregate market shares for each plan/provider in census block groups across the Seattle area and compare these estimates to the overall share of households subscribing to wireline broadband reported in the ACS. I also show that the model is capable of matching other moments in the

## Figure B1. CenturyLink

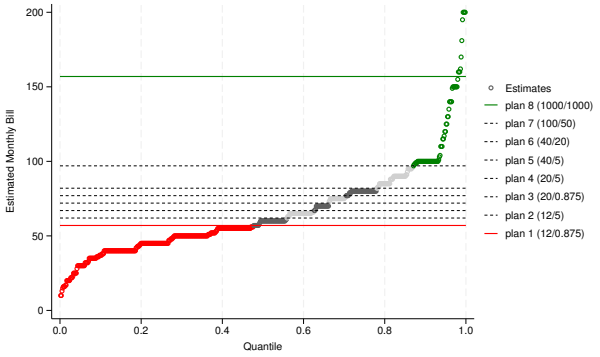
(a) Full Distribution



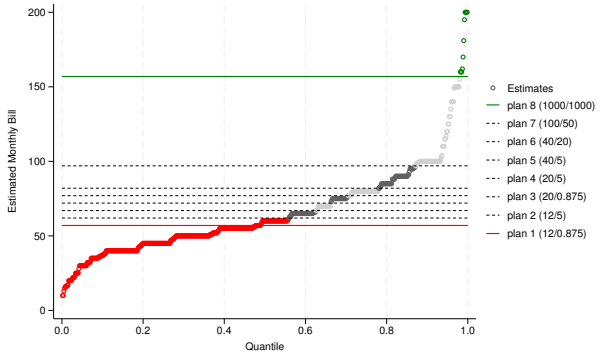

(b) Midpoint Rule




(c) Less than Rule

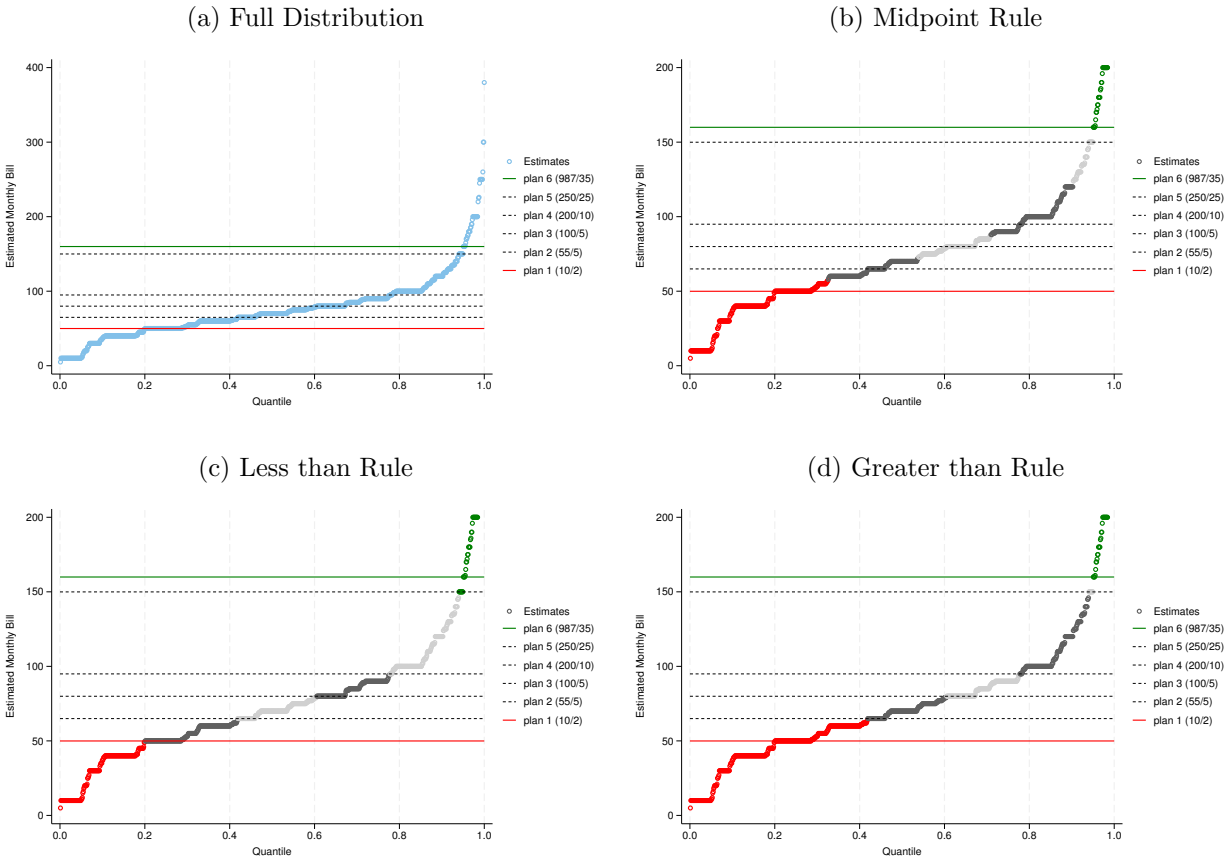



(d) Greater than Rule




*Notes*: Seattle Technology Adoption Survey 2018, FCC Urban Rate Survey 2018. This figure shows the distribution of CenturyLink subscribers' estimated monthly bills with CenturyLink's menu of subscriptions overlayed. The lowest priced plan (in red) is 12/0.875 mbps download/upload speed. The highest priced plan (in green) is 1,000/1,000 mbps download/upload speed. The alternating dark and light shaded points in the distribution denote households assigned in "intermediate" plans that lie in between the lowest and highest priced plans. Panel (a) displays the full distribution of households' estimated monthly bills. Panel (b) displays the assignment of households to broadband plans based on the "Midpoint Rule", my preferred matching rule. Panels (c) and (d) display the assignment of households to broadband plans based on the "Less than Rule" and "Greater than Rule", which I use to test the robustness of my demand estimates to my matching method.

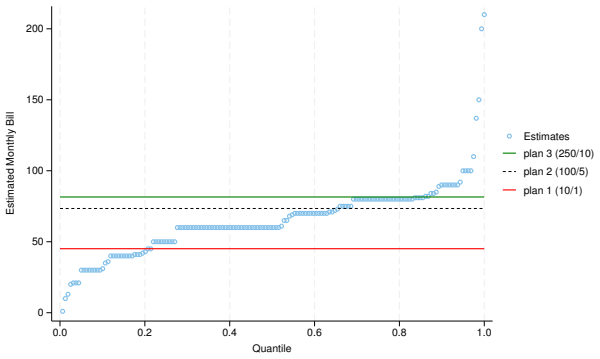
**Figure B2. Comcast**



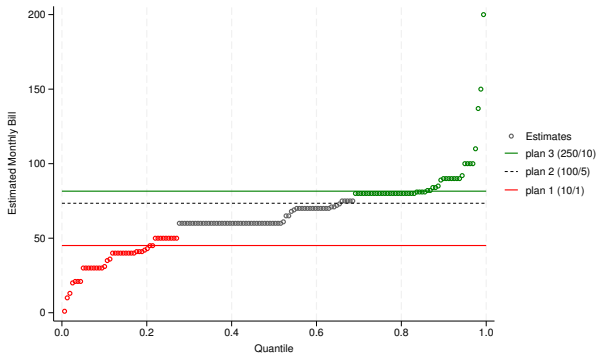

*Notes*: Seattle Technology Adoption Survey 2018, FCC Urban Rate Survey 2018. This figure shows the distribution of Comcast subscribers' estimated monthly bills with Comcast's menu of subscriptions overlayed. The lowest priced plan (in red) is 10/2 mbps download/upload speed. The highest priced plan (in green) is 987/35 mbps download/upload speed. The alternating dark and light shaded points in the distribution denote households assigned in "intermediate" plans that lie in between the lowest and highest priced plans. Panel (a) displays the full distribution of households' estimated monthly bills. Panel (b) displays the assignment of households to broadband plans based on the "Midpoint Rule", my preferred matching rule. Panels (c) and (d) display the assignment of households to broadband plans based on the "Less than Rule" and "Greater than Rule", which I use to test the robustness of my demand estimates to my matching method.

**Figure B3. Wave**

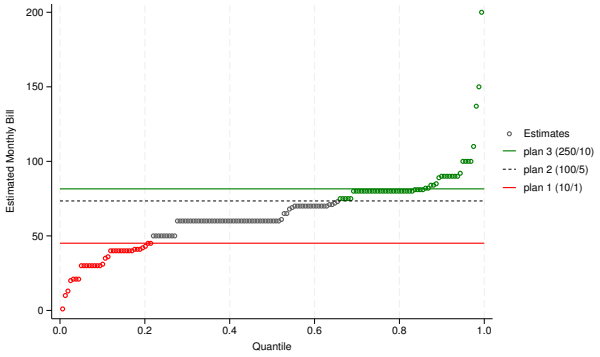
(a) Full Distribution



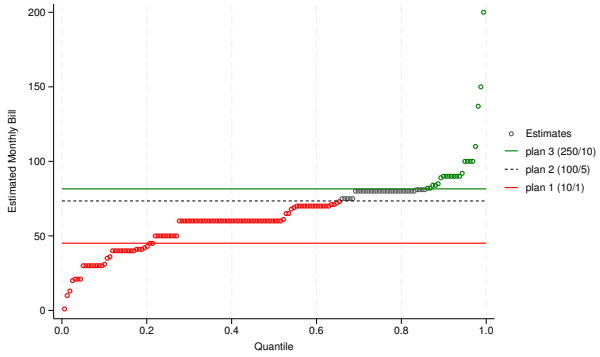

(b) Midpoint Rule




(c) Less than Rule




(d) Greater than Rule




*Notes*: Seattle Technology Adoption Survey 2018, FCC Urban Rate Survey 2018. This figure shows the distribution of Wave subscribers' estimated monthly bills with Wave's menu of subscriptions overlayed. The lowest priced plan (in red) is 10/1 mbps download/upload speed. The highest priced plan (in green) is 250/10 mbps download/upload speed. The alternating dark and light shaded points in the distribution denote households assigned in "intermediate" plans that lie in between the lowest and highest priced plans. Panel (a) displays the full distribution of households' estimated monthly bills. Panel (b) displays the assignment of households to broadband plans based on the "Midpoint Rule", my preferred matching rule. Panels (c) and (d) display the assignment of households to broadband plans based on the "Less than Rule" and "Greater than Rule", which I use to test the robustness of my demand estimates to my matching method.

## Table B2. Demand Estimates: Plan Matching Robustness (return)

| Parameters | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| **Baseline Utility:** $(\bar{\alpha}, \bar{\beta})$ | | | | | | |
| Log Price | -5.298 | (1.796) | -3.151 | (1.763) | -7.030 | (1.884) |
| Log Download Speed | 0.489 | (0.492) | 0.131 | (0.488) | 0.943 | (0.510) |
| Log Upload Speed | -0.010 | (0.240) | 0.105 | (0.237) | -0.175 | (0.248) |
| Comcast | 0.764 | (0.529) | 0.921 | (0.530) | 0.622 | (0.541) |
| Wave | 0.198 | (0.886) | 0.664 | (0.884) | -0.430 | (0.903) |
| Constant | 17.139 | (6.371) | 9.097 | (6.244) | 23.080 | (6.675) |
| **Log Price × Income:** $(\alpha_i)$ | | | | | | |
| Income [25k, 50k) | 1.159 | (0.410) | 0.943 | (0.344) | 0.976 | (0.425) |
| Income [50k, 75k) | 1.832 | (0.407) | 1.542 | (0.341) | 1.469 | (0.423) |
| Income [75k, 100k) | 1.882 | (0.411) | 1.467 | (0.346) | 1.459 | (0.428) |
| Income [100k, 150k) | 2.009 | (0.389) | 1.601 | (0.327) | 1.653 | (0.402) |
| Income [150k, 200k) | 2.126 | (0.420) | 1.722 | (0.353) | 1.779 | (0.436) |
| Income 200k+ | 2.722 | (0.403) | 2.222 | (0.340) | 2.401 | (0.416) |
| **Log Download Speed × Demographics:** $(\beta_i)$ | | | | | | |
| Bachelors Degree or Higher | -0.006 | (0.087) | 0.133 | (0.087) | -0.147 | (0.093) |
| Household Size (4+) | -0.036 | (0.077) | -0.029 | (0.080) | -0.032 | (0.079) |
| **Log Upload Speed × Demographics:** $(\beta_i)$ | | | | | | |
| Bachelors Degree or Higher | 0.010 | (0.085) | -0.076 | (0.077) | 0.175 | (0.100) |
| Household Size (4+) | 0.181 | (0.072) | 0.157 | (0.066) | 0.189 | (0.081) |
| **Demographics:** $(\lambda_i)$ | | | | | | |
| Income [25k, 50k) | -3.775 | (1.710) | -2.940 | (1.463) | -2.970 | (1.753) |
| Income [50k, 75k) | -6.105 | (1.709) | -5.011 | (1.464) | -4.513 | (1.757) |
| Income [75k, 100k) | -6.255 | (1.728) | -4.628 | (1.486) | -4.405 | (1.778) |
| Income [100k, 150k) | -5.817 | (1.641) | -4.233 | (1.412) | -4.239 | (1.676) |
| Income [150k, 200k) | -6.383 | (1.792) | -4.829 | (1.549) | -4.837 | (1.838) |
| Income 200k+ | -8.673 | (1.725) | -6.758 | (1.494) | -7.188 | (1.757) |
| Bachelors Degree or Higher | 0.686 | (0.271) | 0.294 | (0.281) | 0.980 | (0.273) |
| Household Size (4+) | 0.554 | (0.321) | 0.530 | (0.335) | 0.560 | (0.316) |
| **Price Coefficients:** $(\bar{\alpha} + \alpha_i)$ | | | | | | |
| Income [0k, 25k) | -5.298 | (1.796) | -3.151 | (1.763) | -7.030 | (1.884) |
| Income [25k, 50k) | -4.139 | (1.779) | -2.208 | (1.750) | -6.053 | (1.867) |
| Income [50k, 75k) | -3.466 | (1.774) | -1.610 | (1.747) | -5.560 | (1.863) |
| Income [75k, 100k) | -3.416 | (1.774) | -1.684 | (1.748) | -5.571 | (1.863) |
| Income [100k, 150k) | -3.289 | (1.767) | -1.550 | (1.743) | -5.377 | (1.855) |
| Income [150k, 200k) | -3.172 | (1.774) | -1.429 | (1.748) | -5.250 | (1.862) |
| Income 200k+ | -2.576 | (1.767) | -0.930 | (1.744) | -4.628 | (1.854) |
| Micro Data | x | | x | | x | |
| Household Survey Respondents | 1,977 | | 1,977 | | 1,977 | |
| Households w/ Wave Access (Choice Set 1) | 618 | | 618 | | 618 | |
| Households w/o Wave Access (Choice Set 2) | 1,359 | | 1,359 | | 1,359 | |
| Objective Value | 4,519 | | 4,647 | | 4,301 | |

*Notes*: This table presents households' estimated preferences for broadband subscriptions. The primary unit of observation is a household × plan coming from microdata on individual households' subscription choices. Standard errors reported in parentheses.

ACS data such as the share of broadband subscriptions by demographic groups, which are relevant to the issue of the digital divide.

Using my demand estimates, I predict the share of households subscribing to each provider at the census block group level (aggregating over census blocks),

$$\hat{\mathcal{S}}_{f,g}(\bar{\theta},\tilde{\theta}) = \frac{\sum_{\ell \in g} H_\ell \hat{\mathcal{S}}_{f,\ell}(\bar{\theta},\tilde{\theta})}{\sum_{\ell \in g} H_\ell}.$$

Table B3 displays the overall share of households with and without broadband in my sample according to the ACS and the predicted shares from the demand model. The overall share of households with broadband predicted by the model (0.82) compares favorably with the ACS data (0.82). Figure B4 shows the correlation between the fitted shares and the ACS data across census block groups.

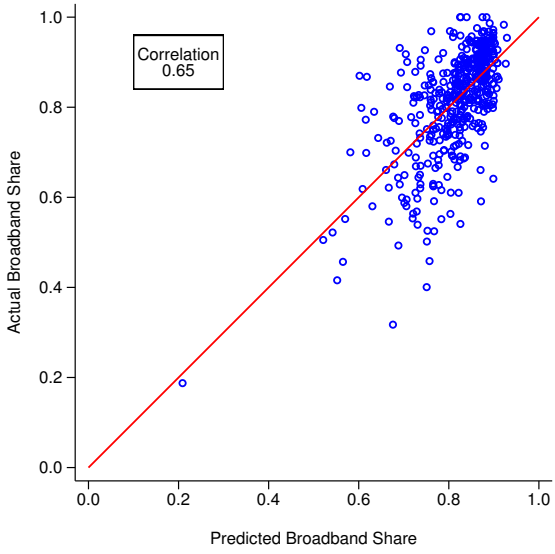
Figure B5 bins census block groups based on demographic characteristics of interest—namely education, SNAP beneficiaries, and race—and compares the share of households with broadband subscriptions based on ACS data and the predictions of the model. Notably, the predicted shares match the correlations in the ACS data relatively well without any of these demographic variables being included in the underlying demand model.

**Table B3. Demand Estimates: Model Fit (return)**

| | Actual (ACS) | | Predicted (Model) | | | | | |
|---|---|---|---|---|---|---|---|---|
| | No Broadband | Broadband | No Broadband | Broadband | CenturyLink DSL | CenturyLink Fiber | Comcast | Wave |
| Model Fit | 0.1836 | 0.8164 | 0.1843 | 0.8157 | 0.1250 | 0.3023 | 0.3884 | 0.0001 |

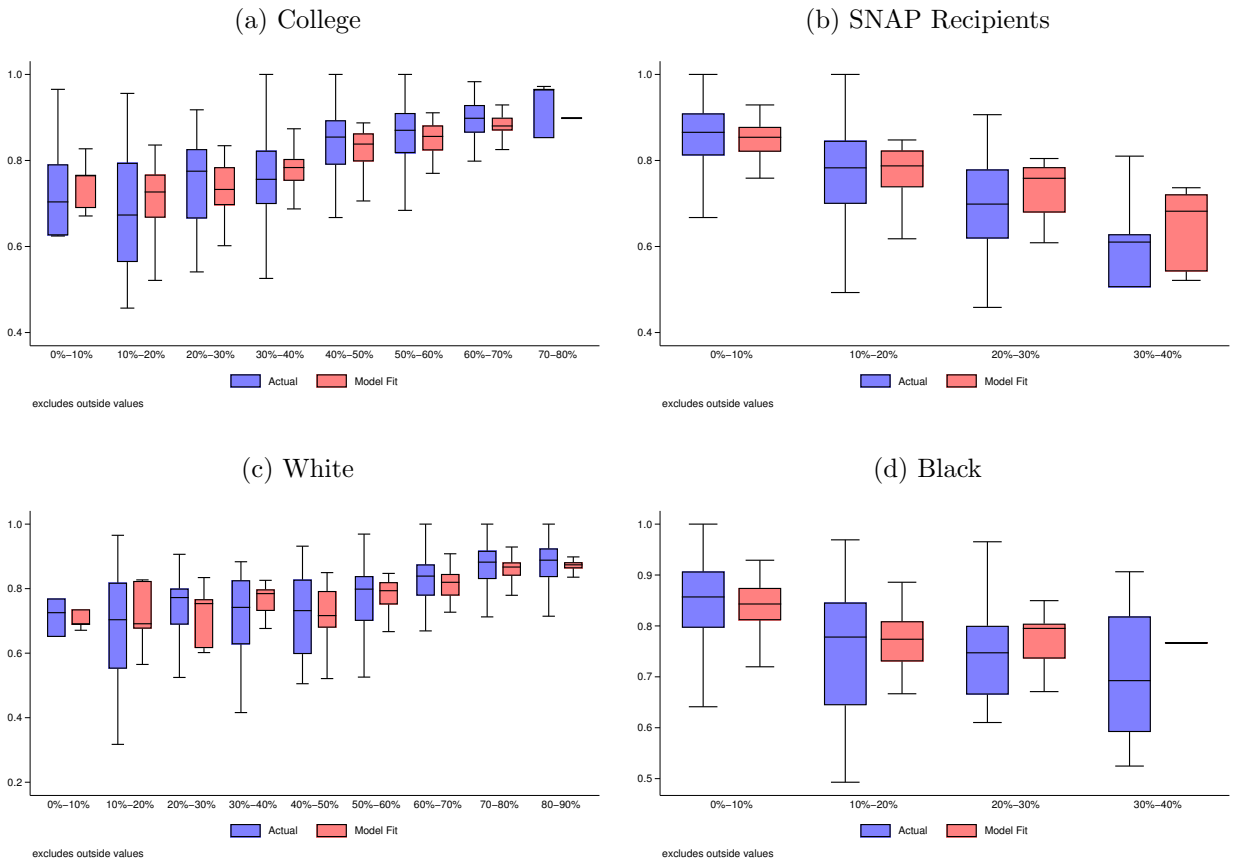
*Notes*: This table summarizes overall actual and predicted broadband shares estimated for 476 census block groups in the Seattle region. "Actual" shares are computed using ACS estimates. "Predicted" shares are computed using demand estimates. "No Broadband" is the share of households that don't purchase wireline broadband. "Broadband" is the share of households that purchase any type of wireline broadband, as calculated by ACS, or the share of households that subscribe to either CenturyLink, Comcast, or Wave, as predicted by the demand model. "DSL" and "Fiber" refer to the share of CenturyLink's DSL and fiber services.

**Figure B4. Demand Estimates: Model Fit (return)**




*Notes*: This figure plots the "Actual" against the "Predicted" share of households that subscribe broadband. The red line is the 45 degree line. The correlation between the actual and predicted shares is 0.65.

**Figure B5. Demand Estimates:**
**Predicted Broadband Shares by Demographics (return)**




*Notes*: This figure plots distributions of the share of households subscribing to broadband across census block groups, binned by the share of households that (a) are college graduates, (b) are SNAP recipients, (c) are white, (d) are black.

# 9 Appendix C: Counterfactual Simulations

In this section, I describe the implementation of my policy counterfactual simulations in detail. To generate the counterfactual simulations, I begin by taking $N = 200$ random draws of demand parameters, $\theta$, from the estimated variance-covariance matrix of my demand model.

Then, for each simulation $n = 1, ..., 200$, I do the following:

1. Given the vector of demand parameters, $\hat{\theta}^{(n)}$, predict providers' period profits in each location (under all possible market structures), $\hat{\pi}^{(n)}_{F,\ell,t}(\hat{\theta}^{(n)})$;
2. Given providers' predicted period profits and observed deployment decisions, estimate providers' sunk cost parameters, $(\hat{\phi}^{(n)}, \hat{\lambda}^{(n)})$;
3. For each period $t = 1, ..., T-1$:
   (i) Draw providers' sunk cost shocks, $\epsilon^{(n)}_{F,\ell,t}$;
   (ii) Given providers' estimated sunk cost parameters and cost shocks, predict providers' deployment decisions $\hat{a}^{(n)}_{F,\ell,t}(\hat{\phi}^{(n)}, \hat{\lambda}^{(n)}, \epsilon^{(n)}_{F,\ell,t})$;
4. Using providers' predicted deployment decisions in period $T-1$:
   (i) Compute the overall share of households subscribing to broadband, $S^{(n)}_b(\hat{\theta}^{(n)}, \hat{a}^{(n)}_{F,\ell,t})$;
   (ii) Compute households' overall consumer surplus, $CS^{(n)}(\hat{\theta}^{(n)}, \hat{a}^{(n)}_{F,\ell,t})$;

The above procedure generates the "baseline" estimates against which I benchmark my policy counterfactuals.

## 9.1 Demand Subsidies

In order to estimate the effects of a demand subsidy program, I follow the same procedure as outlined above but modify the last step to account for the subsidy to low-income households as follows:

4. Using providers' predicted deployment decisions in period $T-1$:
   (i) Perturb the prices of providers' broadband plans for low-income households by the amount of the subsidy, $\tilde{p}_j = p_j - y$;
   (ii) Compute the overall share of households subscribing to broadband, $\tilde{S}^{(n)}_b(\hat{\theta}^{(n)}, \hat{a}^{(n)}_{F,\ell,t})$;
   (iii) Compute households' overall consumer surplus, $\tilde{C}S^{(n)}(\hat{\theta}^{(n)}, \hat{a}^{(n)}_{F,\ell,t})$;

For each simulation, I calculate the cost of the demand subsidy as the difference in the overall share of households subscribing to broadband given the subsidy, relative to the baseline, multiplied by the value of the subsidy times the total number of households:

$$C^{(n)} = y\mathcal{H}(\tilde{S}^{(n)}_b - S^{(n)}_b).$$

## 9.2 Supply Expansion

In order to estimate the effects of a supply expansion program, I begin by calculating the minimum compensation each provider would be willing to accept to deploy new (or upgraded) service to each unserved (or underserved), populated location in the market based on the parameters estimates from my structural model.

Specifically, with my sunk cost estimates I back out the minimum payment required to induce CenturyLink to deploy or upgrade to fiber, as well as the minimum payment required to induce Comcast to deploy cable in each location, in period $T-1$.

For CenturyLink, in locations where the firm is a potential entrant, this payment is given by:

$$\mathcal{P}_{L,\ell,T-1} \equiv \Big(\rho \bar{V}^{e}_{L,\ell,T}(x_{\ell,T}) + \epsilon^{e}_{L,\ell,T-1,e}\Big) - \Big(\rho \bar{V}^{f}_{L,\ell,T}(x_{\ell,T}) - \phi_f + \epsilon^{e}_{L,\ell,T-1,f}\Big),$$

where $\bar{V}_{L,\ell,T}(.)$ represents CenturyLink's value function after drawing sunk cost shocks $\epsilon_{L,\ell,T-1}$'s.

Similarly, in locations where the CenturyLink has already deploy DSL, this payment is given by:

$$\mathcal{P}_{L,\ell,T-1} \equiv \Big(\rho \bar{V}^{d}_{L,\ell,T}(x_{\ell,T}) + \epsilon^{d}_{L,\ell,T-1,d}\Big) - \Big(\rho \bar{V}^{f}_{L,\ell,T}(x_{\ell,T}) - \phi_u + \epsilon^{d}_{L,\ell,T-1,f}\Big).$$

Likewise for Comcast, in locations where the firm is a potential entrant, this payment is given by:

$$\mathcal{P}_{M,\ell,T-1} \equiv \Big(\rho \bar{V}^{e}_{M,\ell,T}(x_{\ell,T}) + \epsilon^{e}_{M,\ell,T-1,e}\Big) - \Big(\rho \bar{V}^{c}_{M,\ell,T}(x_{\ell,T}) - \phi_c + \epsilon^{e}_{M,\ell,T-1,c}\Big),$$

where again $\bar{V}_{M,\ell,T}(.)$ represents Comcast's value function after drawing sunk cost shocks $\epsilon_{M,\ell,T-1}$'s.

Now with these payments in hand, I can calculate the cost of different supply-side subsidy programs. To calculate the total cost of deploying fiber and cable to each populated location without fiber service and cable service, respectively, I simply sum payments over relevant provider-locations:

$$C \equiv \sum_{F,\ell} \mathcal{P}_{F,\ell}.$$

When policymakers face a budget constraint, I assume that they choose to subsidize provider-locations in order of least to most costly such that they maximize the number

of locations reached. Given a budget, $\mathcal{B}$, the cost of the program is:

$$C \equiv \sum_{r=1}^{R} \mathcal{P}_{F,\ell}^{r} \text{ s.t. } C \leq \mathcal{B},$$

where $r$ indexes provider-locations in order of least to most costly.

In order to operationalize the supply subsidies in terms of counterfactual simulations, I follow the same procedure as previously outlined but modify the last step as follows:

4. Using providers' predicted deployment decisions in period $T-1$:
   (i) Determine the payment required for CenturyLink to deploy fiber in each candidate location, $\mathcal{P}_{L,\ell}^{(n)}(\hat{\phi}^{(n)}, \hat{\lambda}^{(n)}, \epsilon_{F,\ell,t}^{(n)})$;
   (ii) Determine the payment required for Comcast to deploy cable in each candidate location, $\mathcal{P}_{M,\ell}^{(n)}(\hat{\phi}^{(n)}, \hat{\lambda}^{(n)}, \epsilon_{F,\ell,t}^{(n)})$;
   (iii) Rank provider-locations in order of least to most costly, $r$;
   (iv) Set policymakers' budget, $\mathcal{B}$;
   (v) Sum over provider-locations by rank so long as total does not exceed budget, $\sum_r \mathcal{P}_{F,\ell}^{r,(n)} \leq \mathcal{B}$;
   (vi) Update providers' predicted deployment decisions to include new locations, $\hat{a}_{F,\ell,t}^{(n)} \to \tilde{a}_{F,\ell,t}^{(n)}$;
   (vii) Compute the overall share of households subscribing to broadband, $\tilde{S}_b^{(n)}(\hat{\theta}^{(n)}, \tilde{a}_{F,\ell,t}^{(n)})$;
   (viii) Compute households' overall consumer surplus, $\tilde{CS}^{(n)}(\hat{\theta}^{(n)}, \tilde{a}_{F,\ell,t}^{(n)})$;

# 10 Appendix D: Providers' Pricing Behavior

I assume that providers set uniform prices for their plans across their coverage areas according to Nash-Bertrand behavior. Specifically, given the current set of plans a provider offers $J_{F,\ell}$ (and competes against $J_{-F,\ell}$) in each census block $\ell$, the provider sets $J_F$ prices to maximize its profit across all the census blocks in its geographic footprint,

$$\max_{p_j, j \in J_F} \sum_{\ell \in \mathcal{M}_F} \sum_{j \in J_{F,\ell}} H_\ell S_{j,\ell}(p_j - c_j),$$

where $H_\ell$ is the number of households in census block $\ell$, $c_j$ is product $j$'s marginal cost, and $\mathcal{M}_F \subset \mathcal{M}$ is the subset of census blocks in which firm $F$ is deployed.

Equilibrium prices satisfy the following first-order conditions,

$$\sum_{\ell \in \mathcal{M}_F} \left( H_\ell S_{j,\ell} + \sum_{k \in J_{F,\ell}} H_\ell \frac{\partial S_{k,\ell}}{\partial p_j}(p_k - c_k) \right) = 0, \forall j \in J_F.$$

Stacking together all providers' FOCs, we can represent uniform pricing behavior in the market as,

$$\begin{bmatrix} \sum_\ell H_\ell S_{1,\ell} \\ \sum_\ell H_\ell S_{2,\ell} \\ \vdots \\ \sum_\ell H_\ell S_{J,\ell} \end{bmatrix} + \sum_\ell \left( \mathcal{O}_\ell * \begin{bmatrix} H_\ell \frac{\partial S_{1,\ell}}{\partial p_1} & H_\ell \frac{\partial S_{2,\ell}}{\partial p_1} & \dots & H_\ell \frac{\partial S_{J,\ell}}{\partial p_1} \\ H_\ell \frac{\partial S_{1,\ell}}{\partial p_2} & H_\ell \frac{\partial S_{2,\ell}}{\partial p_2} & \dots & H_\ell \frac{\partial S_{J,v}}{\partial p_2} \\ \vdots & \vdots & \ddots & \vdots \\ H_\ell \frac{\partial S_{1,\ell}}{\partial p_J} & H_\ell \frac{\partial S_{2,\ell}}{\partial p_J} & \dots & H_\ell \frac{\partial S_{J,\ell}}{\partial p_J} \end{bmatrix} \right) \begin{bmatrix} p_1 - c_1 \\ p_2 - c_2 \\ \vdots \\ p_J - c_J \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

where $\mathcal{O}_\ell$ represents the "ownership" matrix as in Nevo (2000).

To simplify the representation of the first-order conditions, I define $\Delta_\ell$ as the matrix product of the ownership matrix and household-weighted derivatives of census block shares with respect to prices,

$$\Delta_\ell \equiv \mathcal{O}_\ell * \begin{bmatrix} H_\ell \frac{\partial S_{1,\ell}}{\partial p_1} & H_\ell \frac{\partial S_{2,\ell}}{\partial p_1} & \dots & H_\ell \frac{\partial S_{J,\ell}}{\partial p_1} \\ H_\ell \frac{\partial S_{1,\ell}}{\partial p_2} & H_\ell \frac{\partial S_{2,\ell}}{\partial p_2} & \dots & H_\ell \frac{\partial S_{J,\ell}}{\partial p_2} \\ \vdots & \vdots & \ddots & \vdots \\ H_\ell \frac{\partial S_{1,\ell}}{\partial p_J} & H_\ell \frac{\partial S_{2,\ell}}{\partial p_J} & \dots & H_\ell \frac{\partial S_{J,\ell}}{\partial p_J} \end{bmatrix},$$

The final equation resembles the "classic" FOC matrix in Nevo (2000), except with uniform prices across census blocks, the firms' FOCs are essentially weighted by census

block size,

$$\begin{bmatrix} \sum_\ell H_\ell S_{1,\ell} \\ \sum_\ell H_\ell S_{2,\ell} \\ \vdots \\ \sum_\ell H_\ell S_{J,\ell} \end{bmatrix} + \left[\sum_\ell \Delta_\ell\right] \begin{bmatrix} p_1 - c_1 \\ p_2 - c_2 \\ \vdots \\ p_J - c_J \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix},$$

or represented in matrix form,

$$\tilde{\mathbf{S}} + \tilde{\mathbf{\Delta}}(\mathbf{p} - \mathbf{c}) = \mathbf{0}.$$

# 11 Appendix E: Consumer Surplus

To quantify the change in consumer surplus resulting from changes in the market, I follow Small and Rosen (1981) to calculate the change in consumer surplus in a discrete choice model. However, because price enters non-linearly into households' indirect utility function in my demand model, I cannot use the standard formula derived by Small and Rosen (1981) to quantify changes in consumer surplus. Small and Rosen (1981) note that price must enter linearly into the indirect utility function in order for their formula to hold. McFadden (1995) shows that it is possible to numerically approximate changes in consumer surplus when price enters non-linearly into the indirect utility function. However, I show that when price enters the indirect utility function as a logarithmic function, it is possible to bound changes in consumer surplus using a simple modification of Small and Rosen (1981).

The standard formula, derived in Small and Rosen (1981), generally used to calculate a change in consumer surplus when a representative consumer's indirect utility function is a linear function of price is,

$$\Delta CS = \frac{1}{\alpha}\Big[\log\big(1+\sum_{j\in J'}\exp(u_{i,j})\big) - \log\big(1+\sum_{j\in J}\exp(u_{i,j})\big)\Big] \tag{4}$$

where consumer $i$'s indirect utility from good $j$ is,

$$u_{i,j} = x_j'\beta - \alpha p_j + \epsilon_{i,j},$$

and $\epsilon_{i,j}$ is i.i.d. extreme value type 1.

More generally, equation (4) is made up of three components: (1) the marginal utility of income, (2) the expected utility of the bundle of goods $J'$, and (3) the expected utility of the bundle of goods $J$.

The marginal utility of income comes from differentiating $u_{i,j}$ with respect to $p_j$,

$$-\frac{\partial u_{i,j,m}}{\partial p_j} = \alpha,$$

and, the expected utility of bundle $J$ when $\epsilon_{i,j}$ is i.i.d. extreme value type 1 is,

$$\mathbb{E}\max\{u_{i,0}, u_{i,1}, ..., u_{i,J}\} = \log\big(1+\sum_{j\in J}\exp(u_{i,j})\big),$$

and the expected utility of bundle $J'$ is analogous.

When price enters consumer $i$'s indirect utility function as a logarithmic function,

$$u_{i,j} = x_j'\beta - \alpha \log(p_j) + \epsilon_{i,j},$$

the only change in the above is the marginal utility of income, which now becomes,

$$-\frac{\partial u_{i,j}}{\partial p_j} = \frac{\alpha}{p_j}.$$

The result is that the marginal utility of income now depends on the price of each good $j$. However, we know that the inverse marginal utility of income will be greatest for the highest priced good,

$$-\frac{\partial p_j^{max}}{\partial u_{i,j}} = \frac{p_j^{max}}{\alpha},$$

and smallest for the least expensive good,

$$-\frac{\partial p_j^{min}}{\partial u_{i,j}} = \frac{p_j^{min}}{\alpha}.$$

In which case, a lower bound of the change in consumer surplus when indirect utility is a function of log price is,

$$\Delta CS^{lb} = \frac{p_j^{min}}{\alpha}\Big[\log\big(1 + \sum_{j\in J'}\exp(u_{i,j})\big) - \log\big(1 + \sum_{j\in J}\exp(u_{i,j})\big)\Big].$$

and an upper bound is,

$$\Delta CS^{ub} = \frac{p_j^{max}}{\alpha}\Big[\log\big(1 + \sum_{j\in J'}\exp(u_{i,j})\big) - \log\big(1 + \sum_{j\in J}\exp(u_{i,j})\big)\Big].$$

To calculate the bounds of the change in consumer surplus in census block $\ell$ using the estimates of my mixed logit demand model when there is change in the market, I use the following formula,

$$\Delta CS_\ell = H_\ell \sum_i \frac{p_j^b}{\alpha_i}\Big[\log\big(1 + \sum_{j\in J'}\exp(u_{i,j})\big) - \log\big(1 + \sum_{j\in J}\exp(u_{i,j})\big)\Big] \cdot \omega_{i,\ell},$$

where $p_j^b$ is either the lowest or highest priced plan offered by CenturyLink.