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ORIGINAL ARTICLE

From universal service to universal connectivity

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Abstract Two features of the century-old policy goal of promoting universal telephone service in the United States have been enduring. Policymakers have focused on (1) wireline telephone (and more recently, fixed-line broadband) services and (2) households. The widespread adoption of mobile telephones compels a fresh examination of this focus. We construct a new measure of *universal connectivity* which accounts for consumers' choices of communications technologies and for their geographic mobility over the course of the day. This measure, in turn, compels a conceptual and empirical investigation of the determinants of mobile telephone diffusion *within* families. Our estimations of intra-household demand for mobile service permit us to develop simulations that estimate the economic impact of modernizing a key element

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of existing universal service policy (viz., the Lifeline Program) to reflect the goal of improving individual connectivity. We find that a policy expansion from a single subsidy per household to multiple subsidies per eligible household members would increase mobile subscriptions by 2.25 million and Lifeline costs by $250 million.

Keywords Consumer demand · Universal service · Fixed · Mobile

JEL Classification L51 · L88 · L96

1 Introduction

Universal telephone service has been a policy goal in the United States for more than a century, and has varied over this period in three principal ways. First, public policies promoting universal service have evolved from implicit cross-subsidization of local telephone service, to explicit mechanisms that offer targeted support to reduce telephone service prices to low-income households which are at risk of not subscribing.[1] Second, the service to which "universal" is deemed applicable has changed. Universal service originally focussed on providing dial-tone availability, but over time policymakers' attention shifted to service subscriptions rather than simply infrastructure deployment. Third, the breadth of universal service has expanded to include not only basic dial tone, but also features such as 911, three-way calling and call-forwarding. The breadth of universal service was further extended to broadband beginning with the Telecommunications Act of 1996, and this broadband goal has been reinforced through subsequent policy initiatives.[2]

While universal service has proven to be a malleable concept, two notable aspects of the discussion surrounding universal service have been enduring fixtures. First, universal service has until very recently been thought of exclusively in terms of wireline services.[3] This fixation on a single, wireline technology for achieving connectivity is curious, if not completely anomalous, when juxtaposed with the underlying network externalities rationale for universal service policies. Specifically, individual consumers only consider their private benefits to communications (relative to the price) when making subscription decisions while not accounting for the social benefits of connectivity writ large (i.e., the network externality). These decisions are, however, independent of the technological means (viz., wireline or wireless) for securing that connectivity. Theoretically (and increasingly in practice) mobile telephony meets individual consumers' communications objectives.[4] Second, public policy efforts around universal service have consistently focused on access (or deployment) of telephony to the household rather than to the individual. Implicit in this focus has been the belief that the

1 See Riordan (2002) for a detailed review of the universal service economics literature.

2 See, e.g., the Broadband Data Improvement Act: Pub. L. 110-385, October 10, 2008, which reports that "[c]ontinued progress in the deployment and adoption of broadband technology is vital to ensuring that our Nation remains competitive and continues to create business and job growth."

3 For a discussion of the recent extension of public efforts to promote universal service via wireless connectivity, see Ukhaneva (2015).

4 See, Macher et al. (2016) for a discussion of consumers' propensities to substitute wireless for wireline telephone service.

deployment of a wireline telephone (or more recently a wireline broadband connection) provides universal access to all household members for their communications needs and/or that wireless technologies that are utilized by individual consumers are sufficiently inferior that they should not be counted in universal service measures.

The rapid emergence and adoption of mobile telephone service by individuals compels an updated discussion of universal service along these two dimensions. In particular, when commercial cellular telephony was introduced in the U.S. in 1983, it was perceived by many as a niche service confined to businesses and wealthy consumers. Subsequent deployment and adoption of mobile has been nothing short of spectacular: today there are more cellphones than U.S. inhabitants by several alternative penetration measures.[5] And while cellular service was initially unreliable (i.e., poor reception, dropped calls), widespread deployment of mobile infrastructure and greater allocation of radio spectrum have not only improved service quality but also enabled expanded device functionality through voice, data and video capabilities.

This diffusion of mobile telephone service both expands communications connectivity beyond what is possible with fixed-line service and permits a reorientation from households to individuals as the proper unit of analysis. For instance, different household members at any moment in time might communicate in different places (i.e., home or away) or in different formats (i.e., voice, data or video) that are not tied in any meaningful way to the household's fixed service.

In light of this evolution, this paper seeks to make three contributions. First, we develop an alternative measure to the historical (viz., household fixed-line) universal service index. We label this alternative measure *universal connectivity*. By accounting for both the diffusion of mobile telephone service within households and the mobility of household members, we estimate Americans' communications connectivity at any moment over the course of the day. The findings indicate that universal connectivity has increased significantly over 2003–2013—a result driven by the rapid adoption of mobile telephone service *within* households.

Second, we examine empirically the economic and demographic drivers of intra-household mobile telephone service adoption using a unique micro-level database over 2003–2013 from the National Center for Health Statistics (NCHS) operating within the Center for Disease Control (CDC). Poisson model estimation results indicate that: (1) mobile and fixed prices and income operate in accordance with accepted microeconomic theory; (2) mobile and fixed telephone service are substitutes; and (3) household member mobility needs and other demographic factors are important determinants of intra-household mobile telephony adoption.

Third, we develop counter-factual simulations using the estimation results to explore alternative policies to promote universal connectivity. The current Lifeline Program serves as our baseline. We simulate a policy expansion of the Lifeline Program from its current single telephone subsidy per eligible household to multiple telephone subsidies for individuals in eligible households. The simulation results indicate that this policy change would increase mobile subscriptions within eligible households by 2.25 million (i.e., a 23% increase) and increase total Lifeline costs by roughly $250 million.

[5] FCC, 19th Annual Wireless Competition Report, Sept. 23, 2016, Para. 45, https://apps.fcc.gov/edocs_public/attachmatch/DA-16-1061A1.pdf.

The rest of this paper is organized as follows: Sect. 2 presents the “universal connectivity” index that examines intra-household mobile diffusion and mobility to determine individuals’ average communications connectivity. Section 3 develops a conceptual model of intra-household mobile telephone demand that informs the empirical methodology. Section 4 presents the empirical approach by detailing the estimation framework, describing the data, and providing descriptive statistics and results. Section 5 presents the estimation results. Section 6 develops simulations based on these estimations intended to capture Lifeline Program policy changes from universal service to universal connectivity. Section 7 offers concluding comments.

2 From universal service to universal connectivity

The intra-household diffusion of mobile telephone service creates the potential to more accurately characterize universal service by shifting from the traditional focus of household-level connectivity to a more granular examination of individual-level connectivity. Depending on technology (viz., fixed or mobile) and location (viz., home or away), individual-level connectivity may vary considerably. Our universal connectivity index is intended to capture the degree to which individuals in the United States are able to communicate over the telephone at any time over the course of a day.

Electronic communication connectivity is made possible by either fixed (i.e., landline) access at home or mobile (i.e., cellphone) access at home or away. Individuals with a landline can reasonably be considered to have the ability to communicate electronically only when at home. Individuals with a cellphone can reasonably be considered to have the ability to communicate electronically at home or away.[6] Finally, individuals without a telephone are assumed unconnected and have no ability to communicate electronically.[7]

We draw upon a unique micro-level database assembled by the National Center for Health Statistics (NCHS) that operates within the Centers for Disease Control (CDC) to construct the universal connectivity index. The NCHS conducts an annual National Health Interview Survey (NHIS) as the principal health information source on the U.S. civilian non-institutionalized population. NHIS interviewers visit and collect data on 35,000–40,000 households and 75,000–100,000 household members each year.[8] Our NHIS sample includes the years 2003–2013.[9]

[6] We assume that individuals have their cellphones with them, have their cellphones turned on, and are located in a mobile service area.

[7] Consistent with the historical measurement of universal service we abstract from the communications potential for individuals who have wireline access to telephone service through their workplace. In this sense, our measure of universal connectivity (and similarly prior measures of universal service) is a conservative measure of the actual connectivity that individuals may enjoy. It parallels, however, the similar omission in the historical measurement of universal service, which has never incorporated workplace access to communications.

[8] See http://www.cdc.gov/nchs/nhis/about_nhis.htm for a detailed overview.

[9] Surveyed households track U.S. population demographic characteristics closely (Macher et al. 2016). We employ CDC-established sampling weights as a robustness check to confirm that the empirical results are not affected by NCHS sampling methods.

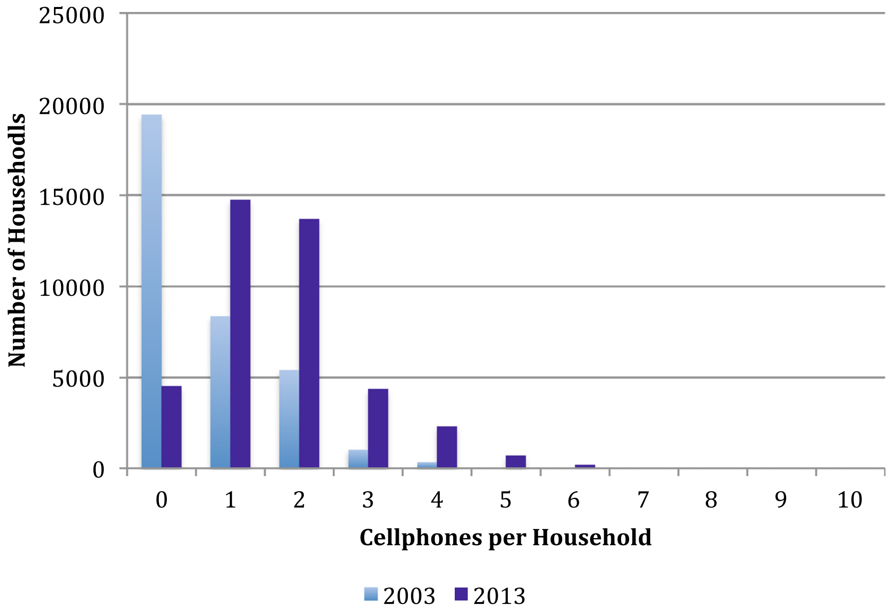

Fig. 1 Distribution of cellphones per household, 2003 and 2013

Sampled households are queried regarding their fixed and mobile service subscriptions. Of particular interest are questions regarding: (1) *whether* the household has no telephone, a cellphone only, a landline only, or both telephone types; and (2) *how many* cellphones are in the household. The NHIS data thus offer direct measures of household fixed and intra-household mobile diffusion over a relatively long time window. Figure 1 compares the frequency distributions of the number of cellphones per household for the first (2003) and last (2013) years of the sample period: the average increases more than two-fold (i.e., from 0.9 to 2.1) over this period. Figure 2 provides the average number of cellphones per household member at different income levels (defined relative to the contemporaneous federal poverty threshold) and over time. While intra-household cellphone adoption is directly related to income, it increases significantly in each income bin over time: the lowest income bin has more cellphones per household member in 2013 than the highest income bin had in 2003.[10]

While the NHIS recorded the number of cellphones per household, neither subscription details (e.g., the carrier, monthly charges, usage allowance) nor associate subscriptions to specific household members were included. This fact necessitates that household mobile telephone distribution be approximated based on the number of household members, the number of cellphone subscriptions, and various house-

[10] Figure 6 in the online Appendix provides the average number of cellphones per household member at different household age categories and over time. See Macher et al. (2017).

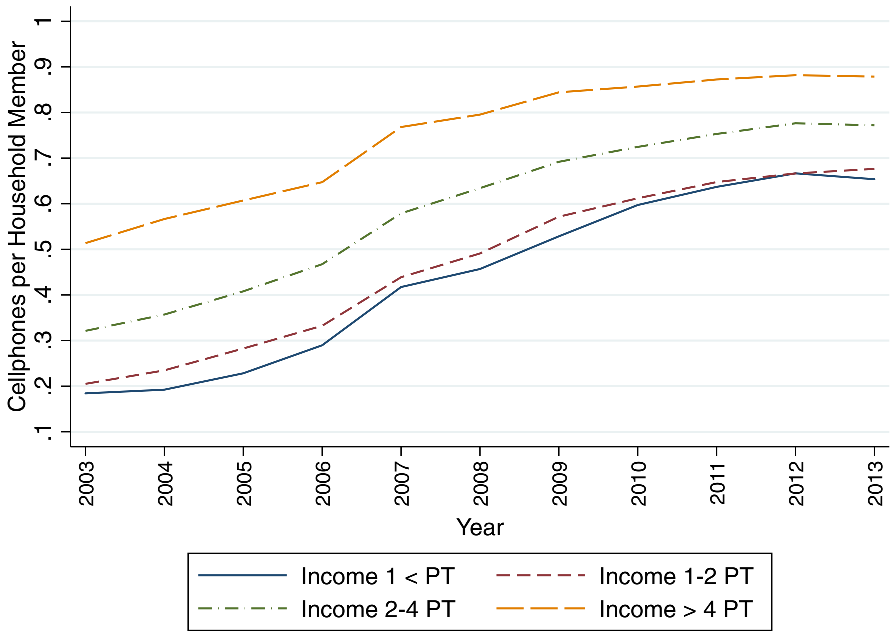

Fig. 2 Cellphones per household member by income, 2003–2013. *Note*: *Income* $<1PT$ represents households with income at or below the poverty threshold; *Income* 1–2*PT* represents households with income between one and two times the poverty threshold, including upper threshold; *Income* 2–4*PT* represents households with income between two and four times the poverty threshold, including upper threshold; *Income* $>4PT$ represents households with income above four times the poverty threshold

hold demographic characteristics. We proceed with this allocation as follows:[11] For households where the number of cellphones equals or exceeds the number of adult members, we assign a cellphone to each adult member. For households where the number of mobile telephones is less than the number of adult members, we use an algorithm to assign mobile telephones to particular household members. Phones are first allocated to adult members who work outside the household. Any remaining unassigned mobile telephones are then allocated inversely by age to other household members over 15 years old. Any remaining mobile telephones are then allocated to health-impaired adults (regardless of age).[12]

We then match this household cellphone distribution to individuals' activities throughout a 24-h day using the "American Time Use Survey" (ATUS). This survey is part of the Census Bureau's Current Population Survey (CPS) and is used to estimate individual "time diaries" over a 24-h period. The ATUS randomly selects

[11] This allocation is driven by: (1) observed empirical regularities in household mobile telephone distribution patterns; (2) survey data of mobile telephone ownership patterns by gender, age, race and education [e.g., Rainie (2013)]; and (3) estimation results described below.

[12] Alternative mobile telephone assignments quantitatively alter the universal connectivity measure only slightly; the qualitative features and implications of the construct remain intact. For example, an assignment based solely on individual household member age (e.g., oldest members of a household get priority in cellphones assignment) produces indistinguishable results from those reported.

household members aged 15 years or older; respondents provide the length of time spent on various activities by hour of the day, distinguishing between workweek and weekend days. The Census Bureau reports the average time spent by the hour on these activities for surveyed households over three time periods: 2003–2006, 2007–2010, and 2011–2013.

We classify each ATUS activity as to where it takes place and how much time is spent, and then create a likelihood that an average individual is either at home or away. Ascribing this likelihood to the entire NHIS sample allows for a determination of whether an average individual is connected at home (i.e., landline access) or away (i.e., cellphone access) at any point in the day. The percentage of individuals in the NHIS sample that are connected is then computed as follows:[13] First, we randomly draw subsamples of individuals considered at home at each hour of the day.[14] Second, we determine connectivity for each selected (i.e., at home) subsample: (1) individuals with a cellphone are connected; (2) individuals with a landline are connected; and (3) individuals with no telephone are not connected. Third, we determine connectivity for each non-selected (i.e., away) subsample: (1) individuals with a cellphone are connected; and (2) individuals with a landline or no telephone are not connected. Fourth, we aggregate the number of connected individuals either at home or away and compare relative to all individuals by each hour in the day and report out.

Figure 3 shows substantial variation in the *universal connectivity* measure not only over the course of a day, but also over the sample window. Connectivity is highest when individuals are at home during the late-evening to early-morning period, drops significantly when individuals head to work or to school during the early-morning to mid-afternoon period, and rises again when individuals return home during the mid-afternoon to late-evening period. And, while this same pattern is present in all the years, connectivity increases substantially with time. This increase is most marked during the early-morning to mid-afternoon and mid-afternoon to late-evening periods.

Figure 4 replicates the universal connectivity index for a stratified set of individuals in households that are below or above the poverty threshold and at the sample beginning (2003) and sample end (2013). This figure provides information for universal connectivity akin to historical observations regarding a digital divide for broadband access. In 2003, the connectivity gap between lower-income and higher-income households approached 15% at its highest point in the day. By 2013, this connectivity gap diminished to roughly 10% at its highest point in the day while overall connectivity has increased substantially for both income subgroups. Individuals who were once

[13] Cellphones are assumed to provide complete coverage and connectivity for individuals throughout the entire day. As this assumption is less plausible in the early sample years than in the latter sample years, this measure may accordingly overstate individual connectivity in our early sample years. As the ATUS only samples individuals at least 15 years old, we exclude those under 15 years old in constructing the connectivity measure. Finally, ATUS data are reported as averages across several years: statistics are available for the 2003–2007 period at http://www.bls.gov/tus/tables/a3_0307.pdf; for the 2007–2011 period at https://www.bls.gov/tus/tables/a3_0711.pdf; and for the 2009–2013 period at http://www.bls.gov/tus/tables/a3_0913.pdf.

[14] For instance, 95.6% of individuals are at home at midnight: Hence, the subsample drawn contains 95.6% of individuals.

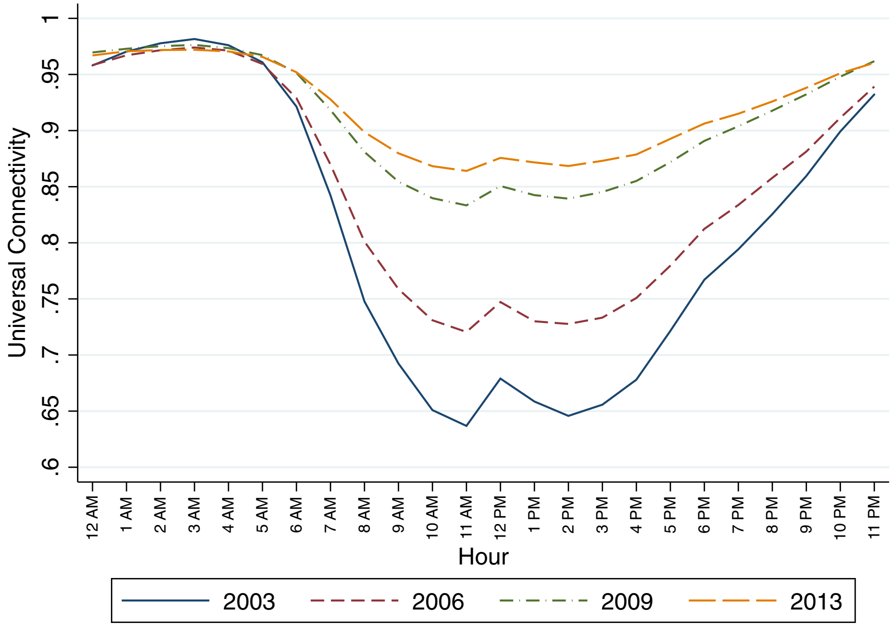

Fig. 3 Universal connectivity, 2003, 2006, 2009, and 2013

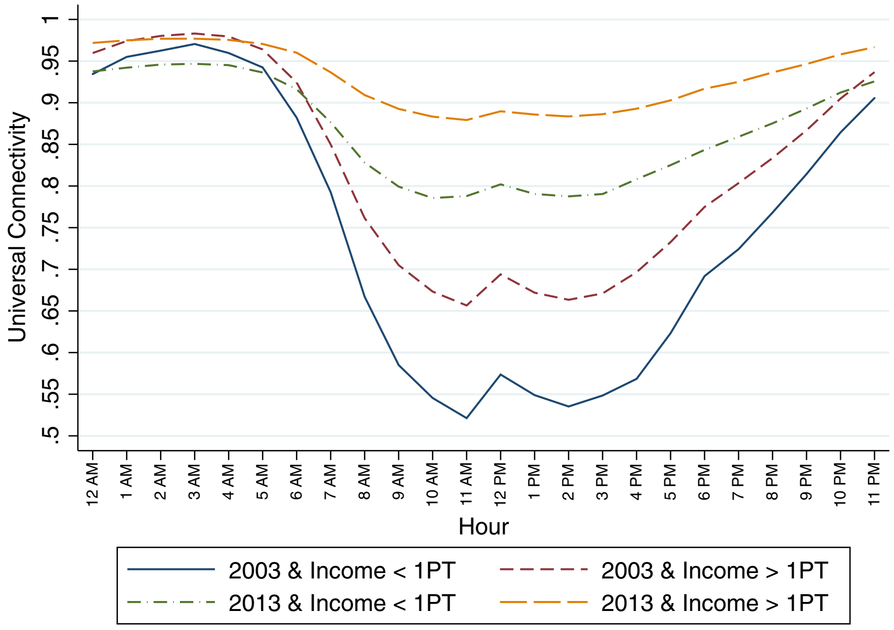

Fig. 4 Universal connectivity below and above poverty threshold, 2003 and 2013. *Note*: See definitions of income categories in the note to Fig. 2

not connected by any means of communication when away are now—by virtue of mobile's rapid diffusion and adoption—increasingly connected at all times.[15]

Data constraints may limit the precision of our connectivity measure in at least three ways. First, within a given family, we cannot directly observe the specific household members who own (or claim) cellphones. While our methodology assigns cellphones to household members sensibly and based on existing research, it is necessarily imprecise. Second, we do not directly observe household members' specific locations at moments over the course of the day. While our methodology assigns locations to two alternatives (i.e., home or away), it is at an aggregate level. Third, our analysis draws upon the average time-profile of individuals as revealed by the ATUS. For particular individuals, who may have different mobility patterns, our analysis may overstate or understate an individual's connectivity. In light of these limitations, our main contribution is a modest one: to introduce in proof-of-concept fashion a potentially more relevant and up-to-date concept of connectivity than historical analyses of universal service have provided. Nonetheless, our specific connectivity measure appears both plausible and evolves sensibly over time.

3 Conceptual framework

Empirical research on mobile telephone service adoption has proceeded at two levels. One research thread examines mobile phone adoption rate differences across countries and over time, typically employing diffusion models to provide insights into the observed cross-country and temporal variation.[16] A second and complementary research thread—akin to the broader literature on new technology adoption [e.g., Goolsbee and Klenow (2002)]—uses household-level demand data and models subscription decisions using discrete choice models.[17] In contrast to these research approaches, we emphasize intra-household mobile demand that manifests in the number of mobile phones per household. This section therefore provides a conceptual framework of the determinants of intra-household mobile telephone demand.

Fixed and mobile subscription decisions presumably derive from the expected utility provided, which most likely depend on: (1) anticipated communication abilities; and (2) anticipated usage intensities.[18] The principal difference between fixed and mobile, however, resides in service access: individuals with landlines can place and receive calls only when at home; individuals with mobile phones can place and receive calls both while at home and away. We assume that usage patterns in the case when both telephones are available are not affected by the particular device itself. We therefore focus on anticipated utilities from achieving service access. To ease exposition, we adopt the language of voice communication by referring to individuals as callers and

[15] Figure 7 in the online Appendix aggregates across a 24-h day to provide an average connectivity in each sample year. Average universal connectivity increases significantly: from 81% in 2003 to 92% in 2013. That is, by 2013 over the course of any day an average of 92% of Americans were connected to the telephone network. See Macher et al. (2017).

[16] See, e.g., Dekimpe et al. (1998), Gruber and Verboven (2001) and Rouvinen (2006).

[17] See, e.g., Ward and Woroch (2010), Macher et al. (2016) and Grzybowski and Verboven (2016).

[18] See, e.g., Taylor (2012) for a detailed discussion.

receivers who respectively place and receive "calls," but the framework is sufficiently general that it can describe any electronic communications exchange (e.g., email, text, voice).

We begin by indexing all n individuals in a respective market by $i \in N = \{1, 2, \ldots, n\}$. Individuals are partitioned into H mutually exclusive and exhaustive households: $h = 1, 2, \ldots, H$, where household h has n_h members denoted by $i \in \{j_1, j_2, \ldots, j_{n_h}\}$. Each household member i also has a "community of interest" consisting of k_i individuals and denoted by $M_i = \{m_{i1}, m_{i2}, \ldots, m_{ik_i}\}$. An individual's community of interest will likely include household members, co-workers, friends and acquaintances, among others. At any moment in time, individual i may desire to communicate with community of interest member j.[19] This desire occurs randomly and independently of current subscription (i.e., landline or cellphone) and location (i.e., home or away).[20] If individual i is able to communicate with member j, she derives utility u_{ij}. As the receiver will also be affected, let v_{ji} represent the utility to receiving member j from communicating with individual i. We assume the caller has more to gain than the receiver (i.e., $u_{ij} > v_{ji}$) if only because the caller initiated communication before the receiver did. The receiver may in fact not want to receive certain calls (e.g., telemarketers), in which case $v_{ji} < 0$.

We further assume that individual i is at home with probability ϕ_i and away with probability $1 - \phi_i$. Mobile service is equally available at home or away, but not with perfect certainty or of high quality. The mobile network may be inoperative in individual i's location, either because of carrier network coverage gaps or weak signals (e.g., if i is indoors). We take landline service quality to be the appropriate benchmark for comparison. Let λ_i represent a quality variable that captures the probability that individual i can successfully connect to the mobile carrier network to place and receive calls. The size of λ_i will depend on the mobile carrier's network capacity and radio spectrum, among other factors. We finally assume that individuals with both landline and cellphone subscriptions will opt for the former service when at home.

With this setup, we can easily express the connectivity concepts described in the previous section for each subscription portfolio: we first compute individual connectivity by summing the likelihoods each individual is connected to the fixed and/or mobile network; we then compute aggregate connectivity by multiplying these individual likelihoods. The benefits of cellphone subscription depend on individual mobility patterns and network carrier quality, among other factors.

The utility derived depends on the landline and cellphone subscriptions of individual i and community of interest member j, their respective locations, and their respective mobile carrier network quality.[21] If neither party owns a landline or a cellphone then no

[19] We abstract from how usage prices may affect calling intensity. Specifically, because most fixed and mobile subscription plans include a "bucket" of minutes, the marginal price of an additional call is zero as long as the subscriber has not exhausted her allowance. We thus consider the effective marginal price of usage to be zero so that every urge to call is price unconstrained.

[20] The urge to communicate likely varies by time of day. The model described here reflects communications demand at a certain point in time.

[21] If i particularly values i to j communication (i.e., $u_{ij} >> u_{ji}$), but j is frequently away (i.e., ϕ_j is low), i's marginal utility increases with j's mobile subscription. This condition may thus lead to inter-personal "side-payments" to support j's subscription even when—absent those payments—j would chose not to

communication can occur, and hence, no utility obtains. If each party owns a landline and/or a cellphone then communication can occur and utility is derived. It is helpful to further divide individual i's community of interest members according to subscription type: Let M_i^L, M_i^C, and M_i^{LC} represent those community of interest members who respectively own landlines only, cellphones only, and both telephones. The utility of individual i having, for example, a landline and a cellphone is given by:

$$\begin{aligned} U_i = &\sum_{j \in M_i^L} \underbrace{[\phi_i + (1-\phi_i)\lambda_i]\phi_j(u_{ij} + v_{ij})}_{i \text{ has both and } j \text{ has only a landline}} \\ &+ \sum_{j \in M_i^C} \underbrace{[\phi_i + (1-\phi_i)\lambda_i]\lambda_j(u_{ij} + v_{ij})}_{i \text{ has both and } j \text{ has only a cellphone}} \\ &+ \sum_{j \in M_i^{LC}} \underbrace{[\phi_i + (1-\phi_i)\lambda_i][\phi_j + (1-\phi_j)\lambda_j](u_{ij} + v_{ij})}_{i \text{ has both and } j \text{ has both}} \end{aligned} \tag{1}$$

Other individual portfolios are easily expressed by eliminating the appropriate terms in Eq. 1: dropping $(1-\phi_i)\lambda_i$ for landline only individuals; and dropping ϕ_i for cellphone only individuals.

Households are assumed to maximize expected utility across all household members and over all possible subscription portfolios $\rho_h = (d_L, d_C)$:[22]

$$Maximize_{\rho_h} W_h(\rho_h) = \sum_{i \in \{j_1, j_2, \ldots, j_{n_h}\}} U_i(\rho_h) - P(\rho_h) \tag{2}$$

where d_L is an indicator of household landline subscription, d_C is a count of household cellphone subscriptions, and the expression $P(\rho_h)$ represents the total household cost of a particular portfolio. Letting p_L and p_C represent the respective landline and cellphone subscription monthly charges, a household with a landline and a cellphone for every member would incur $P(\rho_h) = d_L p_L + d_C p_C$ in monthly expenditures.[23]

The model illustrated here captures several salient features. First, mobility—embodied in the ϕ_i and ϕ_j parameters—plays an important role in the utility maximization of mobile telephone service subscriptions. Second, mobile network quality—embodied in the λ_i and λ_j parameters—similarly affects utility maximization. Third, the respective prices associated with different fixed and mobile portfolios affect consumption at any given level of utility. The relative importance of these factors on intra-household mobile telephone adoption is ultimately an empirical question, however, and it is to that effort that we now turn.

Footnote 21 continued
subscribe. Such side-payments are most frequent between family members. See Becker (1974, 1981) for discussion.

22 This objective function is implied by assumptions given in Harsanyi (1955, 1978). Aribarg et al. (2010) provide empirical support for this approach in the case of cellphone adoption models.

23 Some firms offer discounts for multiple cellphone subscriptions. Our data are not sufficiently granular to capture this phenomenon empirically, and as such, we make the simplifying assumption that household mobile expenditures are additive in these different charges.

4 Empirical analysis

In this section, we examine empirically intra-household mobile adoption over 2003–2013. We first delineate the empirical model employed. We then describe the NHIS and non-NHIS data assembled and the variables used in estimation. We then present descriptive statistics and empirical results.

4.1 Estimation framework

To capture intra-household mobile diffusion, we specify a Poisson model with number of cellphones per household member as a dependent variable:

$$\mathbb{E}\left(\frac{Y_h}{n_h}|X_h\right) = exp[X_h'\beta], \tag{3}$$

where Y_h is the number of cellphones subscribed; n_h is the number of household h members (the "exposure" variable); and X_h represents a host of explanatory variables, including fixed and mobile prices, household income, mobile network quality and diffusion measures, household nodal and mobile tendencies, and household demographic characteristics, that we describe in detail below. The β coefficients are estimated by likelihood maximization.

We transform this equation by multiplying both parts by n_h in the following way:

$$\mathbb{E}(Y_h|X_h, n_h) = n_h \times exp[X_h'\beta] = exp[log(n_h) + X_h'\beta]. \tag{4}$$

Now the expected number of cellphones per household is linear in the exponential of explanatory variables and the logarithm of the exposure variable (i.e., household size).

Given the potential for prices and intra-household mobile diffusion to be jointly determined, we discuss below endogeneity corrections to improve parameter estimate consistency.

4.2 Data and variables

As with the development of our universal connectivity measure, the empirical analysis draws from the annual NHIS data over 2003–2013. The combined dataset has roughly 314,000 observations. NHIS respondents provide not only fixed (i.e., yes/no) and mobile (i.e., yes/no; how many) subscription information, but also detailed demographic and health information on the household and individual household members. The public-use portion of the NHIS offer a rich array of information, but unfortunately masks households' geographic locations. By application to and approval from the CDC, we secured access to the confidential portion of the NHIS that provides household geo-codes. Using these household-level geocodes, we link the NHIS data to location-specific data from the following public and private data sources: the Federal Communications Commission (FCC), the Cellular Telephone and Internet Association (CTIA), the U.S. Census Bureau (Census), the U.S. Bureau of Labor Statistics

(BLS), the U.S. Geological Survey (USGS) and the U.S. Department of Agriculture (DoA). The combined geo-coded data thus provide a unique ability to comprehensively examine the determinants of intra-household mobile adoption across several dimensions and over a long time window.

We separate the explanatory variables into four categories: (1) fixed and mobile subscription prices and household income; (2) fixed and mobile network quality and coverage; (3) household members' "nodal" (i.e., home) or "mobile" (i.e., away) tendencies; and (4) household demographic characteristics. We describe the variables within each category in turn.

Prices and Income—We measure fixed service prices beginning with the basic flat monthly charges for 3141 wire centers located throughout the U.S. in 2002.[24] As wire centers are not necessarily coincident with county boundaries, we use population weights within wire centers to construct county-level fixed service prices.[25] Fixed service prices are then updated over 2003–2013 using the Consumer Price Index (CPI) for local exchange service. *Fixed-line Price* thus measures the average monthly landline subscription price per household, and varies over geography and time. The robustness of this measure was examined using the FCC's "Reference Book of Rates, Price Indices, and Household Expenditures for Telephone Service" (Reference Book), which reports annual survey results of local monthly landline rates for 95 U.S. cities: Year-to-year Pearson price correlations average 0.96 across the sample, and thus help to confirm that the principal source of fixed price variation is captured by spatial disaggregation at the sample beginning.[26]

While many mobile service plans exist, each usually entails a flat rate for a "bucket" of minutes. Mobile service prices thus represent average monthly expenditures for usage levels within the allowance. We measure mobile service prices beginning with the average monthly revenue per user (ARPU) using the CTIA's semi-annual "Wireless Industry Indices" survey of member companies.[27] This survey captures more than 95% of all U.S. mobile subscribers over 2003–2013. Mobile prices are largely geographically invariant over our sample window, but state and local taxes create spatial price variation.[28] We therefore adjust mobile prices by incorporating data from the

[24] These data were provided to us by Rosston et al. (2008). While many local phone carriers offer "measured service" in which customers pay smaller monthly subscription charges and—after a call or minute allowance—marginal charges per minute, industry sources indicate that the percentage of customers who avail themselves of this option is *de minimis*. We accordingly focus on monthly rate variations.

[25] Population weights are necessary because we only know the county where each household resides but not the household's relevant wire center within that county. The price measure thus represents a population-weighted county-level average of wire center prices.

[26] The FCC Reference Book was produced by the Industry Analysis and Technology Division within the FCC's Wireline Competition Bureau. This annual publication provided local exchange carrier (LEC) landline rates in 95 U.S. urban areas until it was discontinued in 2008.

[27] ARPU includes revenue related to service provision, such as roaming charges, long distance toll calling, usage-related charges, activation fees, voicemail and other services fees. ARPU does not include revenue related to handset rental or purchase charges.

[28] FCC Competition Reports indicate national carriers' market share of total mobile service revenue increased from 87% in 2007 to 96% in 2013. These national carriers largely implemented uniform pricing over this period. Any limited time promotional pricing offers were generally available on a nationwide basis. While price variation due to regional carriers might have existed in the earliest years of the sample,

Committee on State Taxation (COST).[29] The COST data provide the prevailing state sales tax rate inclusive of general sales taxes. Local tax rates for each state are taken to be the average between those imposed in the largest city and the capital city. Federal taxes are reported separately. Any flat fees (e.g., 911, Universal Service Fund) are converted to percentages based on average monthly residential bills.[30] *Mobile Price* thus measures the average monthly mobile revenue per user adjusted for state and local tax variations, and varies over geography and time.

Household income is taken directly from annual NHIS surveys, and is categorized relative to the federal poverty threshold using four indicator variables: (1) below the threshold *(Income* <1*PT)*; (2) between one and two times the threshold *(Income* 1–2*PT)*; (3) between two and four times the threshold *(Income* 2–4*PT)*; and (4) more than four times the threshold *(Income* >4*PT)*. The first income category serves as the baseline in the empirical estimation. Finally, we include a variable that indicates if someone in the household is a welfare recipient (*Welfare Recipient HH*) as such households are eligible to receive federal assistance for telephone subscriptions.

Mobile Quality and Network Effects—Variables that represent relative mobile service quality and network effects are included in the estimation. To capture the potential for (high-quality) landline service to damp intra-household mobile subscription demand, we include an indicator variable of household fixed-line subscription: *Wireline HH* is one if the household has a landline subscription, and is zero otherwise.[31] Additionally, to account for the potential for changes in household income to affect the strength of any "wireline" effect on the demand for intra-household mobile telephone demand, we include a set of interaction terms between *Wireline HH* and income levels.

To control for mobile quality, we use the USGS topographical index, which measures the terrain and surface composition in counties throughout the US. Our measure, *Mountainous*, ranges from plains (1), to open low hills (13), and to high mountains (21). We also include year fixed effects to account for any inter-temporal mobile quality improvements that have occurred as a result of radio transmission advances, radio spectrum availability, or infrastructure build-out.

To account for potential network effects that may accompany additional household-level cellphone subscriptions, we include a mobile diffusion measure: *Mobile Penetration*, which captures the county-level cellphone subscription penetration rate

Footnote 28 continued
it has largely disappeared along with these regional carriers. Any variation in local price indices that arises from regional carriers is small relative to the variation that arises from state and local taxes.

29 COST reports are available beginning in 1999 and every three years thereafter (i.e., 2001, 2004, 2007 and 2010). See COST (1999, 2002, 2005, 2008, 2011) and Mackey (2008, 2011) for specific mobile telecommunications service information.

30 The first two COST reports provide a single tax rate that blends state and local taxes for fixed and mobile service. The latter COST reports separate taxes levied on fixed and mobile service.

31 Voice Over Internet Protocol (VoIP) introduction over 2003–2013 allowed households to utilize a computer or cable connection instead of traditional Time Division Multiplex (TDM) connection for communication. While VoIP raises the possibility that households do not identify a computer- or cable-connected telephone as a "traditional" landline, we discount this possibility given the NHIS question wording: "Is there at least one telephone *inside* your home that is currently working and is not a cellphone?" This question does not capture communications involving computer connections or cellphones, but potentially does capture communications involving cable connections.

for the respective household. The variable is lagged by one period, consistent with the assumption that consumers observe last period's county mobile penetration rate in making current period decisions regarding mobile telephone service adoption. This model assumption severs the potential for endogeneity between our dependent variable and *Mobile Penetration* as mobile telephones per household member at time t cannot cause changes in *Mobile Penetration* in time $t-1$.

Nodal versus Mobile—several variables that are designed to capture the nodal (i.e., home) and mobile (i.e., away) tendencies of household members are included in the estimation. The conceptual model indicates that the utility from alternative subscription decisions depends on the likelihoods that potential subscribers are home or away. As these likelihoods vary with age, we accordingly account for household age using several indicator variables: (1) household members under age 31 *(Young HH)*; (2) household members between ages 31 and 45 *(Young–Middle HH)*; (3) household members between ages 45 and 64 *(Middle–Old HH)*; and (4) household members over age 64 *(Old HH)*. As these variables capture households where all members are respectively within a specific age interval, the baseline represents households where members fall across age intervals. We also control for age-related nodal versus mobile tendencies via retirement: *Retired HH* is one if at least one household member is retired, and is zero otherwise. We expect that older and/or retired households are either more "nodal" or more wary of "new" technology, and hence do not derive as much utility from mobile adoption, *ceteris paribus*. We nevertheless expect wealthy retired households to adopt cellphones more intensively, however, as they are both more mobile and less technology-phobic than their less-well-off elderly counterparts: *Wealthy Retired HH* is one if the household is considered wealthy and retired, and is zero otherwise.

The likelihood that potential subscribers are home or away also likely depends on whether any household members are children. As parents desire "anywhere, anytime" communications with children, we expect cellphone adoption rates to be higher in households with children than households without children. Children obviously differ in age profiles and subsequent mobile "needs," however, which suggests that households with younger children will have lower intra-household cellphone adoption rates and households with older children will have higher intra-household cellphone adoption rates. We control for these possibilities using two child-related household variables: *Child 0–10 YO HH* is one if at least one household member is between the ages of zero and ten, and is zero otherwise; and *Child 11–18 YO HH* is one if at least one household members is between the ages of 11 and 18 years old, and is zero otherwise.

Employment- and school-related requirements also affect the likelihoods that potential subscribers are home or away. Households with members employed outside of the home or full-time students are likely to find the incremental benefits of cellphone subscription higher than otherwise: *Ratio Working HH* measures the ratio of working to total household members; *PT Employed HH* is one if at least one household member is employed part-time, and is zero otherwise; and *Student HH* is one if at least one household member is a full-time student, and is zero otherwise. Households with members working inside the home suggests a greater nodal presence, which should reduce intra-household cellphone adoption: *Homemaker HH* is one if at least one household member is a stay-at-home adult, and is zero otherwise.

Health-related factors within the household also affect nodal versus mobile tendencies, and hence the value placed on fixed and mobile service. The NHIS survey provides detailed information on whether any household member faces a health issue or physical impairment. Households with a health-impaired youth are expected to have a greater need for "anywhere, anytime" communication, and are subsequently more inclined to cellphone adoption: *Limited Youth HH* is one if at least one household member identifies as a health-impaired youth, and is zero otherwise. Households with a health-impaired adult are expected to have a stronger nodal presence, however, and are correspondingly less inclined to cellphone adoption: *Limited Adult HH* is one if at least one household member identifies as a health-impaired adult, and is zero otherwise.

To control for the possibility that intra-household mobile subscriptions vary geographically, we include county-level population characteristics: *Population Density* measures the county-level population density of the respective household. For a given level of mobile service quality, households in more rural areas may derive greater utility than households in more urban areas. We also include state fixed effects to account for any unobserved geographical variations that may influence households' mobile subscriptions.

Finally, household ownership might affect the nodal versus mobile tendencies of household members. Ownership generally confers a greater nodal attachment. *Own Home* is one if the household owns the home, and is zero otherwise.

Demographic—We include several household demographic variables in the estimation. Following standard practice in Poisson regressions, we include a logged exposure variable whose parameter estimate is constrained to unity: *Family Size* represents a count of the number of household members.[32]

Riordan's (2002) literature survey identifies several demographic factors that may affect the likelihood households subscribe to fixed or mobile service. We account for household racial composition using a set of indicator variables: *White HH*, *Black HH*, *Hispanic HH* and *Native American HH* are one if the household identifies as that respective race, and is zero otherwise. White households serve as the baseline category in the empirical analysis. We account for household gender using two indicator variables: *Female HH* and *Male HH* are one if the household is respectively entirely female or entirely male, and are zero otherwise. We account for household marital status using an indicator variable: *Divorced HH* is one if any household members are divorced, and is zero otherwise. We account for household citizenship using an indicator variable: *All US Citizen HH* is one if all household members are U.S. citizens, and is zero otherwise. We account for household education using an indicator variable: *Educated HH* is one if at least one household member has a 4-year college or graduate degree, and is zero otherwise.

Finally, we capture household member composition differences using detailed age-related information: *Unrelated Adults HH* is one if any adult household members are unrelated, and is zero otherwise; and *Children* represents a count of the number of children (under 18 years of age) in the household. Table 1 provides descriptive statistics of all of the variables.

32 We estimated the model without exposure variable, and confirm that estimation results are nearly identical to those presented in Table 3.

Table 1 Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Number of cellphones	1.34	1.169	0	10
Price and income variables				
Fixed-line price	15.15	2.857	9.44	26.77
Mobile Price	54.26	3.157	39.48	60.28
Income <1PT	0.16	0.369	0	1
Income 1–2PT	0.21	0.405	0	1
Income 2–3PT	0.30	0.457	0	1
Income >4PT	0.33	0.471	0	1
Welfare recipient HH	0.287	0.452	0	1
Quality and network effects variables				
Wireline HH	0.76	0.426	0	1
Mobile penetration	0.86	0.175	.37	1.88
Mountainous	9.01	7.195	1	21
Population density (in 1 K)	2.36	7.292	.001	71.61
Nodal variables				
Retired HH	0.21	0.403	0	1
Wealthy retired HH	0.06	0.229	0	1
Young HH	0.14	0.346	0	1
Young–middle HH	0.08	0.264	0	1
Middle–old HH	0.19	0.392	0	1
Old HH	0.14	0.346	0	1
Limited young HH	0.06	0.239	0	1
Limited adult HH	0.20	0.399	0	1
Child 0–10 YO HH	0.25	0.432	0	1
Child 11–18 YO HH	0.21	0.405	0	1
Student HH	0.05	0.225	0	1
Ratio working HH	0.51	0.387	0	1
PT employed HH	0.10	0.305	0	1
Homemaker HH	0.13	0.336	0	1
Own home	0.62	0.486	0	1
Demographic variables				
Black HH	0.148	0.355	0	1
Hispanic HH	0.161	0.368	0	1
Native American HH	0.007	0.086	0	1
Unrelated adults HH	0.166	0.372	0	1
Children	0.680	1.102	0	13
Educated HH	0.321	0.467	0	1
Female HH	0.201	0.401	0	1
Male HH	0.154	0.361	0	1

Table 1 continued

Variable	Mean	Std. Dev.	Min	Max
Divorced HH	0.172	0.377	0	1
All US citizen HH	0.868	0.338	0	1
Family size	2.525	1.511	1	18
Instruments				
Percent water	9.74	15.174	.01	75
Telecommunications wage	47,704	5957.9	33,677	66,405
Percent democrat	0.37	0.291	0	1
N obs	314,297			

5 Estimation results

We account for potential endogeneity between intra-household mobile adoption and fixed and mobile service prices.[33] The identification strategy requires a set of instruments that are observable and correlated with these prices, but are not correlated with intra-household mobile demand. One instrument uses Bureau of Labor Statistics (BLS) data on average telecommunications worker wages. Wage rates are considered an effective instrument for endogenous prices because they are correlated with the cost (and hence, prices) of telephone service, but are uncorrelated with telephone demand: *Telecommunications Wage* represents the median pay of telecommunications equipment installers and repairers and vary by state and by year. A second instrument uses data on the partisan composition (i.e., Democrat or Republican) of the representative state public utility commission (PUC) for each household. The partisan composition of the state PUC should correlate with prices—given respective pro-consumer and pro-business tendencies between political parties—but be uncorrelated with intra-household mobile demand: *Percent Democrat* represents the percentage of Democrats in the state PUC for each household and vary by state and by year.[34] A third instrument uses United States Geological Survey (USGS) data on the proximate (i.e., county-level) topography of each household. The topography of a geographic area likely affects the cost (and hence, prices) of providing telecommunications service, but is unlikely to affect intra-household mobile demand: *Water* measures the percentage of county area covered by water for the respective household.[35]

We employ a count model using maximum likelihood estimation and adjust standard errors for heteroscedasticity and clustering (by year and state). Descriptive statistics indicate a dependent variable mean of 1.34 and variance of $(1.169)^2 = 1.37$, suggest-

[33] The model is estimated using Stata via the *ivpoisson* routine.

[34] These data were generously provided to us by Fremeth et al. (2014). Data are collected daily and then averaged over the year for all states except Alaska (which is assumed 100% Republican). See Fremeth et al. (2014) for a detailed description.

[35] USGS topography data are posted in the Natural Amenities Scale file and available at http://www.ers.usda.gov/data-products/natural-amenities-scale.aspx.

ing no evidence of overdispersion. A formal null hypothesis test of no overdispersion cannot be rejected at the 5% significance level (see Cameron and Trivedi (2005), pp. 670–671). These results suggest that Poisson model estimation is appropriate. Variance inflation factor (VIF) analysis indicates no regressor achieves a VIF statistic above 5.5 (i.e., below the general rule of 10) and a mean VIF statistic of 1.87, thus, indicating that multicollinearity is not a concern here.

Table 2 provides the main empirical findings. The estimation results are encouraging, as most of the explanatory variables enter with the expected signs and achieve statistical significance. The correlation between the actual number of cellphones per household and the estimated prediction is 0.66, which suggests a good model fit. We briefly discuss the main findings in each variable category: (1) prices and income; (2) mobile quality and network effects; (3) household "nodal" (i.e., home) or "mobile" (i.e., away) tendencies; and (4) household demographic characteristics.

Prices and Income—Fixed and mobile prices affect intra-household cellphone adoption differently: *Fixed Price* is insignificant; *Mobile Price* is negative and significant ($p < 0.1$). A reduction in fixed price does not affect the number of cellphones per household, while a 1% reduction in mobile price increases the number of cellphones per household by 5%.[36]

Household income has a positive and statistically significant ($p < 0.01$) effect on intra-household mobile adoption, and moreover, exhibits a consistent pattern. For example, households that have fixed-line subscriptions and with income levels between one and two times *(Income* 1–2*PT)*, between two-four times *(Income* 2–4*PT)*, and more than four times *(Income* >4*PT)* the poverty threshold increase intra-household mobile adoption respectively by 18, 43 and 67%, in comparison to the households with income levels below the poverty threshold *(Income* <1*PT)* and holding all other variables at their respective means. Finally, households that receive welfare *(Welfare Recipient HH)* have lower levels of intra-household cellphone adoption than non-welfare recipient households.

Mobile Quality and Network Effects—Intra-household mobile adoption is negatively impacted by fixed subscription service: *Wireline HH* is negative and statistically significant ($p < 0.01$). Notice, however, that the interaction variables between *Wireline HH* and income in Table 2 indicate that this propensity for wireline service to dampen intra-household mobile demand dissipates as household incomes increase. We find that fixed-line subscription decreases the number of cellphones by 63% in the households below the poverty threshold, but only reduces the number of cellphones by 28 and 15% and has almost no impact on the number of cellphones in the households with income levels between one and two times, between two-four times, and more than four times the poverty threshold, respectively.

The geographic (*Population Density*) and topographical (*Mountainous*) variables both enter the model with negative coefficients, but neither achieves statistical signifi-

[36] These percentage changes are calculated using the following formula: $\frac{Y_h^1}{Y_h^0} = e^{\hat{\beta}_k \Delta X_{hk}}$, where Y_h^0 is the initial number of cellphones per household; Y_h^1 is the number of cellphones per household when the independent variable of interest X_{hk} changes; ΔX_{hk} is the change in the independent variable; and $\hat{\beta}_k$ is the estimated coefficient associated with X_k.

Table 2 Estimation results. Poisson

	β / SE		β / SE
DV: Number of cellphones			
Price and income variables			
Fixed-line price	−0.017	Income 2–3PT	0.064***
	(0.150)		(0.010)
Mobile price	−0.092*	Income >4PT	0.046***
	(0.048)		(0.014)
Income 1–2PT	0.039***	Welfare Recipient HH	−0.061***
	(0.009)		(0.007)
Quality and network effects variables			
Mobile penetration$_{t-1}$	0.439***	Wireline HH × Income 1–2PT	0.123***
	(0.074)		(0.011)
Population density (in 1K)	-0.001	Wireline HH × Income 2–3PT	0.293***
	(0.002)		(0.012)
Ln(Mountainous)	−0.002	Wireline HH × Income >4PT	0.465***
	(0.011)		(0.017)
Wireline HH	−0.457***		
	(0.016)		
Nodal variables			
Retired HH	−0.146***	Child 0-10 YO HH	−0.179***
	(0.008)		(0.005)
Wealthy retired HH	0.086***	Child 11–18 YO HH	0.190***
	(0.008)		(0.005)
Young HH	0.110***	Student HH	0.079***
	(0.006)		(0.008)
Young–middle HH	0.071***	Ratio Working HH	0.168***
	(0.002)		(0.009)
Middle–Old HH	0.002	PT Employed HH	0.047***
	(0.007)		(0.005)
Old HH	-0.231***	Homemaker HH	-0.062***
	(0.010)		(0.005)
Limited youth HH	−0.002	Own Home	0.070***
	(0.005)		(0.006)
Limited adult HH	−0.050***	Ln(Family Size)	1.000
	(0.006)	(Exposure)	
Demographic variables			
Black HH	−0.089***	Female HH	0.115***
	(0.019)		(0.008)
Hispanic HH	−0.140***	Male HH	0.144***
	(0.011)		(0.008)

Table 2 continued

	β / SE		β / SE
Native American HH	−0.103***	Divorced HH	0.001
	(0.026)		(0.004)
Unrelated adults HH	−0.031***	All US citizen HH	0.082***
	(0.005)		(0.010)
Children	−0.115***	Constant	4.265**
	(0.004)		(1.940)
Educated HH	0.092***		
	(0.013)		
State and time effects	Yes		
Test of overdispersion (*p*-value)	1.00		
Correlation between DV and prediction	0.66		
N obs	313,568		

* Significant at 10%; ** significant at 5%; *** significant at 1%

cance. Intra-household mobile adoption does not appear to differ statistically between urban or rural households, or among households of different terrains and surface compositions.

Lagged mobile penetration does appear to have an effect on household-level cellphone subscriptions: $Mobile\ Penetration_{t-1}$ is positive and statistically significant ($p < 0.01$). This result confirms that more extensive adoption of mobile telephones in the vicinity of the focal household creates significant network effects.

Nodal versus Mobile—The estimation results indicate that households with more "mobile" than "nodal" members have higher intra-household mobile adoption rates. Household age is an important determinant of cellphone penetration within the household and in agreement with the conceptual framework above. In comparison to the mixed age category baseline, *Old HH* have lower adoption rates, *Young–Middle HH* have higher adoption rates, and *Young HH* have the highest adoption rates. These age categories each achieve statistical significance ($p < 0.01$), but the *Middle–Old HH* age category does not. The results also indicate that *Retired HH* have lower intra-household mobile adoption rates ($p < 0.01$) and *Wealthy Retired HH* have higher intra-household mobile adoption rates ($p < 0.01$), relative to the mixed age category baseline.

The presence and age of children in the household have distinct effects on intra-household adoption patterns: Households with at least one child member aged ten or younger *(Child* 0–10 *YO HH)* have lower intra-household cellphone adoption levels ($p < 0.01$), while households with at least one child member aged eleven or older *(Child* 11–18 *YO HH)* have higher adoption levels ($p < 0.01$). In unreported regressions using goodness of fit tests, we examined different child age thresholds to determine the age that children adopt cellphones.[37] The Poisson model estimation

[37] We determine goodness of fit in Poisson model estimation using the squared coefficient of correlation between fitted and observed values of the dependent variable.

results indicate a child enhances intra-household cellphone penetration at age ten in 2003 and at age eight in 2013. These results support the notion that intra-household cellphone adoption patterns decrease with age over time.

The employment- and school-related variables affect the likelihoods that potential subscribers are home or away in ways consistent with our conceptual framework. Households that are more "mobile" due to work and school requirements have higher mobile adoption rates compared to households with more "nodal" characteristics: Households with a greater ratio of members working full-time *(Ratio Working HH)*, with at least one member working part-time *(PT Employed HH)*, and with at least one full-time student member *Student HH* have higher cellphone adoption rates. Each of these coefficients achieves statistical significance ($p < 0.01$). By contrast, households with at least one stay-at-home adult member *Homemaker HH* have lower mobile adoption levels ($p < 0.01$). Finally, home ownership *(Own Home)* has a positive and statistically significant effect on intra-household cellphone adoption ($p < 0.01$).

Demographic—The estimation results reveal that several demographic factors impact intra-household mobile adoption patterns. Household ethnicity has a common effect: *Black HH*, *Native American HH*, and *Hispanic HH* have increasingly lower intra-household adoption levels ($p < 0.01$), in comparison to the *White HH* baseline. Households comprised of unrelated adult members (*Unrelated Adults HH*) have significantly lower mobile adoption patterns than households with related adults.[38] All female (*Female HH*) and all male (*Male HH*) households have respectively higher mobile adoption levels ($p < 0.01$), in comparison to mixed-gender households. Households comprised of all US citizens (*All US Citizen HH*) have higher intra-household cellphone adoption levels ($p < 0.01$), in comparison to households with at least one non-US citizen.

6 Policy simulations

In our analysis of fixed and mobile penetration, we find compelling evidence that universal connectivity increased significantly for the US population over 2003–2013. This increase in connectivity—regardless of time or place—has necessarily improved consumer welfare. Individuals with smartphones and high-speed broadband connectivity can achieve near continuous and real-time access to web-hosted information, creating the prospects for enhanced productivity, improved safety, and (perhaps) a greater sense of community.[39] In short, universal connectivity advances the century-old goal of universal service in markedly new dimensions. Yet while this adoption pattern is encouraging, Fig. 4 indicates a significant connectivity gap remains between individuals above and below the federal poverty threshold. With this gap in mind, we utilize the intra-household cellphone adoption estimates above to simulate the economic effects of policies aimed at increasing connectivity.

[38] The possibility exists that other unobserved family characteristics, such as whether children living in the home are with someone other than a father or a mother, may impact cell phone adoption rates. Our data, however, do not permit us to test for these effects.

[39] It is estimated that 80% of the cellphones in use as of 2016 were smartphones. See, FCC 19th Wireless Competition Report, Para. 121, Chart VII.A.1.

The baseline for this exercise is the most prominent demand-side policy to promote universal service: the Lifeline Program. Lifeline was introduced in 1984, and provides a telephone subscription subsidy for low-income households.[40] Eligibility is triggered by household incomes at or below 135% of the federal poverty guidelines or by household members' participation in a qualifying state, federal or Tribal assistance program.[41] The Lifeline Program originally offered subsidies for fixed-line subscription only, but was broadened in 2008 to mobile subscription while maintaining the limitation of a single subsidy per household. The Lifeline Program had over 13 million participants and approximately $1.5 billion in expenditures in 2015.[42]

Based on the long-standing policy desire for connectivity, our simulation extends Lifeline's focus from universal service to universal connectivity. In particular, we relax the policy constraint that limits each household to a *single* subsidy for a *single* telephone subscription and instead offer each household multiple subsidies for multiple telephone subscriptions equal to the number of eligible household members (i.e., as many subsidies as adult members). The intra-household mobile adoption estimates above are used to simulate the impact on cellphone subscriptions in the event that all adult members of Lifeline-eligible households receive subsidies. The Lifeline subsidy expansion simulation is performed using the most recent year of the sample data (2013). During that year, eligible households on non-Tribal land receive a uniform $9.25 telephone subsidy per month; eligible households on Tribal land receive an additional $34.25 telephone subsidy per month.

We first identify households in the data that are eligible under Lifeline rules to receive the subsidy.[43] We then assume that 30% of eligible households take up the

[40] Another demand-side program in place during our data window was "Link-Up America," which subsidizes initial phone service subscriptions for low-income households. Three federal supply-side programs designed to encourage universal service deployment are: High Cost, Libraries and Schools, and Rural Health Care. These programs respectively provide subsidies to telecommunications carriers, schools, and healthcare facilities to increase connectivity. An analysis of whether these supply-side programs may impact intra-household mobile telephone service demand is left for future research. Additionally, telephone companies were historically encouraged to deploy payphones to provide telephone access. With the introduction and diffusion of mobile telephone service these policy efforts have subsided.

[41] These qualifying programs include Medicaid; Supplemental Nutrition Assistance Program (Food Stamps or SNAP); Supplemental Security Income; Federal Public Housing Assistance (Section 8); Low-Income Home Energy Assistance Program' Temporary Assistance for Needy Families; National School Lunch Program's Free Lunch Program; Bureau of Indian Affairs General Assistance; Tribally-Administered Temporary Assistance for Needy Families; Food Distribution Program on Indian Reservations; Head Start (if income eligibility criteria are met); and other applicable state-level assistance programs.

[42] A 2016 FCC Order further expanded the Lifeline Program to allow eligible households subsidies on fixed broadband service subscription. See https://www.fcc.gov/document/fcc-modernizes-lifeline-program-digital-age for more detail.

[43] Eligible households are considered those: (1) with incomes at or below 124% of the poverty threshold (i.e., the closest threshold among income categories in our data to the 135% level used by the FCC); or (2) with at least one member participating in a federal (i.e., SNAP, Medicaid, SSI) or state or county low-income qualifying program. NHIS data indicates whether a household participates in one of these portals, but there are a few miscellaneous state-specific eligibility programs that exist which are impossible to capture. The vast majority (84%) of Lifeline subscribers enter the program via the eligibility criteria identified. See http://usac.org/_res/documents/about/quarterly-stats/LI/Subscribers-by-Eligibility-Program.pdf. As our data include a small percentage (i.e., below 1%) of Native Americans households, we exclude them from the simulation analysis due to insufficient sample size.

program after its expansion. This percentage is consistent with historically observed take-rates for Lifeline Program-eligible households.[44] We then assume that every adult member receives a subsidy if the eligible household participates. We then incorporate these assumptions and the parameter estimates to examine the impact of this expansion of the Lifeline Program.

The policy experiment results are presented in Table 3. We first calibrate the model and establish a baseline using columns (1) and (2). We compare the actual and predicted number of cellphones and the actual and predicted number of cellphones per household member for the whole sample (24,016 households) and Lifeline Program-eligible subsample (7713 households). Rows 1 and 2 indicate that the respective number of actual and predicted cellphones is 40,556 and 40,760 for the whole sample and 11,564 and 10,867 for the Lifeline-eligible subsample. Rows 3 and 4 indicate that the predicted and actual number of cellphones per household member are in agreement for the whole sample, but the model under-predicts the actual number of cellphones per household member for the Lifeline-eligible subsample. The model thus appears to make fairly accurate predictions with the whole sample, but is less precise with the subsample.

In columns (3)–(6) we examine the modification of the Lifeline Program. We compare the policy intervention results to model predictions (i.e., the benchmark) rather than to actual data. Columns (3) and (4) show the impact of relaxing the current one subsidy per household constraint to allow for multiple subsidies per household members (i.e., one per eligible adult member) on the predicted number of cellphones and predicted number of cellphones per household member for the whole sample and the Lifeline-eligible subsample. Because cellphone subscription prices change only for eligible households, changes in the number of cellphones results from changes in these households' telephony decisions.[45] Any increases in the total number of cellphones are thus the same for the whole sample and for the Lifeline-eligible subsample. Comparing columns (3) and (4) with their respective baseline in column (1) and (2) indicates that relaxing Lifeline eligibility criteria to include all eligible adult household members increases the number of cellphone subscriptions by roughly 2500 and increases the number of cellphones per household member by 0.03 for the whole sample and 0.10 for the Lifeline eligible subsample.

Columns (5) and (6) put these gains in a different perspective. Among the whole sample, this policy expansion would generate a 6% increase in total cellphone subscriptions and a 4% increase in cellphones per household member. Among eligible households, however, the impact of a multi-subsidy per household expansion is considerably larger: the number of cellphone subscriptions increases by 23% and the number of cellphones per household member increases by 17%.

Figure 5 illustrates the impact of the Lifeline Program policy expansion on universal connectivity. In the absence of any policy change, universal connectivity of eligible

[44] See Burton et al. (2007) for a detailed discussion and analysis of the history and determinants of observed take rates. USAC statistics indicate 33% Lifeline Program take-rates in November, 2015. See http://usac.org/_res/documents/about/quarterly-stats/LI/Subscribers-by-Eligibility-Program.pdf.

[45] In limiting any increase in cellphone subscriptions to eligible households, the simulation abstracts from any positive network effects that changes in subscriptions among eligible housseholds may have on subscriptions among non-eligible households. Consequently, our simulation is a conservative estimate of the total subscription increase associated with the policy change.

Table 3 Policy experiment

	Baseline		*Policy experiment (lifeline expansion)*			
	Whole sample (1)	Eligible households (2)	Whole sample (3)	Eligible households (4)	Change (%) whole sample (5)	Change (%) eligible sample (6)
1. Actual number of cellphones	40,556	11,564	–	–	–	–
2. Predicted number of cellphones	40,760	10,867	43,209	13,317	6%	23%
3. Actual cellphones per HHM	0.77	0.67	–	–	–	–
4. Predicted cellphones per HHM	0.76	0.59	0.79	0.69	4%	17%
N obs	24,016	7713	24,016	7713		

In the policy experiment, it is assumed that all adults in a household get Lifeline discount, and the program take rate is 30%

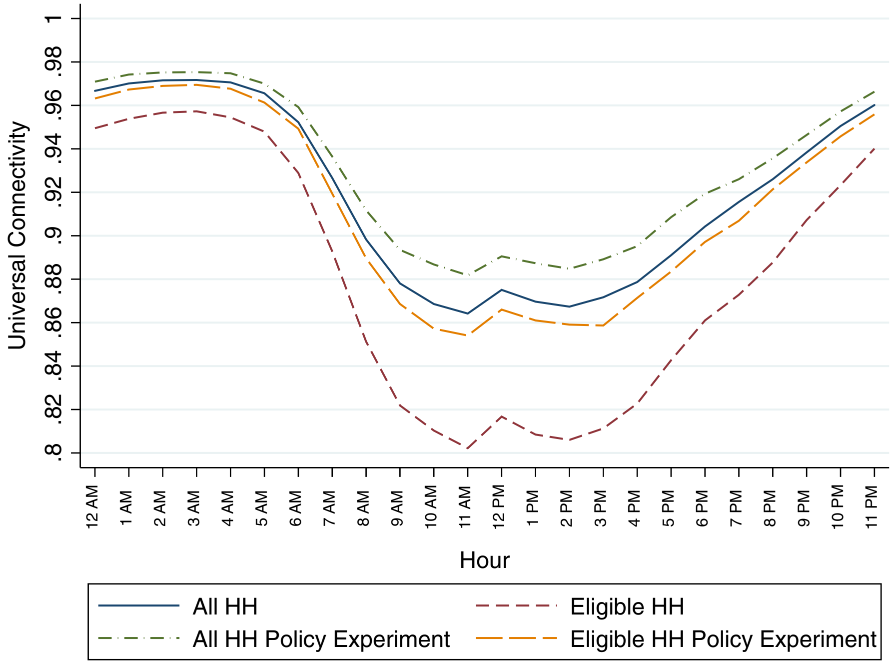

Fig. 5 Universal connectivity. Policy experiment. 2013

households (Eligible HH) significantly lags all households (All HH). With the policy change, universal connectivity increases significantly not only for all households (All HH Policy Experiment), but also and in particular for eligible households (Eligible HH Policy Experiment). The greatest gains occur during the daylight hours.

In an ideal setting, policymakers are able to fully quantify the benefits and costs of policy changes. The societal benefits of enhanced connectivity associated with moving from universal service to universal connectivity are, however, difficult to determine. Indeed, similar challenges to quantify benefits have plagued universal service policies over the years. It is possible, however, to estimate the costs associated with this Lifeline Program policy expansion. The total number of non-Tribal mobile Lifeline subscribers was 9,779,760 in 2013.[46] Table 3 indicates that multi-subsidy per household expansion would increase the number of cellphone subscriptions among eligible consumers by 23%. Expanding the Lifeline Program would thus generate 2.25 million more mobile telephone subscriptions. Given the annualized monthly subsidy of \$9.25 per subscription, the total incremental cost associated with this policy change is roughly \$250 million.[47]

46 See Ukhaneva (2015) for more detail.

47 This increase does not include changes in the costs of administering the change in the Lifeline program or any economic distortions that may occur as a consequence of alternative public financing mechanisms to fund the program expansion. Additionally, we do not examine the potential for the *de novo* costs of a universal service policy to be reduced by reductions in expenditures on existing universal service funds other than Lifeline.

7 Conclusion

For nearly a century, the household has been the unit of analysis when considering the universality of telephone service. The exploding adoption of mobile telephones by consumers over the past 25 years compels a significant shift in focus. With over 380 million wireless subscriptions in the United States,[48] the "universality" of communications across both geographic space and the population is substantially higher than only a few years ago. In this paper, we seek to shift the historical focus on households' adoption of a telephone to the *connectivity* of individuals across space and time. We have constructed a measure of universal connectivity that, unlike traditional measures of universal service, accounts for the connectedness of individuals over the course of the day. Such a metric arguably provides a more robust and relevant measure for policymakers to gauge the ability of individuals to fully avail themselves of the benefits of 21st century communications technologies. While our specific measure is focused on the ability of consumers to place and receive voice-based communications, the construct of universal connectivity is quite general and may be reasonably extended to measure connectivity that incorporates broadband data and video communications.

The shift from a household-level analysis to a focus on individual access to communications motivates the need to develop a model that examines the intensity of intra-household demand for wireless telephone service. Our conceptual framework is built on the microeconomic foundations of utility generation from two-way communications between individuals, and our empirical analysis draws from a large and granular database that offers a unique window into wireless telephone adoptions by individuals.

A number of insights emerge from our empirical analysis. For instance, while the bulwarks of microeconomic demand analysis—price and income—are seen to be important determinants of demand, our analysis points to other less obvious factors affecting the intra-household proliferation of cellphones. These include the important role of the mobility of household members as drivers of wireless demand intensity within households, the importance of the quality of wireless networks as a driver of demand intensity, and the significant role of mobile network externality effects.

Finally, we provide policy simulations that explore the consequence of a change in universal service policies that would move the policy more toward an individual rather than household focus. In particular, we examine the consequence of eliminating the current policy that restricts each eligible household to the receipt of a single universal service subsidy. The simulations provide both an estimate of the gains to universal connectivity that would accompany such a change as well as an indication of the cost associated with that change.

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[48] See statistics published by the International Telecommunications Union http://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx.

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