Variation in broadband access among undergraduate populations across the United States

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Abstract

Increasing numbers of students require internet access to pursue their undergraduate degrees, yet broadband access remains inequitable across student populations. Furthermore, surveys that currently show differences in access by student demographics or location typically do so at high levels of aggregation, thereby obscuring important variation between subpopulations within larger groups. Through the dual lenses of quantitative intersectionality and critical race spatial analysis alongside a QuantCrit approach, we use Bayesian multilevel regression and Census microdata to model variation in broadband access among undergraduate populations at deeper interactions of identity. We find substantive heterogeneity in student broadband access by gender, race, and place, including between typically aggregated subpopulations. Our findings speak to inequities in students' geographies of opportunity and suggest a range of policy prescriptions at both the institutional and federal level.

Keywords: broadband, digital divide, educational access, QuantCrit

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Introduction

Education equity conversations have expanded in recent years to include the role that technology plays in producing student outcome disparities, including differences in technological literacy and access to online learning tools (Buzzetto-Hollywood et al., 2018; J. K.-H. Ma et al., 2019; Tawfik et al., 2016). Disparate access to broadband, also known as the "digital divide" (Van Dijk, 2020), represents a central component of enduring technological inequalities and is connected to numerous student outcomes at the K-12 level such as course engagement, grades, and standardized test scores (J. M. Bauer et al., 2020; Hampton et al., 2020). At the postsecondary level, broadband access represents an essential gateway to opportunity and success as it is related to the number of application submissions (Dettling et al., 2018), online course enrollment (Skinner, 2019b), and completion of required coursework (Rosenboom & Blagg, 2018; Whistle & West, 2020). Nevertheless, millions of students in the United States lack high-speed internet in their homes (Kelley & Sisneros, 2020). The COVID-19 pandemic has only exacerbated these barriers, with greater numbers of students relying on at-home service to complete education-related tasks (Whistle & West, 2020), a trend likely to continue.

Despite a growing body of literature, prior work on broadband access among college students often lacks specificity in the populations under study. Whether through data limitations or modeling choices, descriptions of differential access are often highly aggregated across individual demographic characteristics such as race, gender, and geography (Perrin, 2021). Analyses that do not disaggregate by gender or that combine multiple heterogeneous ethnicities into single racial categories (e.g., Asian) can erase heterogeneity of experience within these aggregations (Castillo & Gillborn, 2022; Garcia et al., 2018; Schudde, 2018). Using overly aggregated data means that policies which rely on broadband access—for example, those meant to encourage the expansion of online learning—may lack the nuance necessary to support equitable college access and success.

Working within the QuantCrit paradigm (Castillo & Gillborn, 2022; Garcia et al., 2018; Gillborn et al., 2018), we use the theoretical frameworks of quantitative intersectionality (Covarrubias, 2011) and critical race spatial analysis (Morrison et al., 2017) to explore students' geographies of opportunity (de Souza Briggs, 2005; Green et al., 2017; Tate IV, 2008) as they relate to broadband access. We combine individual-level Census microdata with Bayesian multilevel modeling techniques to produce estimates of broadband access among undergraduate student populations at deeper intersections of identity and place than we have found reported elsewhere. In using Bayesian multilevel models, we offer estimates that provide reasonable bounds for even small populations and that are straightforward to interpret. We find substantial variation in in-home broadband access among college students by gender, race/ethnicity, and state. While nearly 25% of undergraduates lack in-home broadband access in the least connected states, nearly 10% lack broadband even in the best connected states. We find similar variation among those who rely on a cellular data plan for internet access, with state-level rates that range from 10% to 24%. Disaggregated by gender, we find that undergraduate men tend to report better broadband access on the order of 1-2 percentage points than undergraduate women across all states, with the inverse being true for those relying on a cellular data plan for internet access. Across the country, differences in both types of broadband access among 162 unique racial/ethnic groups defined by the U.S. Census range as much as 33 percentage points. Among the 23 Hispanic[1] ethnicities distinguished by the Census, we find variation not only between genders within and across ethnicities but also within gender-ethnic identity across California, Florida, and Texas, three states with large and growing Hispanic populations (Krogstad, 2020). We present figures on each of these levels of variation in broadband access to demonstrate the connection between identity, place, and a key higher education resource.

At a moment when a number of COVID-19-prompted initiatives have great potential to transform how students engage with school (Darling-Hammond et al., 2020) and legislators work to craft responsive policy that will support such goals (Klein, 2021; Morton, 2022), dominant discourses that homogenize subgroup differences may impede equitable policy impact. Thus, nuanced data on who does and does not currently have access is urgently needed. Through our

[1]Throughout this paper, we use the term *Hispanic* when discussing our findings as it is the pan-ethnic group label assigned by the United States Census. We note, however, that the term is neither without contention nor is perfectly aligned with other categories like Latino/a/e/x, especially among higher education students (Salinas & Lozano, 2017). Therefore, we use the term *Latinx* when discussing this population more generally as distinct from when we are using data from the Census.

critical approach to quantitative analysis (Castillo & Gillborn, 2022; Garcia et al., 2018; Morrison et al., 2017) we add such nuance.

Background

Participation in higher education continues to demonstrate positive returns, with those who attend earning higher wages and showing greater civic engagement (Doyle & Skinner, 2016, 2017; J. Ma et al., 2019; Skinner & Doyle, 2021). As a result, college access and success for all students remains a central concern for postsecondary stakeholders. Nevertheless, significant differences in participation by state (Skinner & Doyle, 2022), gender (Conger & Long, 2013), and race/ethnicity remain, with 82% of Asian students, 69% of White students, 64% of Hispanic students, and 57% of Black students enrolling immediately after high school graduation (Irwin et al., 2021). Black and Hispanic student populations also remain more heavily concentrated in less selective colleges (Baker et al., 2018) and experience lower six-year graduation rates (Shapiro et al., 2017) than their White counterparts. Research working to explain these differences tends to fall within four main categories: precollege/K-12 experiences, institutional match, institutional quality/context, and academic/social experiences while in college (Ciocca Eller & DiPrete, 2018). Across these categories, differences in attainment are often attributed to multiple systemic resource disparities that include fewer educational opportunities in P-12 due to the intersection of neighborhood-based funding formulas and residential segregation, lack of college-going support and preparation, information asymmetries, and financial restrictions—all of which can compound for multiply-marginalized students (Flores et al., 2017; Orfield, 2013; Ovink & Delaney, 2018). In this study, we explore one particular resource of increasing importance to higher education: broadband internet access.

Originally used by a small number of people for national defense and research purposes (Leiner et al., 2009), the internet is now a hub of resources ranging from telehealth (Bauerly et al., 2019; Tomer et al., 2020) and "e-government" (Dharma et al., 2010) to education and community involvement (Kelley & Sisneros, 2020; Sallet, 2019; Stern & Adams, 2010). A big part of this shift was due to the introduction of broadband technologies, which, at the turn of the century, revolutionized culture and society by increasing and diversifying activities that could be accomplished digitally (Ting, 2011). Compared to older telephone-based dial-up modem technology, the "always online" structure of broadband decreased the time and labor required to use online networking systems to conduct intended tasks (Mack, 2020). As broadband technology has grown to include a number of technologies such as digital subscriber line (DSL), cable, satellite, wireless, fiber optic, and cellular networks, high-speed and high-capacity digital connections have grown increasingly integral to accessing the proliferation of online platforms essential for productive social life (Tomer et al., 2020). Yet while many consider this diversity of online activities to be an indicator of ubiquity, the "global commons" (Ryan, 2010) are still largely stratified by race, class, geographical location, and other social indices (Reddick et al., 2020).

Of particular concern to education stakeholders is the necessity of broadband for learning and the impact of broadband on student outcomes. A wide breadth of research explores these topics in the K-12 space, with studies connecting the availability of high-speed internet to educational access among students in remote locations (Aguilar et al., 2021; Arnett, 2021; Chandra et al., 2020; Fox & Jones, 2019) and engagement in the classroom (Fox et al., 2012; McKenzie & Ritter, 2015). Data on K-12 students specifically shows that high internet speeds are concentrated in more affluent schools and that 2.75 million students, many of whom are disproportionately poor and/or students of color, lack the high-speed access necessary for online learning activities (Horrigan, 2014).

Despite its being "critical in preparing all students for college and careers in the digital age," (Fox & Jones, 2016), there is less research exploring broadband access for students once they reach postsecondary education. Existing research has documented the relationship between broadband connectivity and both college application submissions (Dettling et al., 2018) and online course enrollment at open access institutions (Skinner, 2019b). Broadband has also been touted as a tool for expanding college access overall, as its relationship to online degree programs offers flexible alternatives for students experiencing geographic and/or time-based constraints that may otherwise make obtaining a degree unfeasible (K. Lee, 2017; Ortagus, 2017; Xu & Xu, 2019). Nevertheless, approximately 3.1 million adults occupy an “education desert” (Hillman, 2016; Klasik et al., 2018) where there is no access to physical or online education due to insufficient broadband service (Rosenboom & Blagg, 2018). A current estimate for minimum download speed necessary for online learning is 2 Mbps, with speeds lower than this threshold causing susceptibility to “performance issues such as slow Internet page display, slow Internet portal performance, slow playback of course videos, the inability to play videos, slow online quiz performance when saving answers or submitting, online quiz lockups, etc.” (Temple College eLearning Department, n.d.). The need for sufficient speed only increases with every additional person using broadband service in the household as bandwidth represents a finite resource that must be shared. A national survey of college students conducted after the first COVID-19 shutdown in March 2020 reported that over half of college students said a poor internet connection was a direct impediment to their coursework (Whistle & West, 2020). This phenomenon has great implications for student success and retention, particularly as it relates to the multitude of ways students now access higher education.

Disparities in access to broadband

Scholars have explored the digital divide across several indices, including place and race/ethnicity (Kelley & Sisneros, 2020; Reddick et al., 2020; Singh et al., 2020). Those investigating an urban/rural divide tend to emphasize the impact of procedural and logistical barriers such as political gridlock (Bauerly et al., 2019) and lack of market competition (Grubesic, 2006) on infrastructure expansion. Historically, service providers have favored more heavily populated areas, leaving rural communities in a “negative feedback of limited capacity, high prices, and low service demand” (Pereira, 2016, p. 2). Even as research and policy initiatives such as USDA’s ReConnect Program have addressed and marginally narrowed the rural/urban digital divide (Summers-Gabr, 2020), rural adults remain less likely to have broadband access in their homes, less likely to have multiple devices permitting online activities, and more likely to report high-speed service as a “major problem” than adults living in urban areas (Vogels, 2021).

Research on racial and socioeconomic divides often underscores community disinvestment and cost barriers (Chatters et al., 2020; Francis & Weller, 2021; Rhinesmith et al., 2019). Black and Hispanic individuals are significantly less likely to have broadband in the home (Reisdorf & Rhinesmith, 2018) as well as more than 10% less likely than White individuals to own a laptop or computer (Atske & Perrin, 2021). While there is no evidence of differences in ownership rates of tablets or smartphones across racial/ethnic groups, Black and Hispanic adults are more likely than other groups to access web-based activities from their phones due to lack of in-home broadband (Atske & Perrin, 2021). In these cases, smartphone use may offer an alternative to traditional at-home connections, particularly because they satisfy what scholars have called "autonomy of internet use," which is the ability to access the web without restraints or surveillance from an external supplier such as an employer (Hargittai & Hinnant, 2008). Smartphone use, however, has not proven a sustainable solution for closing gaps in access to internet-based educational opportunities (Fairlie, 2017). While smartphones have evolved, they do not have the same technological capacity as laptops and other broadband-supported devices. This may be particularly troublesome for students who need to access a variety of web-based tools including videoconferencing, online portals, and discussion boards. Furthermore, segmented access between in-home broadband and smartphones may create an "overlapping effect" on the already-existing divide by exacerbating gaps in communications competence such as computer skills (H. Lee et al., 2015).

Recognizing that broadband access exists more on a spectrum than a hard dichotomous split, some scholars have begun to conduct more granular analyses on, for example, within-rural and within-urban communities rather than across communities alone (Beede & Neville, 2015). They have also begun to explore access barriers as they simultaneously operate across racial and socioeconomic status, with mechanisms such as historic redlining slowing infrastructure development (Hall, 2021; Skinner et al., 2023) and costs disproportionately excluding poor communities of color (Fairlie, 2017), even when they reside in metropolitan areas (Reddick et al., 2020). Scholars conceptualize these nuanced barriers as a direct impediment to community resilience for multiply-marginalized communities, with the digital divide obstructing "social cohesion," economic opportunity, crisis response, and community health (Rothschild, n.d.). To support our analyses that continue in this spirit of nuance, we turn to two critical frameworks, which we discuss in the next section.

Analytic framework

Over-simplified approaches to racial positioning in the United States have roots in the lasting legacies of colonization and slavery that position White as normative and any non-White identity as collectively Black or "other" (Anderson & Duncan, 1996; Jones, 2015; Mwangi, 2014). Research on the multiplicity of racial/ethnic identities, however, highlights significant differences in life experience across populations, including racialization and discrimination (Drouhot & Garip, 2021), health inequalities (Brown et al., 2016), K-12 school performance (Davis-Kean & Jager, 2014), and educational attainment (Mwangi, 2014). Relying on aggregated racial categories may obscure important within-group differences, thereby distorting inter-group community needs and working against remedies of enduring inequities. Recent education-focused research has emphasized the need for greater heterogeneous data collection and analysis, particularly in work with large administrative data sets as they relate to race (Ford et al., 2020; Viano & Baker, 2020). While parsimonious models have the advantage of simplicity and, in some cases, statistical power, approaches that categorically consolidate racial groups and relegate smaller subgroups to "other" or drop them entirely from the analysis systematically erase populations of people who differ greatly in cultural, social, and geographical background (Khunti et al., 2020).

We organize the structure of our analyses—how we operationalize our data, construct our models, and interpret our results—using the QuantCrit paradigm, which takes a critical approach to quantitative data analysis, particularly as it relates to race, racism, and structural oppressions that beget inequity (Castillo & Gillborn, 2022; Garcia et al., 2018; Gillborn et al., 2018). Citing Gillborn et al. (2018), Castillo & Gillborn (2022) write " 'QuantCrit' rests on five principles; 1) the centrality of racism; 2) numbers are not neutral; 3) categories are neither 'natural' nor given: for 'race' read 'racism'; 4) voice and insight (data cannot speak for itself); and 5) a social justice/equity orientation," (p. 2). Disaggregating broadband access by race/ethnicity in addition to other intersecting layers of identity—gender and place—allows for a more nuanced consideration of the digital divide among college students, one that takes into account structural oppressions that might be the cause and result of differences in access. So that we can better map students' geographies of opportunity (de Souza Briggs, 2005; Green et al., 2017; Tate IV, 2008) as they relate to broadband access, we use a combination of two critical frameworks: quantitative intersectionality and critical race spatial analysis.

Intersectionality is at once a social theory and an analytic framework that can be used to map patterns between multifaceted social identities and social power structures/dynamics. We emphasize quantitative intersectionality (Covarrubias, 2011) as an analytic tool for geographic spatial analysis, which prompts us to consider the multiplicity of identity and experience that shape and are shaped by an individual's spatial reality (Collins, 2000; Crenshaw, 1989; Rice et al., 2019). In one example of a quantitative intersectional analysis, López et al. (2018) use mixed effects logistic regression models to estimate differences in college graduate rates at intersections of race, gender, and class, "revealing social inequalities for race–gender–class social locations that may remain invisible in conventional approaches to studying inequality in education," (p. 181). In this study we disaggregate the racial identity classifications Asian, Native American/Alaska Native, Hispanic, and multiracial or "other" into more detailed constitutive ethnicities, as well as by gender within group, to better understand the relationship between student identity and access to broadband.

Partnered with quantitative intersectionality, we use critical race spatial analysis (CRSA) to understand differences in the distribution of broadband access across geographical space. Rooted in Du Bois' conceptualization of the "color-line," the spatial manifestation of White segregationist ideologies (Du Bois, 1903), CRSA has been used by scholars to layer data and visualize geographic patterns of educational opportunity (Lubienski & Dougherty, 2009; Morrison et al., 2017; Pacheco & Velez, 2009; Singleton, 2016). In direct resistance to purportedly neutral or objective statistical approaches that reinforce and "legitimate racist inequities" (Gillborn et al., 2018, p. 160), CRSA calls for analyses that both re-appropriate quantitative methods in the use of liberatory praxis (Morrison & Garlick, 2017) and incorporate mixed methods to prioritize community agency in knowledge production. While our study does not include a qualitative component, it follows the tenets of CRSA to (1) interrogate "the intersections of space, power, and knowledge in order to expose geographies that perpetuate or disrupt inequities" (Annamma et al., 2017, p. 4), (2) reject pseudo-genetic notions of racial permanence that perpetuate false ideologies of cultural deficiencies (Covarrubias, 2011; Morrison et al., 2017), and (3) center racism as a direct cause for spatial inequities in educational resources. Employing CRSA allows us to consider how broadband, as a geographically-based form of educational capital, exists not only across students' racial and gendered identities but also across the power-laden constructions of space students occupy. Taken together our analytical framework guides our quantitative analyses through our use of disaggregated data and Bayesian statistical methods, which we describe further in the following sections.

Data

Data for this study come from IPUMS USA 1% microdata data files (Ruggles et al., 2021), which collects data from the United States decennial Census and yearly American Community Survey (ACS). The ACS first began asking about in-home broadband access in the early 2010s, but due to changes in how the FCC defined broadband in 2015,[2] we limit our analysis to the years 2016 to 2019. We combine data across all years so that we can increase the number of observations and thereby improve our ability to provide estimates of broadband access for otherwise small population groups. Our results, therefore, are representative of the full four-year period. Because of confidentiality restrictions in publicly-available Census data, we trade highly detailed individual-level demographic data for less specificity about respondents' geographic locations. With these data we are able to locate persons in households at the state-level, including Washington D.C. To focus on college student broadband access, we limit our sample in each year to those persons who have a high school equivalent diploma and report being enrolled in postsecondary education at

[2] In 2010, the FCC defined broadband as service with minimum download speeds of at least 4 Mbps (megabits/sec). In 2015, the minimum speed required to meet the definition of broadband was 25 Mbps.

the undergraduate level.[3] We do not include those students who live in group quarters, such as college dormitories, since broadband measures are not given for those observations. Across the four years of the survey, our data set contains $N = 471{,}899$ unique observations which represent $N_{pop} = 56{,}488{,}281$ undergraduate students who live off-campus.

We collect information on the state of residence, gender, and race/ethnicity of each observation. Gender in our data is limited to a binary representation of male and female (*SEX*).[4] The Census defines race at two levels. At the highest level of aggregation (*RACE*) are nine categories—American Indian / Alaska Native, Black, Chinese, Japanese, (non-Chinese, non-Japanese) Asian / Pacific Islander, other race, two races, three or more races, and White. Within these categories, the Census defines 139 more specific racial identities (*RACED*) during the sample period, including a number of specific multiracial/multiethnic identities that come from respondents selecting more than one option and write-in values on the Census form.

For historical reasons tied to the formation of a pan-Hispanic identity in the United States (Mora, 2014), "Hispanic/Spanish/Latino" ethnicities are coded in U.S. Census data using a separate variable (*HISPAN* and the more detailed version *HISPAND*) that, similar to the variables for race, provide higher level aggregations (4 groups) and more specific ethnic identities (23) within the larger aggregations.[5] For our models, described in more detail below, we need to combine *RACED* and *HISPAND* into a single vector of categorical values representing students' racial/ethnic identification. Briefly, we discuss our considerations and ultimate process for creating this new variable.

One method would be to interact all possible values of *RACED* with those in *HISPAND*, creating a new variable with 3,197 (23×139) potential racial/ethnic identities. Even if not all cells were filled, however, this approach would create too many distinct groups and prove intractable to estimate and report. Another option would be for us to interact *RACED* and *HISPAND* as before,

[3] Using IPUMS variables: *GRADEATT* == 6 & *EDUC* >= 6

[4] In each year of data, the Census instrument specifically asks "What is Person X's sex?" and gives two options, *Male* and *Female*, with instructions to "Mark (X) ONE box." There is not a separate question about gender identity to distinguish. We make two notes. First, we cannot distinguish different interpretations—*e.g.*, biological versus gender identity—of this question among respondents. Second, respondents considering gender were given a limited choice set of gender identities without an option to write in another answer. We use the term *gender* throughout the paper to describe the binary option set, noting the limitations inherent in the data.

[5] See https://usa.ipums.org/usa-action/variables/HISPAN#description_section.

but keep only a limited number of intersections of Hispanic and racial identity. We decided against this approach as well since it would require a number "researcher degrees of freedom" (Simmons et al., 2011) that would rely too heavily on our non-expert judgment regarding the complexity of Hispanic/Latinx identity among postsecondary students in the United States (Salinas & Lozano, 2017).

Instead, we take a two-step approach to incorporate Hispanic ethnicities into the primary race/ethnicity variable provided by the Census. First, if a respondent selected any Hispanic identity, we code them with that identity mutually exclusive of their racial categorization according to the detailed race variable. Second, we create a new variable in which we append all specific Hispanic ethnicities in *HISPAND* to the values in *RACED*. In addition to being the most tractable and transparent, this approach is also in alignment with how other non-Latin American and Caribbean ethnicities are coded by the Census, that is, contained in the detailed *RACED* variable. The result is a single detailed racial/ethnic group variable with 162 unique values. In addition to state, gender, and race, we also collect information on each observation's Census region, age, and yearly family income adjusted to real 2019 dollars.

As our outcomes of interest, we investigate two binary values of broadband access. The first represents household access to fixed broadband (*CIHISPEED*) through telephone line (DSL), coaxial copper line (cable modem), or optical fiber. All those who indicated they had access in their household to one of these technologies were coded as one with all others coded as zero. Our second outcome represents access to the internet through a cellular data plan via a smart phone or mobile device (*CIDATAPLN*). While Census data allow for a person to indicate that they have access to the internet both through in-home fixed line and a cellular data plan, we redefine the second outcome to represent those who rely on a cellular data plan for internet access, with zero representing those who either have in-home broadband access or no broadband access at all.

Methodology

We work within a Bayesian framework to estimate the proportion of undergraduates with access to broadband. For the straightforward descriptive statistics we want to provide, we could estimate simple proportions without recourse to Bayes. Though easy to interpret, these estimates would not provide estimates of error. With a frequentist inferential approach, we could compute standard errors for our estimates; however, many undergraduate populations would be too small to compute confidence intervals of reasonable precision. We would either have to drop these small groups from the analysis or aggregate them into larger groups in order to provide informative confidence intervals. Both of these choices are antithetical to our QuantCrit framework. Furthermore, frequentist standard errors/confidence intervals are most often interpreted in terms of significance testing over long term repeated samples. Because we rely on a cross-sectional population census, frequentist inference based on repeated sampling is not as appropriate as Bayesian inference which understands data as fixed and parameters variable. In this section, we more fully describe our Bayesian methodology, ending with its utility in supporting the rich heterogeneous estimates we want to produce.

We estimate the proportion of undergraduates with in-home (or cellular-only) broadband access, θ, using

$$P(\theta \mid X) \propto P(X \mid \theta) \times P(\theta) \tag{1}$$

in which our prior beliefs, $P(\theta)$, are updated with data on access, X, via the likelihood, $P(X \mid \theta)$, to produce a posterior distribution of new estimates, $P(\theta \mid X)$, (Gelman et al., 2014). To speed estimation, we reduce the dimensionality of our data by collapsing our initial individual-level data set so that each row contains a unique demographic cell, j, that represents the intersection of state (51 categories), gender (2), race/ethnicity (162), age (10), and income (13). When collapsing the data, we sum each binary outcome measure of broadband access, the number of observations that comprise the demographic cell, and each observation's survey weight (*PERWT*). Respectively, these three numbers give the number of those within each demographic cell with access to each broadband measure, n_j, the total number of observations comprising the demographic cell, N_j, and the total population represented by that demographic cell, N_{pop}. The collapsed analysis data set is comprised of $N_J = 50{,}469$ unique undergraduate demographic groups representing students across the United States.

In our likelihood function, we model the counts of persons in each demographic group with access to broadband, n_j, out of the total, N_j, as a binomial distribution

$$n_j \sim Binomial(N_j, \theta_j) \tag{2}$$

where θ_j is the probability that a member of group j has broadband access, or, synonymously, the proportion of group j with broadband access. We estimate θ_j in a logistic regression model that takes the form

$$\begin{aligned}\hat{\theta}_j = logit^{-1}(\beta_0 + \beta^{female} * female_j + \alpha_{raceeth[j]} + \alpha_{age[j]} + \alpha_{income[j]} \\ + \alpha_{region[j]} + \alpha_{state[j]} + \alpha_{state.raceeth[j]} + \alpha_{state.raceeth[j]} * female_j)\end{aligned} \tag{3}$$

in which we include a grand mean, β_0, β_{female} for the single binary category, and random effects, α, for Census region, state of residence, and demographic categories. In line with our theoretical frameworks, the two terms, $\alpha_{state.raceeth[j]}$ and $\alpha_{state.raceeth[j]} * female_j$, represent interactions between each state, race/ethnicity, and gender, which introduce flexibility in our model and allow our results to vary along intersections of these dimensions rather than simply in an additive form through non-interactive intercept shifts. We place weakly informative normal priors appropriate for the logistic scale on each regression parameter: $\alpha \sim N(0, \sigma)$, $\beta \sim N(0, 2)$. Group random effect parameters share a common variance term, σ, each of which are given a truncated standard normal prior: $\sigma \sim N_+(0, 1)$. In effect, our use of weakly informative priors means that posterior distributions are more greatly influenced by the information gained from the data than any strong prior beliefs on our part as researchers. We fit two versions of equation 3 using the R statistical and Stan probabilistic programming languages (R Core Team, 2021; Stan Development Team, 2021), one for each broadband access measure: (1) in-home access to a fixed line and (2) access solely through a cellular data plan.

In order to make our results easier to interpret, we present predicted probabilities of broadband access for each demographic group, $\hat{\theta}_j$, that we compute from the posterior distributions of our regression parameters. To account for the fact that each observation in the Census microdata file represents more than one person, we follow the literature on multilevel regression with poststratification (Kennedy & Gelman, 2019; Little, 1993; D. K. Park et al., 2004) and use the summed values of *PERWT*, N_{pop}, to poststratify or reweight demographic group-specific estimates when aggregating them to higher levels using

$$\hat{\theta}_{ps} = \frac{\sum_{j \in J} N_{pop} \hat{\theta}_j}{\sum_{j \in J} N_{pop}}. \tag{4}$$

For example, should we wish to estimate the overall percentage of undergraduates in the state of Kentucky with access to broadband in the home, we would average the predicted probabilities across all subpopulations in the state, giving more weight to those demographic cells who represented a greater share of the undergraduate population in the state. Equation 4 is sufficiently flexible that we are able to present results from the two models through a large number of aggregations—within state, gender, race/ethnicity, or interactions thereof—while taking into account within-group distributions across other demographic dimensions (e.g., family income and age).

There are two key benefits in using a Bayesian multilevel regression model that align with tenets of critical quantitative analyses (Castillo & Gillborn, 2022): the ability to provide estimates for disaggregated subgroups and ease of interpretation. To the first end, multilevel models with random effects allow for the sharing of information (sometimes framed as "borrowing strength") across the different levels of the model (Gelman et al., 2014). This is particularly important when attempting to produce estimates for small demographic groups. For example, the number of American Indian / Alaskan Native undergraduates is very small in some states, particularly when this broad aggregation is decomposed into more specific tribal identities and affiliations as well as further separated by gender, income, and age. With a multilevel model and random effects framework, we can produce estimates of broadband access among Indigenous undergraduates in each state with uncertainty in the estimates reflected in the spread of the posterior distribution.

This leads to the second benefit of interpretability. Compared to frequentist models with point estimates and confidence intervals estimated based on asymptotic theory, posterior distributions from Bayesian models are directly interpretable as estimates of the unknown parameter with the uncertainty in that estimate shown in the spread of the distribution. Whereas a positive frequentist point estimate from a regression model with a 95% confidence interval that crosses zero will be deemed not statistically significant and therefore unable to provide evidence (fail to reject the null), a Bayesian posterior with a similar spread in its 95% credible interval could be interpreted as positive with some probability less than 95%. While Bayesian multilevel models, like all statistical models, are not a panacea, they support producing estimates in a more directly interpretable manner for small groups that otherwise would be combined or dropped from most frequentist models. This is important for our goal of revealing otherwise hidden variation in broadband access among college students as it aligns with gender, race/ethnicity, and place.

Results

We present four levels of results at ever-increasing degrees of disaggregation across identity and place. We begin with differences across states, moving next to differences across the full range of racial/ethnic identities available in our data. Next, we unpack three commonly aggregated racial groups—Asian, multiracial/multiethnic, and American Indian / Alaska Native—showing differences across gender and constitutive ethnic identities within these groups. Finally, we demonstrate the full flexibility of our estimation framework to show differences within Hispanic undergraduate populations across gender, ethnicity, and three states: California, Florida, and Texas. All results we present come from the same two fitted models, aggregated to different levels of detail.

Differences across the states

We begin in Figure 1 with state-level differences in broadband access across the full population of undergraduate students. In the top panel, the full posterior distribution of predicted values of in-home broadband access within the state is represented by the black dot (median value) and vertical lines (95% credible intervals). The national median of in-home broadband access, 85.9%, is shown by the horizontal dashed line with its 95% credible interval shaded behind it. As Figure 1 shows, state-level median percentages of in-home broadband access among undergraduates range from 4.6 percentage points (p.p.) above the national median in North Dakota ($\theta_{q50} = 90.5$, $CI_{95} = 88.5/92.2$) to 11.5 p.p. below the national median in Mississippi ($\theta_{q50} = 74.4$, $CI_{95} = 73.1/75.7$). This represents a difference of approximately 16.1 p.p. in in-home broadband access among undergraduates across the states. Based on non-overlapping credible intervals, students in approximately 20 states have access to broadband in the home at rates greater than the national median whereas students in 18 states have lower access.

State-level percentages of students who rely on a cellular data plan to access the internet are shown in the bottom panel of Figure 1. Because most undergraduates have some access to broadband, the percentage of those who rely on a cellular data plan within a state are largely the inverse of those who have in-home access, as can be seen across both panels of Figure 1. Across the country, 13.5% of undergraduates rely on a cellular data plan for internet access. This number varies from 4.1 p.p. below the national median in North Dakota ($\theta_{q50} = 9.4$, $CI_{95} = 8.9/11.3$) to 10.8 p.p. above the national median in Mississippi ($\theta_{q50} = 24.3$, $CI_{95} = 23.1/25.7$), a range of 14.9 p.p. Based once again on non-overlap in credible intervals, students in 24 states are less likely than the national median to rely on a cellular data plan to access the internet compared to students in 18 states who are more likely than the national median to have such a reliance. Along with the top panel, Figure 1 demonstrates that undergraduates experience broadband access at highly variable rates depending upon the state in which they live.

Differences across race/ethnicity

In Figure 2, we re-aggregate our results to show differences in broadband access across the United States among the 162 unique racial/ethnic identities categorized by the Census. In the left panel are the percentages of those with in-home access; in the right panel are those who rely on a cellular data plan. Once again, national medians with their 95% credible intervals are plotted—85.9% with in-home access compared to 13.5% who rely on cellular data plans—this time with vertical dotted lines and shading. The numbers on the y-axis align with the categorical numbers assigned to racial/ethnic populations by the Census. Similar to the prior figure, center dots and horizontal lines represent the median and 95% credible intervals of broadband access. A concordance with the population names associated with these codes as well as posterior estimates of broadband access for all groups can found in Appendix Table A1. Appendix tables A2 and A3 report posterior estimates further broken out for men and women, respectively.

Our primary purpose in presenting Figure 2 is to give a sense of the wide range of differences in broadband access across student racial/ethnic populations. Compared to the national median, those identified as White and Chinese (code 811) are 7.4 p.p. more likely to have in-home broadband access ($\theta_{q50} = 93.3$, $CI_{95} = 91.1/95.0$); conversely, those identified as Navajo (code 315) are 26.2 p.p. less likely ($\theta_{q50} = 59.7$, $CI_{95} = 55.4/64.0$). This represents a difference in in-home broadband access among undergraduates by race/ethnicity of 33.6 p.p. The same two groups represent the extreme range of students who access broadband through a cellular data plan. Whereas those identified as both White and Chinese are 7 p.p. less likely than the national median to rely on cellular data plans ($\theta_{q50} = 6.5$, $CI_{95} = 4.9/8.6$), those identified as Navajo are 18.8 p.p. more likely ($\theta_{q50} = 32.3$, $CI_{95} = 28.4/36.2$), a difference of 25.8 p.p.

Taken together, the two panels of Figure 2 show wide degrees of difference in broadband access among undergraduates by race/ethnicity. We also note the differing degrees of uncertainty in our estimates for some racial/ethnic groups, particularly those who comprise a comparatively small share of the overall undergraduate student population. Compared to the largest student populations, whose credible intervals for estimates of their broadband access span less than 1 p.p., estimates for some small populations such as the Inupiat credibly range approximately 20 p.p. This larger spread may reflect uncertainty due to small population size as well as greater variation in broadband access among the population of students. With the next few figures, we further unpack variation by race/ethnicity by focusing on differences within three populations — Asian, multiracial/multiethnic, and American Indian / Alaska Native — that are often represented by single categorical values in quantitative analyses, or, as is often the case for multiracial/multiethnic and Indigenous populations, left out of analyses altogether.

Differences within Asian student populations

Figure 3 shows similar types of variation for Asian undergraduate populations, though, on average, with less uncertainty due to larger population sizes. Compared to the national medians (dotted lines), the aggregate Asian undergraduate population is more likely to have in-home broadband access (+2.8 p.p.; $\theta_{q50} = 88.7$, $CI_{95} = 88.4/89.0$) and less likely to rely on a cellular data plan (-2.7 p.p.; $\theta_{q50} = 10.8$, $CI_{95} = 10.5/11.0$). However, there is much within-group variation among Asian students, who identify with diverse ethnicities that include South Asian, East Asian, Southeast Asian, and various Oceanian identities. Differences range from 4.9 p.p. more than the aggregate Asian median among Taiwanese students to 10.3 p.p. less among Burmese students for in-home access and 4.6 p.p. less among Taiwanese students to 9.2 p.p. more among Burmese students than the aggregate Asian median for cellular data plan access. Across all ethnicities that comprise the Asian student population, men are again generally more likely than women to have in-home broadband access whereas women are more likely than men to rely on cellular data plans for internet access.

Differences within multiracial/multiethnic student populations

Figure 4 presents difference across the 69 racial/ethnic identities that comprise the multiracial/multiethnic undergraduate student population, sometimes designated as *other* in quantitative analyses. Compared to the national median, students in this aggregate group are 2.4 p.p. more likely to have access to broadband in the home ($\theta_{q50} = 88.3$, $CI_{95} = 87.8/88.8$) and 2.3 p.p. less likely to rely on cellular data plans for internet access ($\theta_{q50} = 11.2$, $CI_{95} = 10.8/11.7$). Within this diverse aggregation, there are both commonly-selected patterns of racial/ethnic identity and write in values afforded by the Census. Differences in in-home access among these groups range from 5.5 p.p. greater the aggregate group average for undergraduate men who identify as both White and Chinese ($\theta_{q50} = 93.8$, $CI_{95} = 91.7/94.4$) to 10.1 p.p. less for undergraduate women who identify as American Indian / Alaska Native and Asian Indian ($\theta_{q50} = 78.2$, $CI_{95} = 65.0/87.1$), a range of 15.6 p.p. For reliance on cellular data plans for internet access, undergraduate men who identify as White and Chinese are 5.1 p.p. less likely ($\theta_{q50} = 6.1$, $CI_{95} = 4.5/8.1$) and women who identify as Black, AIAN, Asian, PI, and Other race (W.I.) are 8.2 p.p. more likely ($\theta_{q50} = 19.4$, $CI_{95} = 11.5/30.3$) than the group average, a range of 13.3 p.p. Once again across all multiracial/multiethnic student populations, men are on average more likely to have access to broadband in the home than women whereas women are more likely than men to rely on cellular data plans for internet access.

Differences within American Indian / Alaska Native student populations

In Figure 5, we show variation in broadband access among undergraduates who are members of the Indigenous tribes that together comprise the aggregated racial/ethnic category of American Indian / Alaska Native (AIAN). As with Figure 1, the top panel of Figure 5 presents percentages of students with in-home broadband access while the bottom panel gives those who rely on a cellular data plan for internet access. New to this figure, we separate values within each tribal group by men and women, represented by red and teal colored dots/lines, respectively. Within each facet, we include two horizontal lines. As before, the dotted line and shading shows the national median value of broadband access across all populations. The added dashed line shows the median value of access for the aggregation of those populations represented in the figure, that is, the value that would be given in a more typical analysis that collapsed these groups into a single category. These two lines allow for three comparisons: (1) the national median with the aggregate group median; (2) each subgroup's access probability with the national median; and (3) each subgroup's access probability with the aggregate group median.

Figure 5 shows that combined, the AIAN population of students has in-home access to broadband 10.4 p.p. below the national median ($\theta_{q50} = 75.5$, $CI_{95} = 74.2/77.1$) and are 8 p.p. more likely than the national median to rely on cellular data plans for internet access ($\theta_{q50} = 21.5$, $CI_{95} = 20.2/22.8$). These aggregate differences, nevertheless, hide a significant degree of variation by gender and across tribal groups. On average, Indigenous male students have greater access to broadband in the home than female students of the same tribal affiliation, ranging from less than 1 p.p. to 7.5 p.p. With one exception, undergraduate women are conversely more likely than undergraduate men to report having access to broadband only through a cellular plan (less than 1 p.p. to 5.8 p.p.). Across groups, South American Indian undergraduate women are 12.9 p.p. more likely to have in-home broadband access than the AIAN median and 2.5 p.p. more likely than the national median ($\theta_{q50} = 88.4$, $CI_{95} = 77.0/94.5$). At the other end of the figure, undergraduate Navajo women are 17.4 and 27.8 p.p. less likely than the AIAN and national median, respectively, to have in-home broadband ($\theta_{q50} = 58.1$, $CI_{95} = 53.6/62.8$). These relationships are reversed for access only through a cellular data plan: South American Indian undergraduate women are 10.3 and 2.1 p.p. less likely to report this type of access than AIAN and national medians whereas undergraduate Navajo women are 12.1 and 20.1 p.p. more likely.

Differences within Hispanic student populations across three states

With our last two figures, we take full advantage of our empirical model and data to focus on a single racial/ethnic undergraduate population across three states in order to show how the interaction between identity and place can influence access to broadband. Specifically, we compare the constitutive groups that comprise the Hispanic population in three states—California, Florida, and Texas—with large and growing Hispanic populations (Krogstad, 2020).

In Figure 6, the panels show the percentage of undergraduates with access to broadband in the home in California, Florida, and Texas. Again, estimates are produced for men and women in each population group and both the national (85.9%) and Hispanic-specific medians (84.3%)

are shown with horizontal dotted and dashed lines. In addition to variation between men and women across different ethnic identifications, each gender-ethnicity probability distribution can be compared across the three states. For example, those identified as Mexican in California have in-home broadband at rates between 85% (men) and 83.4% (women). These values split the Hispanic national median of 84.3% for in-home broadband access and are 1 to 2.5 p.p. lower than the national median. In Florida, comparable rates are 85.8%/83.3%, which again split the Hispanic national median, but place Mexican men nearly at the national median for in-home broadband access. In Texas the rates are 82.6%/80.8%, which are both below the Hispanic national median and 3.3 to 5.1 p.p. lower than the national median.

Figure 7 show similar relationships across gender, ethnic, and state differences in the percentage of Hispanic undergraduates who rely on a cellular data plan for internet access (15%). As with other racial/ethnic groups, Hispanic women are generally more likely to rely on cellular data plans for internet access than men, though we find an exception in Nicaraguan men in Texas who are slightly more likely to rely on cellular data plans than women. Given that this relationship is not repeated in California or Florida and that we again see within gender-ethnicity variation in broadband access across other ethnic groups, these results demonstrate how place can interact with identity to change students' geographies of opportunity.

Discussion

Our results show a great deal of variation in broadband access across the country among recent undergraduate students. With each successive disaggregation of the data, we demonstrate the variability in access that is hidden in more aggregated measures, showing the connection between intersecting identities (Covarrubias, 2011), place (Morrison et al., 2017), and broadband access, a key facet of students' geographies of opportunity (de Souza Briggs, 2005; Green et al., 2017; Tate IV, 2008). Before discussing the implications of this heterogeneity, we first note a few limitations for our study.

First, we rely on racial/ethnic categories determined by the U.S. Census in our analyses. While we report the association between broadband access and racial/ethnic identity at greater specificity than is typically reported, no categorizations are complete or permanent (Viano & Baker, 2020). Using labels given by the Census, we run the risk of reifying race and identifying persons in ways that they would not identify themselves. The label *Hispanic* represents a particularly salient example. As we noted in the introduction, we choose to use *Hispanic* when discussing our findings as it is what is given by the Census, noting, however, its contention as a pan-ethnic label (Salinas & Lozano, 2017). For undergraduate Latino/a/x Census respondents who do not specifically identify with the *Hispanic* label, we miss nuance in their access to broadband as it differs from the larger racial categorization into which they fall. For all group labels, Census statisticians must make a number of data editing and aggregation decisions to arrive at the final published categories.[6] These data cleaning decisions also reflect the point that no categorizations are without bias and reflect the historical power of the state to define and surveil parts of its population (Starr, 1987). Though we use Census microdata to support greater insights into broadband access among college students, we cannot separate our purpose completely from other (mis)uses of them.

Our choice to append Hispanic ethnic categories to other racial categories means that we do not necessarily consider intersections of race and Hispanic ethnicities—for example, white-identifying Hispanic students versus Black-identifying Hispanic students—that may be salient for undergraduate students and their access to broadband in the United States. In this instance, we believe our choice is most in line with how other ethnicities are represented in the Census (within the primary detailed racial variable) and required the fewest "researcher degrees of freedom" (Simmons et al., 2011) as we built our analysis data set. That noted, our decision to operationalize Hispanic identities in this manner also represents a subjective choice and one that could and should be explored in future research on broadband access among college students. We also face a related limitation in how we operationalize gender identity. As we noted above, the variable we must use conflates gender with sex and is limited to a binary male/female categorization. Thus while we use detailed

[6] See https://usa.ipums.org/usa-action/variables/RACE#editing_procedure_section for more information on how the U.S. Census creates and assigns racial/ethnic categories to Census respondents.

categories of race/ethnicity intersected with gender to show heterogeneity within otherwise more greatly aggregated groups, the groups we model remain imperfectly aligned with the full range of gender, racial, and ethnic identities college students might claim for themselves. Because our study relies exclusively on quantitative analyses, we cannot further unpack undergraduate students' embodied experiences with technology.

Yet despite these limitations, we are able to describe variation in how students access broadband at much deeper intersections of identity and place than we have found reported elsewhere. In alignment with the QuantCrit paradigm (Castillo & Gillborn, 2022; Garcia et al., 2018; Gillborn et al., 2018; Schudde, 2018), we provide directly interpretable estimates of broadband access based upon data with reduced population aggregation and without dropping small population groups in order to model differences of experience. Even for small undergraduate populations, we provide estimates with reasonable degrees of certainty about the likelihood a student embodying that identity will have access to broadband. That we find such variation at the state level suggests that there is likely to be even more local variation for students attending specific schools or living in particular communities. By showing variation in access within commonly aggregated groups, we also demonstrate how technologies of counting and averaging can erase substantial within-group differences. This is particularly important for those multiply marginalized populations (Crenshaw, 1989, 1991) who may lose out on key supports because their unique needs are obscured by aggregations or single-dimensional understandings of identity.

Many students attend college close to home (Skinner, 2019a), which suggests that race- and income-based differences in in-home broadband access among undergraduates are the same as those experienced by the broader public, that is, related to histories of racist housing policy and differential access to public services, utilities, and amenities (Rothstein, 2017; Skinner et al., 2023). For students who move to attend college but do not live on campus, race- and class-based heterogeneity in broadband access may be related both to (1) differential sorting *around* institutions and (2) differential sorting *to* institutions. For the first group, off-campus students who engage in homophilic sorting, whether by choice or structural limitation, will face the same race- and class-based broadband access differences as their neighbors. For the second group, students who attend well-resourced institutions may find a more robust set of off-campus housing options that cater to their needs (including broadband access) due to the involvement of their university in the local real estate market (Garton, 2021). Conversely, students attending less resourced institutions may have fewer options and bear higher costs if they have to purchase broadband access on the open market as a typical consumer. Such that institutional resources are related to the demographic profile of the average student who attends (Cottom, 2017; Schudde & Goldrick-Rab, 2016), we would expect race- and income-based differences in broadband access among undergraduate students who relocate based on their chosen institution. The large geographic scale of our study means that we cannot differentiate between these potential mechanisms, which we leave for future studies that are more geographically focused on areas around particular institutions.

In alignment with our quantitative intersectional framework, we provide different estimates of broadband access for men and women. With very few exceptions, we find that women report lower rates of in-home broadband access than men. Conversely, women are more likely to report that they access broadband only through a cellular data plan. Unlike with well-documented patterns of race- and income-based residential segregation, which can be connected to disparities in broadband access (Skinner et al., 2023), gender-based disparities cannot be readily associated with spatial sorting along gender lines. Instead, Census data suggest that proportionately weaker broadband access for women is due to income-based differences. Among our sample, undergraduate women are more likely to be in poverty and have lower personal and family incomes than undergraduate men. They are also more likely to have any children and children under 5 years of age in the household than their male counterparts. These facts suggest that all else equal, female undergraduates may be less able to afford the cost of in-home broadband, especially when they have access through a cellular data plan, in the face of lower wealth coupled with the high cost of childcare (Hernández Kent, 2022). Future research that further unpacks gender-based inequities in broadband access is warranted.

Disaggregating commonly aggregated racial/ethnic groups, we find substantial heterogeneity in broadband access. While we do not have enough space in the paper to go through every subpopulation, we provide findings for Asian, mulitiracial/multiethnic, American Indian / Alaska Native, and Hispanic students. To take one example, we find that Navajo students have some of the lowest rates of in-home broadband access of all Indigenous students, who, as a group, already report lower rates of access than the national average. Conversely, Navajo students are far more reliant upon cellular data plans for Internet access. Why is this the case? While Indigenous peoples of all tribal affiliations across the continent have faced multiple oppressions at the hands of the United States government, it is the combination of the size, rurality, and unique history of the lands of the Navajo Nation that have led to particularly diminished broadband access and over-reliance on cellular data plans. A recent report of poor broadband access in the Navajo Nation reservation (C. Park, 2020) directly ties poor connectivity and high costs to a history of federal oppression that has "left many Native people without access to basic infrastructure, including food, running water, safe and adequate housing, telecommunications service, and healthcare" (p. 5). As a large tribe with a large proportion of members who live on the reservation (Norris et al., 2012), many Navajo Nation students in particular are affected by lack of broadband access. While better data reporting of broadband access on tribal lands is needed (C. Park, 2020), we argue that based on long alternating histories of educational interference and neglect (Tachine, 2015), the federal government has an affirmative role in supporting broadband access among Indigenous populations as a means of increasing educational equity.

Finally, we demonstrate differences in broadband access across the states, both in the aggregate and across individuals with the same racial/ethnic and gender identities. While our reading of the literature that uses critical race spatial analysis tends to focus on smaller geographic areas, we find states to be salient units of analysis to understand race- and class-based inequities. Despite the fact that ISPs tend to serve specific local and regional markets, many states have created laws that limit municipalities' options when it comes to regulating or providing broadband services (J. Bauer et al., 2023). Since cities often want to offer incentives to ISPs or provide their own broadband utilities to fill in gaps in service that generally affect lower-income residents and communities of color, these state policies have the effect of exacerbating existing inequities due to residential segregation (Alliance, 2017, 2020). While further research on undergraduate access to broadband would benefit from investigations at smaller geographic scales (as suggested above), it remains the case that state-level telecommunications policy contributes to race- and class-based systems of oppression that differentially limit students' geographies of opportunity depending upon where they live.

Even were higher education to return to its pre-pandemic patterns of attendance, access to high-speed broadband will remain an important component of higher education access. Recently, the Biden administration announced its intention to support "100 percent high-speed broadband coverage" across the country as part of the American Jobs Plan (The White House, 2021). This is an important goal. Yet prior work in addition to our own shows that people differ in their access to broadband, not only depending on where they live, but also the social identities they occupy (Attewell, 2001; Campos-Castillo, 2015; Dharma et al., 2010; Grubesic, 2006; Reddick et al., 2020; Rosenboom & Blagg, 2018). As higher education increasingly relies on regular, high speed internet access to complete assignments and take classes, systemic oppressions underlying disparities in broadband access, unacknowledged and unmitigated, will filter through and compound existing disparities in college access, persistence, and graduation.

It remains important for those concerned with higher education policy to understand which postsecondary student populations lack in-home broadband access or are reliant on expensive and slow cellular data plans. Our results suggest a few policy considerations. At the state and federal level, policymakers should target telecommunication infrastructure improvements in communities with the greatest need. Simultaneously, they should provide targeted subsidies to residents in communities with limited, high-cost broadband options. Priority should be given to neighborhoods and populations historically neglected by infrastructural improvements due to racist policies and practices (Skinner et al., 2023). Education policymakers, like institutions, should similarly consider broadband costs in their formulas for assessing student financial need. In the face of limited funding, priority should again be given to students living in poorly connected areas.

Though our findings as reported may be too broad for the specific context at many institutions, they provide strong evidence that colleges and universities should interrogate how they estimate broadband access among their own student populations. If administrators currently rely on only a few aggregated categories of race, for example, or do not consider how student identities may interact with where they live, then they should reconsider disaggregating those statistics to make sure multiply marginalized students are not lost in the average. Such that the institution has access to institutional aid for its students, it should also consider the monthly cost for broadband in the area when assessing student need. Finally, institutions that provide online course options for their students—now the majority of colleges and universities (Xu & Xu, 2019)—should help faculty create course content that degrades gracefully in the face of low-speed or low-quality broadband. In this way, even students with limited broadband access, such as those who rely on a cellular data plan, can access core course content. We realize that with this last suggestion, we ask many already squeezed institutions to provide further financial and human capital resources. We argue, however, that the equity-focused missions of many postsecondary institutions, particularly those that would increase access through online course offerings, demands mitigation of technological barriers in order to fight race- and class-based systems of oppression that continue to limit educational opportunities for students.

Conclusion

Guided by a QuantCrit approach, we add to the literature by producing estimates of broadband access among undergraduate students at deeper intersections of identity and place. In doing so we gain a richer understanding of who is most and least likely to have broadband access as well as the form—in the home or limited to a mobile device—that that access is likely to take. We hope our findings will help state-level policymakers and university administrators alike understand the need for better, more targeted policies and programs of support for students who require broadband to be successful in meeting their postsecondary goals. We look forward to future research that further unpacks and disaggregates technological barriers student populations face in their higher educational journeys, particularly as they relate to systemic structures of race-, gender-, and place-based inequities.

Throughout our paper, we have framed in-home broadband access positively and cellular data plan-only access negatively. We conclude with the important point that while the challenges faced by students who rely on mobile devices for internet access are real, so too is the resilience of these students. Because every observation in our sample represents an active student, our data include individuals who, despite difficulties, were pursuing higher education. Observing student communities with lower than average in-home broadband access or greater than average reliance on cellular data plans, we bear witness to people who are serious about meeting their educational goals in an era of increasing technological demands. Those interested in fighting for educational justice should meet these students with the same degree of effort.

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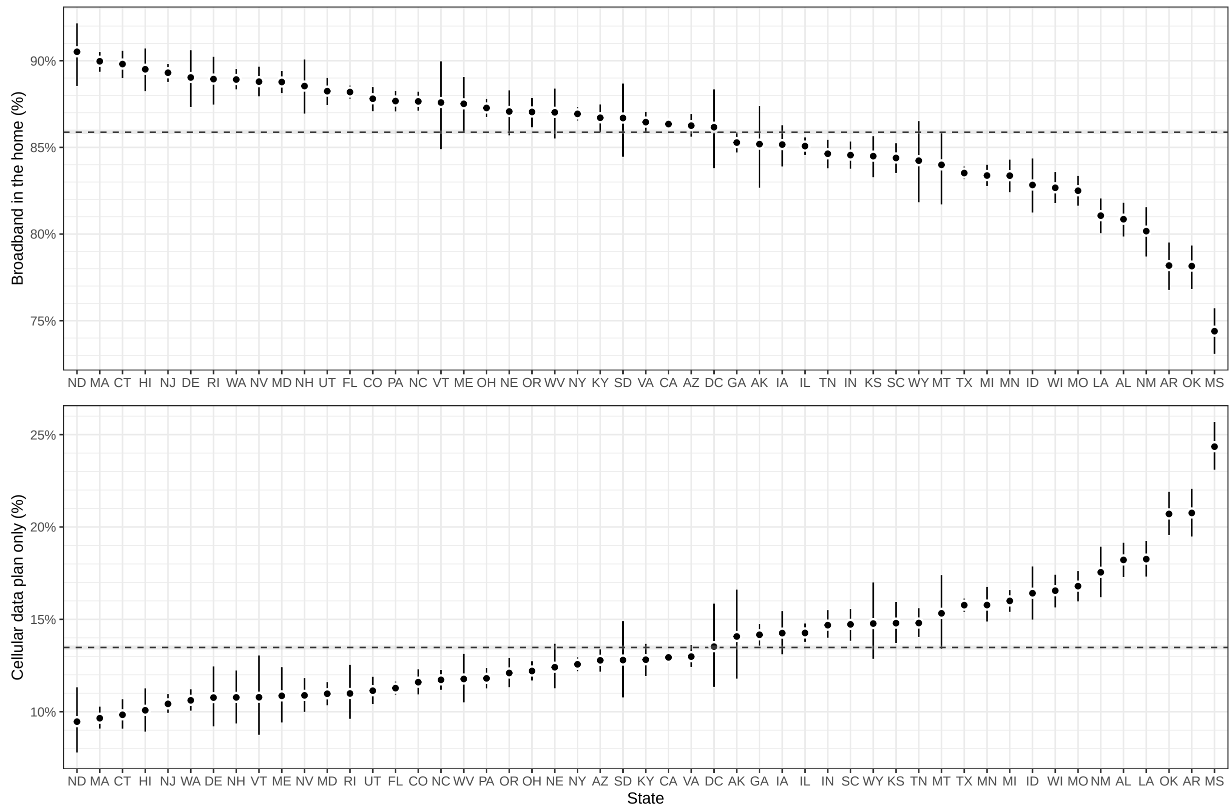


Figure 1: State-level comparison of in-home broadband access (top panel) and access only through a cellular data plan (bottom panel). Center dots and lines represent medians and 95% credible intervals, respectively, for posterior predicted probabilities. The horizontal dashed line and shaded area show the national median and 95% credible interval.

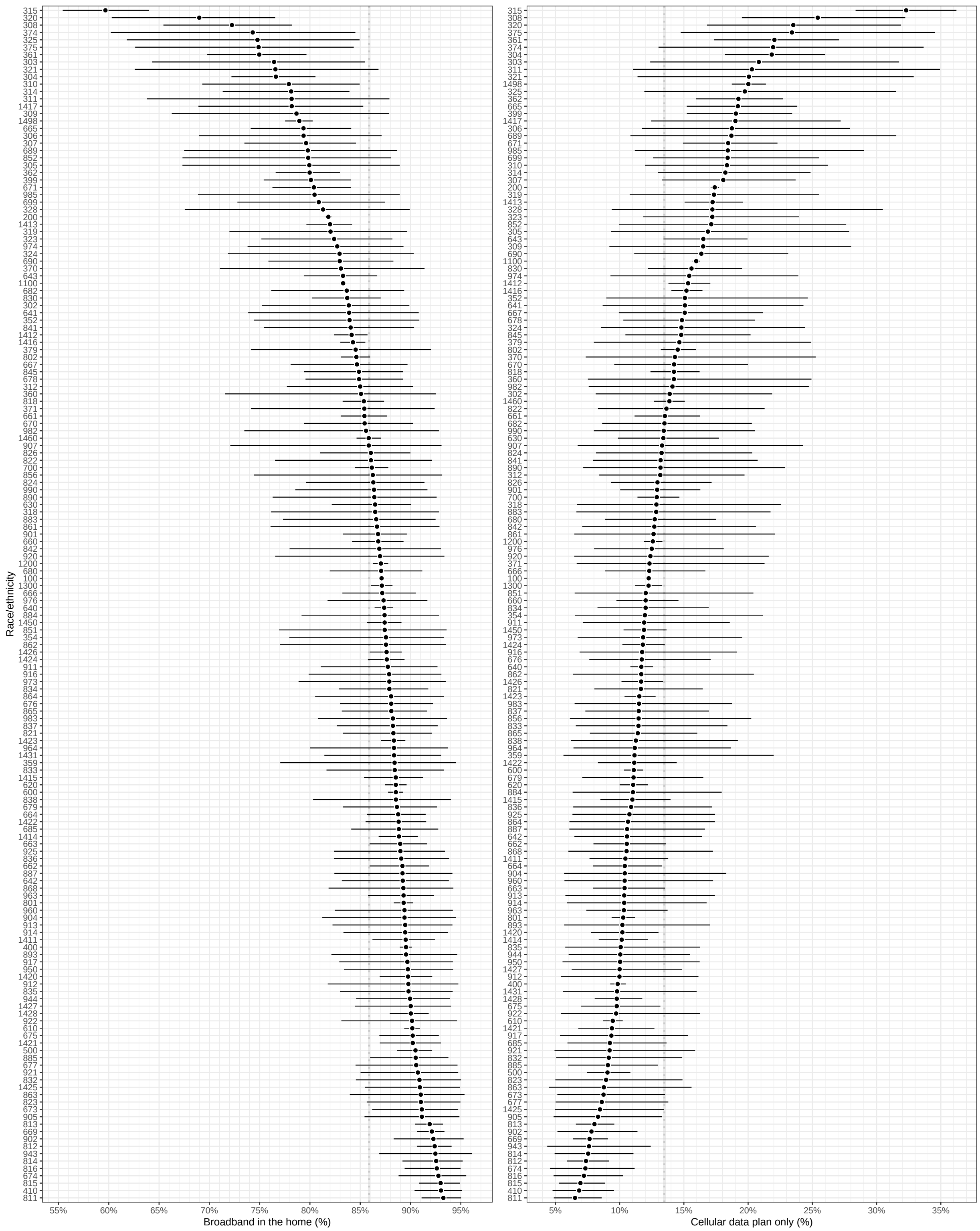


Figure 2: Race/ethnicity comparison of in-home broadband access (left panel) and access only through a cellular data plan (right panel). Numbers on the *y*-axis correspond to U.S. Census codes and can be linked the names given by the Census as well as specific posterior values in Appendix Table A1. See Appendix tables A2 and A3 for further disaggregation for men and women by racial/ethnic group, respectively.

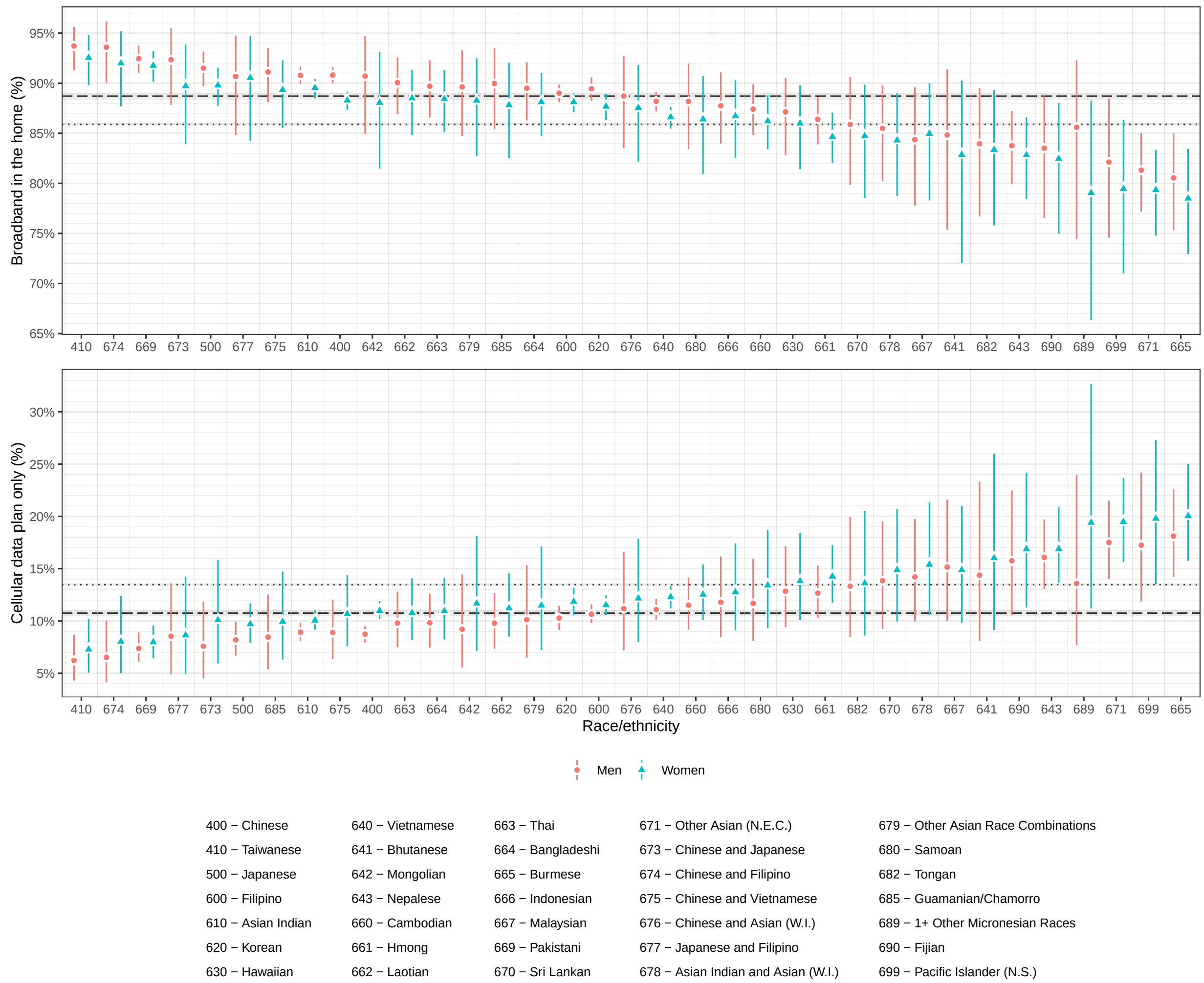
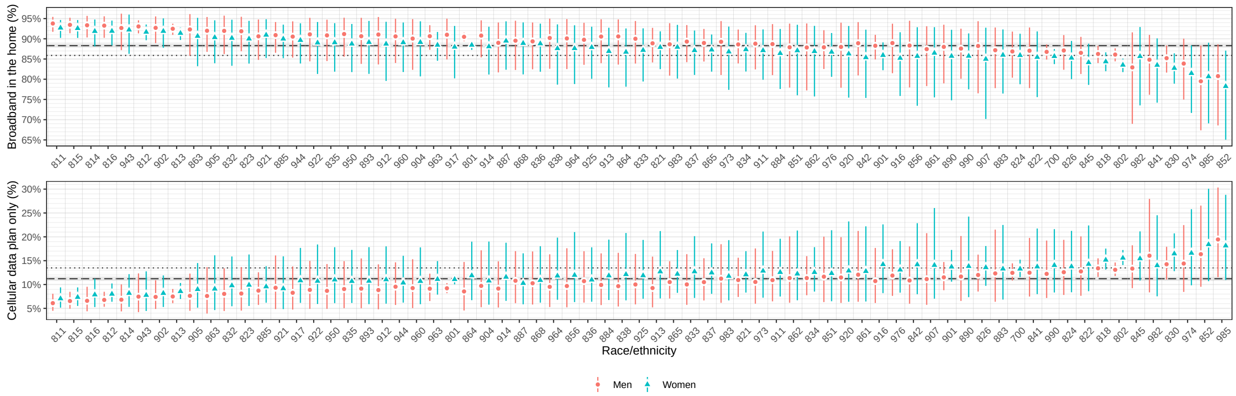
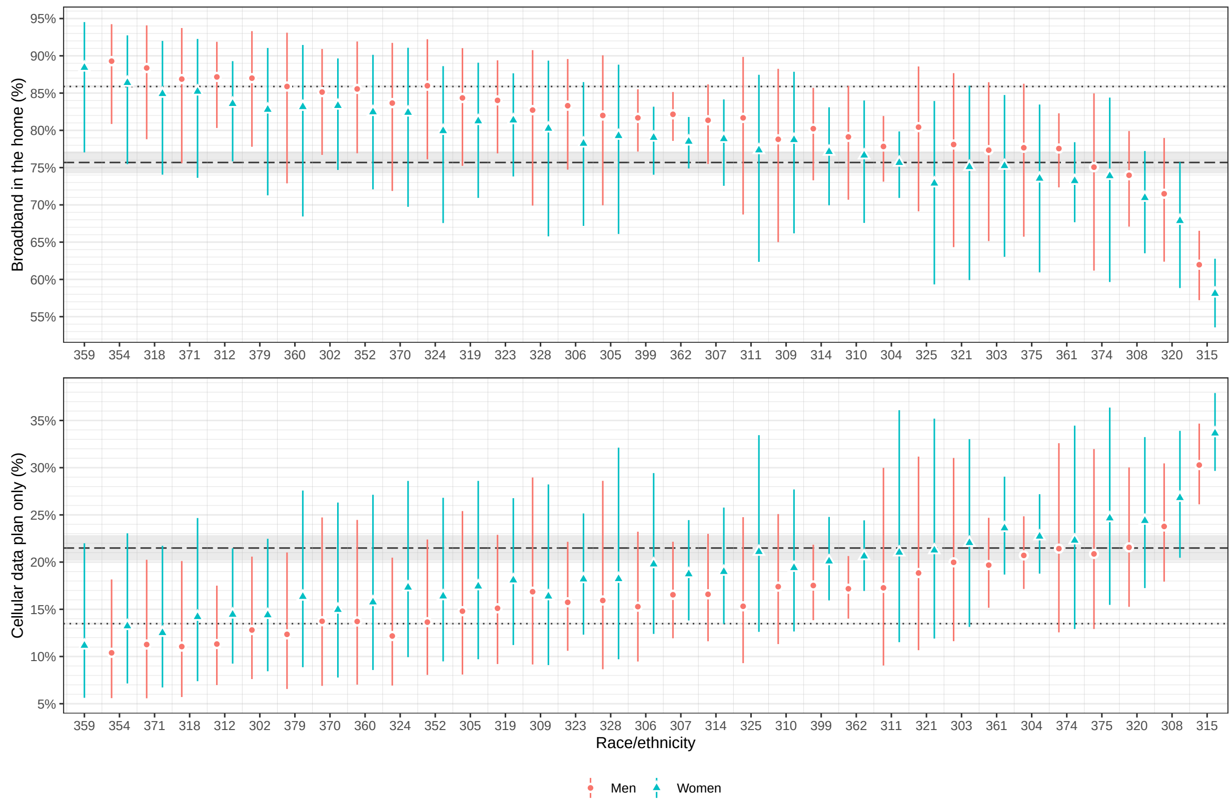


Figure 3: In-home broadband access (top panel) and access only through a cellular plan (bottom panel) for Asian populations. The horizontal dashed line and shaded area represent the overall median / 95% credible interval for this population. The horizontal dotted line and shaded area represent the national median / 95% credible interval. Refer to Appendix tables A2 and A3 for specific values.



700 − Other Race (N.E.C.)
801 − White and Black
802 − White and AI/AN
811 − White and Chinese
812 − White and Japanese
813 − White and Filipino
814 − White and Asian Indian
815 − White and Korean
816 − White and Vietnamese
818 − White and Other Asian Race(s)
821 − White and Native Hawaiian
822 − White and Samoan
823 − White and Guamanian
824 − White and PI (W.I.)
826 − White and Other Race (W.I.)
830 − Black and AI/AN
832 − Black and Chinese
833 − Black and Japanese
834 − Black and Filipino
835 − Black and Asian Indian
836 − Black and Korean
837 − Black and Asian (W.I.)
838 − Black and Other Asian Race(s)
841 − Black and PI (W.I.)
842 − Black and Other PI Race(s)
845 − Black and Other Race (W.I.)
851 − AI/AN and Filipino
852 − AI/AN and Asian Indian
856 − AI/AN and Other Race (W.I.)
861 − Chinese and Hawaiian
862 − Chinese, Filipino, Hawaiian
863 − Japanese and Hawaiian
864 − Filipino and Hawaiian
865 − Filipino and PI (W.I.)
868 − Other Asian Race(s) and PI Race(s)
883 − Filipino and Other Race (W.I.)
884 − Asian Indian and Other Race (W.I.)
885 − Asian (W.I.) and Other Race (W.I.)
887 − Chinese and Korean
890 − PI and Other Race (W.I.)
893 − Native Hawaiian Or PI Other Race(s)
901 − White, Black, AI/AN
902 − White, Black, Asian
904 − White, Black, Other Race (W.I.)
905 − White, AI/AN, Asian
907 − White, AI/AN, Other Race (W.I.)
911 − White, Chinese, Hawaiian
912 − White, Chinese, Filipino, Hawaiian
913 − White, Japanese, Hawaiian
914 − White, Filipino, Hawaiian
916 − White, AI/AN and Filipino
917 − White, Black, and Filipino
920 − White, Asian, Other Race (W.I.)
921 − White, Filipino, Other Race (W.I.)
922 − White, Asian (W.I.), Other Race (W.I.)
925 − White, PI, Other Race (W.I.)
943 − Asian, PI, Other Race (W.I.)
944 − Asian, NH/PI, and Other Race
950 − White, Black, AI/AN, Asian
960 − White, AI/AN, Asian, PI
963 − White, Asian, PI, Other Race (W.I.)
964 − White, Chinese, Japanese, Native Hawaiian
973 − Black, Asian, PI, Other Race (W.I.)
974 − AI/AN, Asian, PI, Other Race (W.I.)
976 − Two Specified Asian, NH/PI, and Other Race
982 − White, Black, AI/AN, PI, Other Race (W.I.)
983 − White, Black, Asian, PI, Other Race (W.I.)
985 − Black, AI/AN, Asian, PI, Other Race (W.I.)
990 − White, Black, AI/AN, Asian, PI, Other Race (W.I.)

Figure 4: In-home broadband access (top panel) and access only through a cellular plan (bottom panel) for multiracial/multiethnic populations typically designated as *other*. The horizontal dashed line and shaded area represent the overall median / 95% credible interval for this population. The horizontal dotted line and shaded area represent the national median / 95% credible interval. Refer to Appendix tables A2 and A3 for specific values.



302 − Apache	309 − Comanche	319 − Potawatomi	352 − Puget Sound Salish	371 − Aleut
303 − Blackfoot	310 − Creek	320 − Pueblo	354 − Yaqui	374 − Inupiat
304 − Cherokee	311 − Crow	321 − Seminole	359 − South American Indian	375 − Yup'ik
305 − Cheyenne	312 − Iroquois	323 − Sioux	360 − Mexican American Indian	379 − Other Alaska Native Tribe(s)
306 − Chickasaw	314 − Lumbee	324 − Tlingit	361 − Other Amer. Indian Tribe	399 − Tribe Not Specified
307 − Chippewa	315 − Navajo	325 − Tohono O Odham	362 − 2+ Amer. Indian Tribes	
308 − Choctaw	318 − Pima	328 − Hopi	370 − Alaskan Athabaskan	

Figure 5: In-home broadband access (top panel) and access only through a cellular plan (bottom panel) for American Indian / Alaska Native populations. The horizontal dashed line and shaded area represent the overall median / 95% credible interval for this population. The horizontal dotted line and shaded area represent the national median / 95% credible interval. Refer to Appendix tables A2 and A3 for specific values.

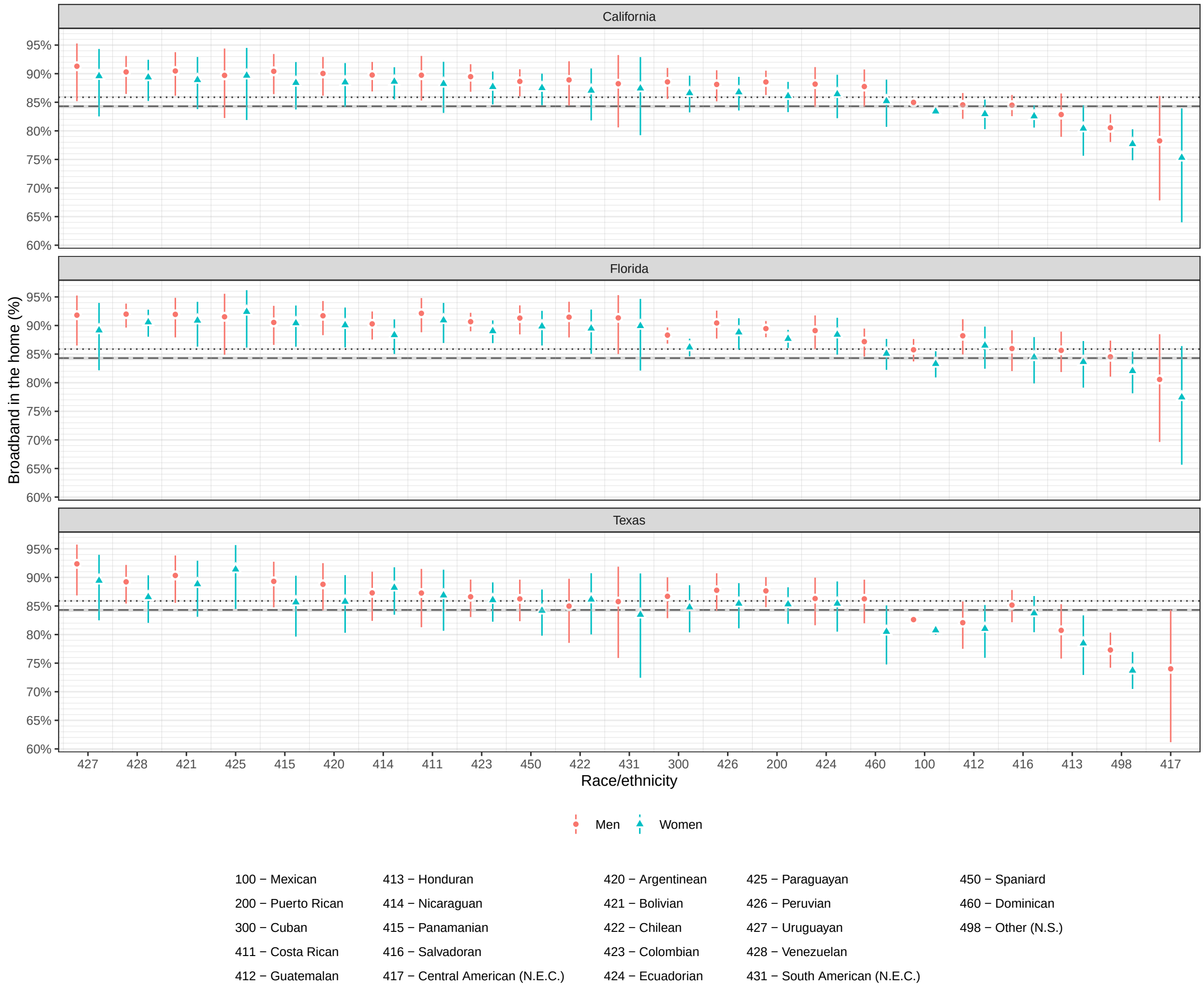


Figure 6: In-home broadband access among Hispanic populations across California, Florida, and Texas. The horizontal dashed line and shaded area represent the overall median / 95% credible interval for this population. The horizontal dotted line and shaded area represent the national median / 95% credible interval. Refer to Appendix Table A4 for specific values.

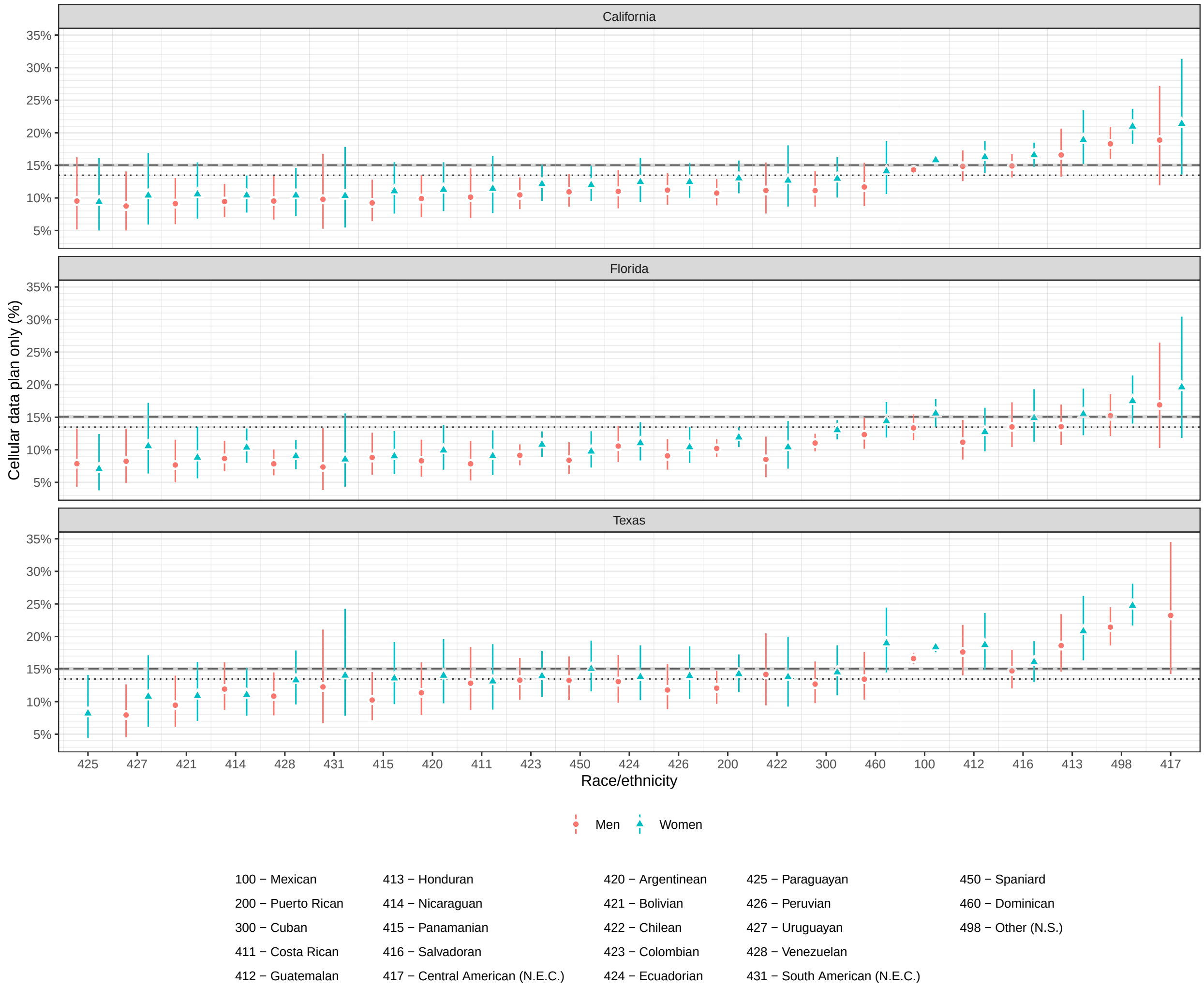


Figure 7: Broadband access only through a cellular plan among Hispanic populations across California, Florida, and Texas. The horizontal dashed line and shaded area represent the overall median / 95% credible interval for this population. The horizontal dotted line and shaded area represent the national median / 95% credible interval. Refer to Appendix Table A5 for specific values.

Table A1: Overall estimates of broadband access by race/ethnicity

Code			Overall	
Census	Figure	Label	Broadband in home	Mobile only
100	100	White	0.87 [0.870,0.872]	0.12 [0.121,0.124]
200	200	Black/African American/Negro	0.82 [0.815,0.822]	0.17 [0.171,0.177]
302	302	Apache	0.84 [0.752,0.899]	0.14 [0.081,0.219]
303	303	Blackfoot	0.76 [0.643,0.855]	0.21 [0.124,0.318]
304	304	Cherokee	0.77 [0.722,0.806]	0.22 [0.182,0.260]
305	305	Cheyenne	0.80 [0.673,0.889]	0.17 [0.093,0.279]
306	306	Chickasaw	0.79 [0.690,0.871]	0.19 [0.117,0.279]
307	307	Chippewa	0.80 [0.735,0.846]	0.18 [0.133,0.237]
308	308	Choctaw	0.72 [0.654,0.782]	0.25 [0.195,0.322]
309	309	Comanche	0.79 [0.663,0.878]	0.17 [0.092,0.280]
310	310	Creek	0.78 [0.693,0.849]	0.18 [0.120,0.262]
311	311	Crow	0.78 [0.638,0.879]	0.20 [0.111,0.349]
312	312	Iroquois	0.85 [0.777,0.902]	0.13 [0.084,0.197]
314	314	Lumbee	0.78 [0.713,0.839]	0.18 [0.130,0.249]
315	315	Navajo	0.60 [0.554,0.640]	0.32 [0.284,0.362]
318	318	Pima	0.86 [0.761,0.928]	0.13 [0.067,0.225]
319	319	Potawatomi	0.82 [0.720,0.896]	0.17 [0.108,0.255]
320	320	Pueblo	0.69 [0.603,0.765]	0.24 [0.168,0.319]
321	321	Seminole	0.77 [0.626,0.868]	0.20 [0.114,0.329]
323	323	Sioux	0.82 [0.752,0.882]	0.17 [0.118,0.240]
324	324	Tlingit	0.83 [0.719,0.903]	0.15 [0.085,0.244]
325	325	Tohono O Odham	0.75 [0.618,0.849]	0.20 [0.119,0.315]
328	328	Hopi	0.81 [0.676,0.899]	0.17 [0.094,0.305]
352	352	Puget Sound Salish	0.84 [0.744,0.909]	0.15 [0.090,0.246]
354	354	Yaqui	0.88 [0.780,0.933]	0.12 [0.065,0.211]
359	359	South American Indian	0.88 [0.770,0.945]	0.11 [0.056,0.220]
360	360	Mexican American Indian	0.85 [0.716,0.925]	0.14 [0.075,0.249]
361	361	Other Amer. Indian Tribe	0.75 [0.698,0.797]	0.22 [0.174,0.271]
362	362	2+ Amer. Indian Tribes	0.80 [0.766,0.830]	0.19 [0.160,0.227]
370	370	Alaskan Athabaskan	0.83 [0.710,0.914]	0.14 [0.074,0.253]
371	371	Aleut	0.85 [0.742,0.924]	0.12 [0.067,0.213]
374	374	Inupiat	0.74 [0.602,0.845]	0.22 [0.130,0.337]
375	375	Yup'ik	0.75 [0.626,0.844]	0.23 [0.148,0.345]
379	379	Other Alaska Native Tribe(s)	0.85 [0.741,0.920]	0.15 [0.080,0.249]
399	399	Tribe Not Specified	0.80 [0.754,0.841]	0.19 [0.152,0.234]
400	400	Chinese	0.90 [0.889,0.901]	0.10 [0.093,0.105]
410	410	Taiwanese	0.93 [0.904,0.951]	0.07 [0.048,0.096]
500	500	Japanese	0.90 [0.887,0.921]	0.09 [0.075,0.108]
600	600	Filipino	0.89 [0.878,0.893]	0.11 [0.103,0.118]
610	610	Asian Indian	0.90 [0.894,0.909]	0.09 [0.087,0.102]
620	620	Korean	0.89 [0.874,0.896]	0.11 [0.100,0.122]
630	630	Hawaiian	0.86 [0.822,0.901]	0.13 [0.099,0.177]
640	640	Vietnamese	0.87 [0.864,0.882]	0.12 [0.108,0.126]
641	641	Bhutanese	0.84 [0.739,0.908]	0.15 [0.087,0.243]
642	642	Mongolian	0.89 [0.832,0.938]	0.11 [0.065,0.164]
643	643	Nepalese	0.83 [0.794,0.867]	0.17 [0.134,0.200]
660	660	Cambodian	0.87 [0.842,0.893]	0.12 [0.098,0.146]
661	661	Hmong	0.85 [0.831,0.877]	0.14 [0.112,0.163]

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...table A1 continued

Code			Overall	
Census	Figure	Label	Broadband in home	Mobile only
662	662	Laotian	0.89 [0.859,0.918]	0.11 [0.080,0.136]
663	663	Thai	0.89 [0.859,0.917]	0.10 [0.079,0.135]
664	664	Bangladeshi	0.89 [0.856,0.915]	0.10 [0.079,0.133]
665	665	Burmese	0.79 [0.741,0.841]	0.19 [0.152,0.238]
666	666	Indonesian	0.87 [0.832,0.905]	0.12 [0.089,0.167]
667	667	Malaysian	0.85 [0.781,0.897]	0.15 [0.099,0.212]
669	669	Pakistani	0.92 [0.907,0.934]	0.08 [0.064,0.091]
670	670	Sri Lankan	0.85 [0.794,0.902]	0.14 [0.096,0.200]
671	671	Other Asian (N.E.C.)	0.80 [0.763,0.841]	0.18 [0.149,0.223]
673	673	Chinese and Japanese	0.91 [0.862,0.947]	0.09 [0.052,0.135]
674	674	Chinese and Filipino	0.93 [0.888,0.955]	0.07 [0.046,0.112]
675	675	Chinese and Vietnamese	0.90 [0.869,0.928]	0.10 [0.070,0.132]
676	676	Chinese and Asian (W.I.)	0.88 [0.830,0.922]	0.12 [0.076,0.171]
677	677	Japanese and Filipino	0.91 [0.845,0.947]	0.09 [0.050,0.138]
678	678	Asian Indian and Asian (W.I.)	0.85 [0.796,0.893]	0.15 [0.103,0.205]
679	679	Other Asian Race Combinations	0.89 [0.833,0.926]	0.11 [0.071,0.165]
680	680	Samoan	0.87 [0.820,0.912]	0.13 [0.089,0.175]
682	682	Tongan	0.84 [0.762,0.894]	0.13 [0.086,0.203]
685	685	Guamanian/Chamorro	0.89 [0.841,0.928]	0.09 [0.059,0.137]
689	689	1+ Other Micronesian Races	0.80 [0.675,0.887]	0.19 [0.108,0.315]
690	690	Fijian	0.83 [0.759,0.883]	0.16 [0.111,0.231]
699	699	Pacific Islander (N.S.)	0.81 [0.728,0.875]	0.18 [0.126,0.255]
700	700	Other Race (N.E.C.)	0.86 [0.845,0.878]	0.13 [0.114,0.147]
801	801	White and Black	0.89 [0.883,0.903]	0.10 [0.094,0.112]
802	802	White and AI/AN	0.85 [0.831,0.860]	0.15 [0.132,0.159]
811	811	White and Chinese	0.93 [0.911,0.950]	0.07 [0.049,0.086]
812	812	White and Japanese	0.92 [0.906,0.941]	0.07 [0.059,0.092]
813	813	White and Filipino	0.92 [0.904,0.932]	0.08 [0.066,0.096]
814	814	White and Asian Indian	0.93 [0.892,0.952]	0.08 [0.049,0.111]
815	815	White and Korean	0.93 [0.908,0.949]	0.07 [0.053,0.089]
816	816	White and Vietnamese	0.93 [0.894,0.950]	0.07 [0.049,0.103]
818	818	White and Other Asian Race(s)	0.85 [0.832,0.874]	0.14 [0.124,0.162]
821	821	White and Native Hawaiian	0.88 [0.833,0.921]	0.12 [0.080,0.165]
822	822	White and Samoan	0.86 [0.765,0.921]	0.14 [0.083,0.213]
823	823	White and Guamanian	0.91 [0.856,0.950]	0.09 [0.050,0.149]
824	824	White and PI (W.I.)	0.86 [0.796,0.914]	0.13 [0.082,0.203]
826	826	White and Other Race (W.I.)	0.86 [0.810,0.900]	0.13 [0.093,0.172]
830	830	Black and AI/AN	0.84 [0.802,0.870]	0.16 [0.122,0.195]
832	832	Black and Chinese	0.91 [0.846,0.950]	0.09 [0.051,0.149]
833	833	Black and Japanese	0.88 [0.816,0.933]	0.11 [0.066,0.184]
834	834	Black and Filipino	0.88 [0.829,0.918]	0.12 [0.083,0.169]
835	835	Black and Asian Indian	0.90 [0.830,0.942]	0.10 [0.058,0.163]
836	836	Black and Korean	0.89 [0.824,0.939]	0.11 [0.064,0.172]
837	837	Black and Asian (W.I.)	0.88 [0.827,0.927]	0.11 [0.073,0.170]
838	838	Black and Other Asian Race(s)	0.89 [0.803,0.940]	0.11 [0.062,0.192]
841	841	Black and PI (W.I.)	0.84 [0.754,0.904]	0.13 [0.079,0.207]
842	842	Black and Other PI Race(s)	0.87 [0.780,0.931]	0.13 [0.071,0.206]
845	845	Black and Other Race (W.I.)	0.85 [0.794,0.892]	0.15 [0.104,0.202]
851	851	AI/AN and Filipino	0.87 [0.769,0.936]	0.12 [0.065,0.204]

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...table A1 continued

Code			Overall	
Census	Figure	Label	Broadband in home	Mobile only
852	852	AI/AN and Asian Indian	0.80 [0.673,0.881]	0.17 [0.100,0.276]
856	856	AI/AN and Other Race (W.I.)	0.86 [0.744,0.931]	0.11 [0.061,0.202]
861	861	Chinese and Hawaiian	0.87 [0.761,0.929]	0.13 [0.065,0.221]
862	862	Chinese, Filipino, Hawaiian	0.88 [0.770,0.935]	0.12 [0.064,0.204]
863	863	Japanese and Hawaiian	0.91 [0.840,0.954]	0.09 [0.045,0.156]
864	864	Filipino and Hawaiian	0.88 [0.805,0.933]	0.11 [0.061,0.174]
865	865	Filipino and PI (W.I.)	0.88 [0.832,0.916]	0.11 [0.077,0.160]
868	868	Other Asian Race(s) and PI Race(s)	0.89 [0.819,0.943]	0.11 [0.060,0.173]
883	883	Filipino and Other Race (W.I.)	0.87 [0.773,0.925]	0.13 [0.066,0.217]
884	884	Asian Indian and Other Race (W.I.)	0.87 [0.792,0.928]	0.11 [0.063,0.179]
885	885	Asian (W.I.) and Other Race (W.I.)	0.91 [0.860,0.938]	0.09 [0.060,0.130]
887	887	Chinese and Korean	0.89 [0.824,0.942]	0.11 [0.061,0.166]
890	890	PI and Other Race (W.I.)	0.86 [0.763,0.926]	0.13 [0.072,0.229]
893	893	Native Hawaiian Or PI Other Race(s)	0.90 [0.821,0.947]	0.10 [0.057,0.170]
901	901	White, Black, AI/AN	0.87 [0.833,0.896]	0.13 [0.100,0.163]
902	902	White, Black, Asian	0.92 [0.883,0.953]	0.08 [0.052,0.114]
904	904	White, Black, Other Race (W.I.)	0.89 [0.812,0.945]	0.10 [0.057,0.183]
905	905	White, AI/AN, Asian	0.91 [0.854,0.949]	0.08 [0.049,0.133]
907	907	White, AI/AN, Other Race (W.I.)	0.86 [0.721,0.931]	0.13 [0.067,0.243]
911	911	White, Chinese, Hawaiian	0.88 [0.811,0.927]	0.12 [0.071,0.186]
912	912	White, Chinese, Filipino, Hawaiian	0.90 [0.818,0.948]	0.10 [0.054,0.161]
913	913	White, Japanese, Hawaiian	0.89 [0.822,0.942]	0.10 [0.058,0.174]
914	914	White, Filipino, Hawaiian	0.89 [0.833,0.937]	0.10 [0.059,0.168]
916	916	White, AI/AN and Filipino	0.88 [0.799,0.931]	0.12 [0.069,0.191]
917	917	White, Black, and Filipino	0.90 [0.829,0.942]	0.09 [0.054,0.153]
920	920	White, Asian, Other Race (W.I.)	0.87 [0.765,0.934]	0.12 [0.065,0.216]
921	921	White, Filipino, Other Race (W.I.)	0.91 [0.850,0.947]	0.09 [0.049,0.159]
922	922	White, Asian (W.I.), Other Race (W.I.)	0.90 [0.831,0.946]	0.10 [0.054,0.163]
925	925	White, PI, Other Race (W.I.)	0.89 [0.824,0.934]	0.11 [0.063,0.174]
943	943	Asian, PI, Other Race (W.I.)	0.92 [0.869,0.961]	0.08 [0.044,0.124]
944	944	Asian, NH/PI, and Other Race	0.90 [0.846,0.939]	0.10 [0.060,0.155]
950	950	White, Black, AI/AN, Asian	0.90 [0.834,0.942]	0.10 [0.056,0.162]
960	960	White, AI/AN, Asian, PI	0.89 [0.825,0.942]	0.10 [0.057,0.173]
963	963	White, Asian, PI, Other Race (W.I.)	0.89 [0.858,0.923]	0.10 [0.074,0.137]
964	964	White, Chinese, Japanese, Native Hawaiian	0.88 [0.800,0.937]	0.11 [0.064,0.186]
973	973	Black, Asian, PI, Other Race (W.I.)	0.88 [0.789,0.935]	0.12 [0.067,0.195]
974	974	AI/AN, Asian, PI, Other Race (W.I.)	0.83 [0.738,0.893]	0.15 [0.093,0.239]
976	976	Two Specified Asian, NH/PI, and Other Race	0.87 [0.818,0.917]	0.12 [0.080,0.181]
982	982	White, Black, AI/AN, PI, Other Race (W.I.)	0.86 [0.735,0.928]	0.14 [0.076,0.247]
983	983	White, Black, Asian, PI, Other Race (W.I.)	0.88 [0.808,0.936]	0.12 [0.065,0.188]
985	985	Black, AI/AN, Asian, PI, Other Race (W.I.)	0.80 [0.689,0.889]	0.18 [0.112,0.290]
990	990	White, Black, AI/AN, Asian, PI, Other Race (W.I.)	0.86 [0.785,0.917]	0.13 [0.080,0.205]
100	1100	Mexican	0.83 [0.830,0.836]	0.16 [0.157,0.163]
200	1200	Puerto Rican	0.87 [0.863,0.878]	0.13 [0.119,0.133]
300	1300	Cuban	0.87 [0.860,0.882]	0.12 [0.112,0.133]
411	1411	Costa Rican	0.90 [0.862,0.924]	0.10 [0.077,0.138]
412	1412	Guatemalan	0.84 [0.824,0.857]	0.15 [0.138,0.171]
413	1413	Honduran	0.82 [0.796,0.842]	0.17 [0.151,0.196]
414	1414	Nicaraguan	0.89 [0.868,0.907]	0.10 [0.084,0.122]

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...table A1 continued

Code			Overall	
Census	Figure	Label	Broadband in home	Mobile only
415	1415	Panamanian	0.89 [0.854,0.912]	0.11 [0.085,0.140]
416	1416	Salvadoran	0.84 [0.830,0.855]	0.15 [0.140,0.164]
417	1417	Central American (N.E.C.)	0.78 [0.689,0.853]	0.19 [0.124,0.272]
420	1420	Argentinean	0.90 [0.869,0.922]	0.10 [0.078,0.130]
421	1421	Bolivian	0.90 [0.869,0.930]	0.09 [0.068,0.127]
422	1422	Chilean	0.89 [0.855,0.916]	0.11 [0.083,0.144]
423	1423	Colombian	0.88 [0.871,0.895]	0.12 [0.104,0.128]
424	1424	Ecuadorian	0.88 [0.858,0.894]	0.12 [0.102,0.135]
425	1425	Paraguayan	0.91 [0.855,0.949]	0.08 [0.050,0.135]
426	1426	Peruvian	0.88 [0.860,0.891]	0.12 [0.101,0.134]
427	1427	Uruguayan	0.90 [0.845,0.940]	0.10 [0.063,0.149]
428	1428	Venezuelan	0.90 [0.879,0.918]	0.10 [0.081,0.118]
431	1431	South American (N.E.C.)	0.88 [0.814,0.931]	0.10 [0.056,0.160]
450	1450	Spaniard	0.87 [0.857,0.891]	0.12 [0.103,0.137]
460	1460	Dominican	0.86 [0.846,0.870]	0.14 [0.127,0.151]
498	1498	Other (N.S.)	0.79 [0.775,0.803]	0.20 [0.187,0.214]

Notes. Census codes (column 1), adjusted codes for figure with all racial/ethnic groups (column 2) and labels (column 3) from the Integrated Public Use Microdata System. We show racial/ethnic labels as they are reported by the census. *W.I.*: write in; *N.E.C.*: not otherwise coded; *N.S.*: not specified. Median posterior estimates with 95% credible intervals in brackets.

Table A2: Estimates of broadband access by race/ethnicity: men

Code			Men	
Census	Figure	Label	Broadband in home	Mobile only
100	100	White	0.88 [0.879,0.883]	0.11 [0.111,0.115]
200	200	Black/African American/Negro	0.83 [0.824,0.834]	0.16 [0.159,0.169]
302	302	Apache	0.85 [0.767,0.909]	0.13 [0.076,0.206]
303	303	Blackfoot	0.77 [0.651,0.865]	0.20 [0.116,0.310]
304	304	Cherokee	0.78 [0.731,0.819]	0.21 [0.172,0.249]
305	305	Cheyenne	0.82 [0.699,0.901]	0.15 [0.081,0.254]
306	306	Chickasaw	0.83 [0.747,0.896]	0.15 [0.095,0.232]
307	307	Chippewa	0.81 [0.755,0.862]	0.17 [0.119,0.222]
308	308	Choctaw	0.74 [0.671,0.799]	0.24 [0.179,0.305]
309	309	Comanche	0.79 [0.650,0.883]	0.17 [0.092,0.290]
310	310	Creek	0.79 [0.707,0.860]	0.17 [0.113,0.251]
311	311	Crow	0.82 [0.687,0.899]	0.17 [0.090,0.300]
312	312	Iroquois	0.87 [0.803,0.919]	0.11 [0.070,0.175]
314	314	Lumbee	0.80 [0.733,0.857]	0.17 [0.116,0.230]
315	315	Navajo	0.62 [0.572,0.665]	0.30 [0.261,0.347]
318	318	Pima	0.88 [0.788,0.941]	0.11 [0.057,0.201]
319	319	Potawatomi	0.84 [0.752,0.910]	0.15 [0.092,0.229]
320	320	Pueblo	0.71 [0.624,0.790]	0.22 [0.153,0.300]
321	321	Seminole	0.78 [0.643,0.877]	0.19 [0.107,0.312]
323	323	Sioux	0.84 [0.769,0.894]	0.16 [0.106,0.221]
324	324	Tlingit	0.86 [0.761,0.922]	0.12 [0.069,0.205]
325	325	Tohono O Odham	0.80 [0.691,0.886]	0.15 [0.093,0.248]
328	328	Hopi	0.83 [0.699,0.908]	0.16 [0.087,0.286]
352	352	Puget Sound Salish	0.86 [0.769,0.919]	0.14 [0.081,0.224]
354	354	Yaqui	0.89 [0.809,0.942]	0.10 [0.056,0.182]
359	359	South American Indian	0.00 [0.000,0.000]	0.00 [0.000,0.000]
360	360	Mexican American Indian	0.86 [0.729,0.931]	0.14 [0.070,0.245]
361	361	Other Amer. Indian Tribe	0.78 [0.724,0.823]	0.20 [0.152,0.247]
362	362	2+ Amer. Indian Tribes	0.82 [0.786,0.851]	0.17 [0.140,0.206]
370	370	Alaskan Athabaskan	0.84 [0.719,0.917]	0.14 [0.069,0.247]
371	371	Aleut	0.87 [0.756,0.937]	0.11 [0.056,0.202]
374	374	Inupiat	0.75 [0.612,0.850]	0.21 [0.126,0.326]
375	375	Yup'ik	0.78 [0.657,0.863]	0.21 [0.129,0.320]
379	379	Other Alaska Native Tribe(s)	0.87 [0.778,0.933]	0.12 [0.066,0.210]
399	399	Tribe Not Specified	0.82 [0.772,0.855]	0.18 [0.138,0.218]
400	400	Chinese	0.91 [0.900,0.916]	0.09 [0.079,0.095]
410	410	Taiwanese	0.94 [0.913,0.956]	0.06 [0.043,0.087]
500	500	Japanese	0.92 [0.897,0.932]	0.08 [0.067,0.099]
600	600	Filipino	0.89 [0.881,0.899]	0.11 [0.098,0.116]
610	610	Asian Indian	0.91 [0.899,0.917]	0.09 [0.081,0.098]
620	620	Korean	0.89 [0.882,0.906]	0.10 [0.091,0.114]
630	630	Hawaiian	0.87 [0.828,0.905]	0.13 [0.094,0.171]
640	640	Vietnamese	0.88 [0.872,0.891]	0.11 [0.101,0.121]
641	641	Bhutanese	0.85 [0.754,0.914]	0.14 [0.081,0.233]
642	642	Mongolian	0.91 [0.849,0.947]	0.09 [0.055,0.144]
643	643	Nepalese	0.84 [0.799,0.872]	0.16 [0.131,0.197]
660	660	Cambodian	0.87 [0.848,0.899]	0.12 [0.092,0.142]
661	661	Hmong	0.86 [0.839,0.886]	0.13 [0.103,0.153]

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...table A2 continued

Code			Men	
Census	Figure	Label	Broadband in home	Mobile only
662	662	Laotian	0.90 [0.869,0.926]	0.10 [0.073,0.126]
663	663	Thai	0.90 [0.866,0.923]	0.10 [0.075,0.128]
664	664	Bangladeshi	0.89 [0.863,0.921]	0.10 [0.074,0.126]
665	665	Burmese	0.81 [0.753,0.850]	0.18 [0.142,0.226]
666	666	Indonesian	0.88 [0.840,0.911]	0.12 [0.085,0.162]
667	667	Malaysian	0.84 [0.778,0.896]	0.15 [0.100,0.216]
669	669	Pakistani	0.92 [0.910,0.937]	0.07 [0.061,0.089]
670	670	Sri Lankan	0.86 [0.798,0.906]	0.14 [0.092,0.195]
671	671	Other Asian (N.E.C.)	0.81 [0.772,0.850]	0.17 [0.140,0.215]
673	673	Chinese and Japanese	0.92 [0.878,0.955]	0.08 [0.045,0.119]
674	674	Chinese and Filipino	0.94 [0.900,0.961]	0.07 [0.041,0.101]
675	675	Chinese and Vietnamese	0.91 [0.881,0.935]	0.09 [0.063,0.120]
676	676	Chinese and Asian (W.I.)	0.89 [0.835,0.927]	0.11 [0.072,0.166]
677	677	Japanese and Filipino	0.91 [0.849,0.948]	0.09 [0.049,0.136]
678	678	Asian Indian and Asian (W.I.)	0.85 [0.802,0.898]	0.14 [0.099,0.198]
679	679	Other Asian Race Combinations	0.90 [0.847,0.933]	0.10 [0.065,0.153]
680	680	Samoan	0.88 [0.834,0.920]	0.12 [0.081,0.160]
682	682	Tongan	0.84 [0.767,0.895]	0.13 [0.085,0.200]
685	685	Guamanian/Chamorro	0.90 [0.854,0.935]	0.08 [0.054,0.125]
689	689	1+ Other Micronesian Races	0.86 [0.745,0.923]	0.14 [0.077,0.240]
690	690	Fijian	0.84 [0.765,0.889]	0.16 [0.106,0.225]
699	699	Pacific Islander (N.S.)	0.82 [0.746,0.885]	0.17 [0.118,0.242]
700	700	Other Race (N.E.C.)	0.87 [0.849,0.886]	0.12 [0.108,0.144]
801	801	White and Black	0.90 [0.894,0.915]	0.09 [0.082,0.103]
802	802	White and AI/AN	0.86 [0.844,0.876]	0.13 [0.118,0.146]
811	811	White and Chinese	0.94 [0.917,0.954]	0.06 [0.045,0.081]
812	812	White and Japanese	0.93 [0.913,0.946]	0.07 [0.053,0.085]
813	813	White and Filipino	0.92 [0.910,0.937]	0.07 [0.061,0.091]
814	814	White and Asian Indian	0.93 [0.903,0.957]	0.07 [0.044,0.100]
815	815	White and Korean	0.93 [0.914,0.952]	0.07 [0.049,0.085]
816	816	White and Vietnamese	0.93 [0.902,0.956]	0.07 [0.044,0.095]
818	818	White and Other Asian Race(s)	0.86 [0.840,0.883]	0.13 [0.116,0.155]
821	821	White and Native Hawaiian	0.89 [0.842,0.927]	0.11 [0.074,0.156]
822	822	White and Samoan	0.87 [0.778,0.928]	0.13 [0.076,0.201]
823	823	White and Guamanian	0.92 [0.869,0.954]	0.08 [0.045,0.136]
824	824	White and PI (W.I.)	0.87 [0.804,0.918]	0.13 [0.078,0.194]
826	826	White and Other Race (W.I.)	0.87 [0.823,0.909]	0.12 [0.085,0.163]
830	830	Black and AI/AN	0.85 [0.816,0.884]	0.14 [0.110,0.179]
832	832	Black and Chinese	0.92 [0.862,0.957]	0.08 [0.044,0.134]
833	833	Black and Japanese	0.90 [0.839,0.944]	0.10 [0.057,0.164]
834	834	Black and Filipino	0.89 [0.839,0.923]	0.11 [0.078,0.159]
835	835	Black and Asian Indian	0.91 [0.845,0.947]	0.09 [0.050,0.149]
836	836	Black and Korean	0.89 [0.825,0.940]	0.11 [0.062,0.170]
837	837	Black and Asian (W.I.)	0.89 [0.842,0.934]	0.10 [0.067,0.155]
838	838	Black and Other Asian Race(s)	0.90 [0.826,0.950]	0.10 [0.054,0.166]
841	841	Black and PI (W.I.)	0.85 [0.762,0.910]	0.12 [0.075,0.198]
842	842	Black and Other PI Race(s)	0.89 [0.809,0.941]	0.11 [0.060,0.180]
845	845	Black and Other Race (W.I.)	0.87 [0.813,0.905]	0.13 [0.092,0.182]
851	851	AI/AN and Filipino	0.88 [0.779,0.938]	0.12 [0.063,0.200]

Continued on next page...

...table A2 continued

Code			Men	
Census	Figure	Label	Broadband in home	Mobile only
852	852	AI/AN and Asian Indian	0.81 [0.686,0.886]	0.16 [0.095,0.266]
856	856	AI/AN and Other Race (W.I.)	0.88 [0.780,0.945]	0.10 [0.052,0.176]
861	861	Chinese and Hawaiian	0.87 [0.783,0.931]	0.12 [0.064,0.212]
862	862	Chinese, Filipino, Hawaiian	0.88 [0.772,0.938]	0.11 [0.062,0.201]
863	863	Japanese and Hawaiian	0.92 [0.858,0.961]	0.08 [0.039,0.137]
864	864	Filipino and Hawaiian	0.91 [0.836,0.948]	0.09 [0.046,0.147]
865	865	Filipino and PI (W.I.)	0.89 [0.844,0.924]	0.11 [0.071,0.149]
868	868	Other Asian Race(s) and PI Race(s)	0.90 [0.823,0.945]	0.10 [0.058,0.169]
883	883	Filipino and Other Race (W.I.)	0.87 [0.778,0.928]	0.12 [0.064,0.215]
884	884	Asian Indian and Other Race (W.I.)	0.89 [0.810,0.936]	0.10 [0.057,0.165]
885	885	Asian (W.I.) and Other Race (W.I.)	0.91 [0.865,0.941]	0.09 [0.057,0.126]
887	887	Chinese and Korean	0.89 [0.817,0.940]	0.11 [0.061,0.170]
890	890	PI and Other Race (W.I.)	0.88 [0.790,0.935]	0.12 [0.066,0.202]
893	893	Native Hawaiian Or PI Other Race(s)	0.91 [0.838,0.952]	0.09 [0.050,0.155]
901	901	White, Black, AI/AN	0.88 [0.849,0.910]	0.12 [0.088,0.147]
902	902	White, Black, Asian	0.93 [0.889,0.955]	0.07 [0.049,0.109]
904	904	White, Black, Other Race (W.I.)	0.90 [0.823,0.949]	0.10 [0.053,0.172]
905	905	White, AI/AN, Asian	0.92 [0.868,0.954]	0.08 [0.045,0.123]
907	907	White, AI/AN, Other Race (W.I.)	0.88 [0.765,0.943]	0.11 [0.057,0.208]
911	911	White, Chinese, Hawaiian	0.89 [0.824,0.933]	0.11 [0.065,0.171]
912	912	White, Chinese, Filipino, Hawaiian	0.91 [0.837,0.954]	0.09 [0.048,0.142]
913	913	White, Japanese, Hawaiian	0.91 [0.840,0.948]	0.09 [0.052,0.158]
914	914	White, Filipino, Hawaiian	0.91 [0.854,0.946]	0.09 [0.052,0.149]
916	916	White, AI/AN and Filipino	0.89 [0.815,0.937]	0.11 [0.061,0.177]
917	917	White, Black, and Filipino	0.91 [0.849,0.950]	0.08 [0.048,0.138]
920	920	White, Asian, Other Race (W.I.)	0.88 [0.779,0.940]	0.11 [0.061,0.199]
921	921	White, Filipino, Other Race (W.I.)	0.91 [0.848,0.948]	0.09 [0.049,0.161]
922	922	White, Asian (W.I.), Other Race (W.I.)	0.91 [0.844,0.952]	0.09 [0.049,0.150]
925	925	White, PI, Other Race (W.I.)	0.90 [0.836,0.940]	0.10 [0.058,0.164]
943	943	Asian, PI, Other Race (W.I.)	0.93 [0.872,0.962]	0.07 [0.042,0.123]
944	944	Asian, NH/PI, and Other Race	0.91 [0.853,0.943]	0.10 [0.057,0.147]
950	950	White, Black, AI/AN, Asian	0.91 [0.856,0.952]	0.09 [0.049,0.143]
960	960	White, AI/AN, Asian, PI	0.91 [0.840,0.950]	0.09 [0.051,0.153]
963	963	White, Asian, PI, Other Race (W.I.)	0.91 [0.873,0.934]	0.09 [0.065,0.123]
964	964	White, Chinese, Japanese, Native Hawaiian	0.90 [0.825,0.949]	0.10 [0.053,0.163]
973	973	Black, Asian, PI, Other Race (W.I.)	0.89 [0.811,0.944]	0.11 [0.060,0.176]
974	974	AI/AN, Asian, PI, Other Race (W.I.)	0.84 [0.750,0.900]	0.14 [0.084,0.225]
976	976	Two Specified Asian, NH/PI, and Other Race	0.88 [0.825,0.921]	0.12 [0.076,0.174]
982	982	White, Black, AI/AN, PI, Other Race (W.I.)	0.83 [0.690,0.916]	0.16 [0.084,0.280]
983	983	White, Black, Asian, PI, Other Race (W.I.)	0.89 [0.809,0.939]	0.11 [0.062,0.185]
985	985	Black, AI/AN, Asian, PI, Other Race (W.I.)	0.79 [0.674,0.884]	0.19 [0.115,0.303]
990	990	White, Black, AI/AN, Asian, PI, Other Race (W.I.)	0.88 [0.801,0.925]	0.12 [0.072,0.192]
100	1100	Mexican	0.84 [0.838,0.847]	0.15 [0.146,0.155]
200	1200	Puerto Rican	0.88 [0.873,0.891]	0.11 [0.106,0.124]
300	1300	Cuban	0.88 [0.870,0.895]	0.11 [0.101,0.125]
411	1411	Costa Rican	0.90 [0.872,0.931]	0.10 [0.071,0.129]
412	1412	Guatemalan	0.85 [0.830,0.866]	0.15 [0.128,0.165]
413	1413	Honduran	0.83 [0.806,0.853]	0.16 [0.140,0.188]
414	1414	Nicaraguan	0.90 [0.874,0.913]	0.10 [0.078,0.117]

Continued on next page...

...table A2 continued

Code			Men	
Census	Figure	Label	Broadband in home	Mobile only
415	1415	Panamanian	0.90 [0.867,0.923]	0.10 [0.075,0.127]
416	1416	Salvadoran	0.85 [0.838,0.866]	0.14 [0.130,0.157]
417	1417	Central American (N.E.C.)	0.79 [0.689,0.858]	0.19 [0.121,0.268]
420	1420	Argentinean	0.91 [0.879,0.930]	0.09 [0.071,0.121]
421	1421	Bolivian	0.91 [0.874,0.934]	0.09 [0.065,0.122]
422	1422	Chilean	0.90 [0.866,0.923]	0.10 [0.076,0.135]
423	1423	Colombian	0.89 [0.881,0.907]	0.10 [0.092,0.118]
424	1424	Ecuadorian	0.88 [0.864,0.902]	0.11 [0.095,0.129]
425	1425	Paraguayan	0.91 [0.857,0.950]	0.08 [0.049,0.133]
426	1426	Peruvian	0.89 [0.869,0.903]	0.11 [0.093,0.126]
427	1427	Uruguayan	0.91 [0.860,0.946]	0.09 [0.056,0.136]
428	1428	Venezuelan	0.91 [0.884,0.923]	0.09 [0.076,0.114]
431	1431	South American (N.E.C.)	0.89 [0.821,0.934]	0.09 [0.054,0.155]
450	1450	Spaniard	0.88 [0.866,0.901]	0.11 [0.094,0.128]
460	1460	Dominican	0.87 [0.857,0.885]	0.13 [0.113,0.141]
498	1498	Other (N.S.)	0.81 [0.791,0.821]	0.18 [0.169,0.200]

Notes. Census codes (column 1), adjusted codes for figure with all racial/ethnic groups (column 2) and labels (column 3) from the Integrated Public Use Microdata System. We show racial/ethnic labels as they are reported by the census. *W.I.*: write in; *N.E.C.*: not otherwise coded; *N.S.*: not specified. Median posterior estimates with 95% credible intervals in brackets.

Table A3: Estimates of broadband access by race/ethnicity: women

Code			Women	
Census	Figure	Label	Broadband in home	Mobile only
100	100	White	0.86 [0.861,0.864]	0.13 [0.129,0.133]
200	200	Black/African American/Negro	0.81 [0.806,0.815]	0.18 [0.177,0.185]
302	302	Apache	0.83 [0.747,0.896]	0.14 [0.084,0.225]
303	303	Blackfoot	0.75 [0.630,0.847]	0.22 [0.131,0.330]
304	304	Cherokee	0.76 [0.709,0.799]	0.23 [0.188,0.272]
305	305	Cheyenne	0.79 [0.661,0.888]	0.17 [0.097,0.286]
306	306	Chickasaw	0.78 [0.672,0.865]	0.20 [0.124,0.294]
307	307	Chippewa	0.79 [0.726,0.841]	0.19 [0.138,0.244]
308	308	Choctaw	0.71 [0.635,0.772]	0.27 [0.205,0.339]
309	309	Comanche	0.79 [0.662,0.879]	0.16 [0.091,0.282]
310	310	Creek	0.77 [0.676,0.840]	0.19 [0.127,0.277]
311	311	Crow	0.77 [0.624,0.875]	0.21 [0.115,0.361]
312	312	Iroquois	0.84 [0.758,0.893]	0.14 [0.092,0.215]
314	314	Lumbee	0.77 [0.699,0.831]	0.19 [0.135,0.258]
315	315	Navajo	0.58 [0.536,0.628]	0.34 [0.297,0.379]
318	318	Pima	0.85 [0.741,0.920]	0.14 [0.074,0.247]
319	319	Potawatomi	0.81 [0.709,0.891]	0.18 [0.112,0.268]
320	320	Pueblo	0.68 [0.588,0.757]	0.24 [0.172,0.332]
321	321	Seminole	0.75 [0.599,0.860]	0.21 [0.119,0.352]
323	323	Sioux	0.81 [0.738,0.877]	0.18 [0.123,0.252]
324	324	Tlingit	0.80 [0.676,0.886]	0.17 [0.099,0.286]
325	325	Tohono O Odham	0.73 [0.593,0.839]	0.21 [0.126,0.334]
328	328	Hopi	0.80 [0.658,0.894]	0.18 [0.097,0.321]
352	352	Puget Sound Salish	0.82 [0.721,0.901]	0.16 [0.095,0.268]
354	354	Yaqui	0.86 [0.755,0.927]	0.13 [0.071,0.230]
359	359	South American Indian	0.88 [0.770,0.945]	0.11 [0.056,0.220]
360	360	Mexican American Indian	0.83 [0.684,0.915]	0.16 [0.086,0.271]
361	361	Other Amer. Indian Tribe	0.73 [0.677,0.784]	0.24 [0.187,0.290]
362	362	2+ Amer. Indian Tribes	0.78 [0.749,0.818]	0.21 [0.169,0.244]
370	370	Alaskan Athabaskan	0.82 [0.697,0.911]	0.15 [0.078,0.263]
371	371	Aleut	0.85 [0.736,0.923]	0.13 [0.067,0.217]
374	374	Inupiat	0.74 [0.597,0.844]	0.22 [0.129,0.345]
375	375	Yup'ik	0.74 [0.609,0.835]	0.25 [0.155,0.364]
379	379	Other Alaska Native Tribe(s)	0.83 [0.713,0.911]	0.16 [0.089,0.276]
399	399	Tribe Not Specified	0.79 [0.741,0.832]	0.20 [0.159,0.248]
400	400	Chinese	0.88 [0.873,0.892]	0.11 [0.102,0.119]
410	410	Taiwanese	0.93 [0.898,0.948]	0.07 [0.050,0.102]
500	500	Japanese	0.90 [0.877,0.916]	0.10 [0.079,0.117]
600	600	Filipino	0.88 [0.871,0.890]	0.12 [0.106,0.125]
610	610	Asian Indian	0.90 [0.885,0.904]	0.10 [0.092,0.110]
620	620	Korean	0.88 [0.863,0.889]	0.12 [0.106,0.132]
630	630	Hawaiian	0.86 [0.814,0.898]	0.14 [0.101,0.184]
640	640	Vietnamese	0.87 [0.855,0.876]	0.12 [0.112,0.133]
641	641	Bhutanese	0.83 [0.720,0.902]	0.16 [0.091,0.260]
642	642	Mongolian	0.88 [0.815,0.931]	0.12 [0.071,0.181]
643	643	Nepalese	0.83 [0.784,0.866]	0.17 [0.136,0.209]
660	660	Cambodian	0.86 [0.834,0.889]	0.13 [0.101,0.154]
661	661	Hmong	0.85 [0.820,0.871]	0.14 [0.117,0.172]

Continued on next page...

...table A3 continued

Code			Women	
Census	Figure	Label	Broadband in home	Mobile only
662	662	Laotian	0.88 [0.848,0.913]	0.11 [0.085,0.146]
663	663	Thai	0.88 [0.851,0.913]	0.11 [0.082,0.141]
664	664	Bangladeshi	0.88 [0.847,0.910]	0.11 [0.082,0.141]
665	665	Burmese	0.78 [0.729,0.834]	0.20 [0.157,0.250]
666	666	Indonesian	0.87 [0.825,0.903]	0.13 [0.091,0.174]
667	667	Malaysian	0.85 [0.783,0.900]	0.15 [0.098,0.210]
669	669	Pakistani	0.92 [0.902,0.932]	0.08 [0.065,0.096]
670	670	Sri Lankan	0.85 [0.785,0.898]	0.15 [0.099,0.207]
671	671	Other Asian (N.E.C.)	0.79 [0.748,0.833]	0.19 [0.156,0.236]
673	673	Chinese and Japanese	0.90 [0.839,0.939]	0.10 [0.059,0.158]
674	674	Chinese and Filipino	0.92 [0.877,0.952]	0.08 [0.050,0.124]
675	675	Chinese and Vietnamese	0.89 [0.855,0.923]	0.11 [0.076,0.144]
676	676	Chinese and Asian (W.I.)	0.88 [0.822,0.918]	0.12 [0.080,0.179]
677	677	Japanese and Filipino	0.91 [0.842,0.947]	0.09 [0.049,0.142]
678	678	Asian Indian and Asian (W.I.)	0.84 [0.788,0.890]	0.15 [0.106,0.213]
679	679	Other Asian Race Combinations	0.88 [0.827,0.925]	0.11 [0.072,0.171]
680	680	Samoan	0.86 [0.810,0.907]	0.13 [0.093,0.187]
682	682	Tongan	0.83 [0.758,0.893]	0.14 [0.086,0.205]
685	685	Guamanian/Chamorro	0.88 [0.825,0.920]	0.10 [0.063,0.147]
689	689	1+ Other Micronesian Races	0.79 [0.664,0.883]	0.19 [0.112,0.326]
690	690	Fijian	0.82 [0.750,0.880]	0.17 [0.113,0.242]
699	699	Pacific Islander (N.S.)	0.79 [0.710,0.863]	0.20 [0.135,0.273]
700	700	Other Race (N.E.C.)	0.86 [0.837,0.875]	0.13 [0.115,0.152]
801	801	White and Black	0.88 [0.873,0.895]	0.11 [0.100,0.122]
802	802	White and AI/AN	0.84 [0.818,0.851]	0.16 [0.141,0.172]
811	811	White and Chinese	0.93 [0.902,0.947]	0.07 [0.052,0.094]
812	812	White and Japanese	0.92 [0.896,0.935]	0.08 [0.064,0.102]
813	813	White and Filipino	0.91 [0.897,0.928]	0.09 [0.070,0.103]
814	814	White and Asian Indian	0.92 [0.881,0.948]	0.08 [0.053,0.122]
815	815	White and Korean	0.93 [0.902,0.946]	0.07 [0.055,0.094]
816	816	White and Vietnamese	0.92 [0.884,0.945]	0.08 [0.053,0.112]
818	818	White and Other Asian Race(s)	0.84 [0.820,0.867]	0.15 [0.131,0.175]
821	821	White and Native Hawaiian	0.88 [0.825,0.918]	0.12 [0.083,0.170]
822	822	White and Samoan	0.85 [0.756,0.918]	0.14 [0.086,0.224]
823	823	White and Guamanian	0.90 [0.839,0.944]	0.10 [0.055,0.163]
824	824	White and PI (W.I.)	0.86 [0.788,0.912]	0.14 [0.084,0.212]
826	826	White and Other Race (W.I.)	0.85 [0.800,0.895]	0.14 [0.097,0.181]
830	830	Black and AI/AN	0.83 [0.789,0.864]	0.16 [0.128,0.207]
832	832	Black and Chinese	0.90 [0.833,0.947]	0.10 [0.054,0.159]
833	833	Black and Japanese	0.87 [0.794,0.926]	0.13 [0.072,0.201]
834	834	Black and Filipino	0.87 [0.819,0.915]	0.13 [0.085,0.178]
835	835	Black and Asian Indian	0.89 [0.819,0.939]	0.11 [0.061,0.173]
836	836	Black and Korean	0.89 [0.818,0.937]	0.11 [0.064,0.178]
837	837	Black and Asian (W.I.)	0.87 [0.811,0.921]	0.12 [0.081,0.186]
838	838	Black and Other Asian Race(s)	0.88 [0.787,0.936]	0.12 [0.067,0.208]
841	841	Black and PI (W.I.)	0.83 [0.742,0.901]	0.14 [0.080,0.217]
842	842	Black and Other PI Race(s)	0.85 [0.754,0.923]	0.14 [0.080,0.229]
845	845	Black and Other Race (W.I.)	0.84 [0.786,0.888]	0.15 [0.109,0.211]
851	851	AI/AN and Filipino	0.87 [0.760,0.935]	0.12 [0.065,0.214]

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...table A3 continued

Code			Women	
Census	Figure	Label	Broadband in home	Mobile only
852	852	AI/AN and Asian Indian	0.78 [0.650,0.871]	0.18 [0.107,0.301]
856	856	AI/AN and Other Race (W.I.)	0.86 [0.734,0.929]	0.12 [0.063,0.210]
861	861	Chinese and Hawaiian	0.86 [0.755,0.929]	0.13 [0.064,0.222]
862	862	Chinese, Filipino, Hawaiian	0.87 [0.757,0.932]	0.12 [0.067,0.213]
863	863	Japanese and Hawaiian	0.91 [0.832,0.952]	0.09 [0.046,0.161]
864	864	Filipino and Hawaiian	0.87 [0.782,0.926]	0.12 [0.067,0.190]
865	865	Filipino and PI (W.I.)	0.87 [0.819,0.911]	0.12 [0.083,0.172]
868	868	Other Asian Race(s) and PI Race(s)	0.89 [0.812,0.941]	0.11 [0.062,0.180]
883	883	Filipino and Other Race (W.I.)	0.86 [0.765,0.923]	0.13 [0.068,0.225]
884	884	Asian Indian and Other Race (W.I.)	0.86 [0.776,0.924]	0.12 [0.068,0.194]
885	885	Asian (W.I.) and Other Race (W.I.)	0.90 [0.852,0.935]	0.10 [0.062,0.138]
887	887	Chinese and Korean	0.89 [0.823,0.943]	0.10 [0.059,0.165]
890	890	PI and Other Race (W.I.)	0.86 [0.748,0.922]	0.14 [0.074,0.242]
893	893	Native Hawaiian Or PI Other Race(s)	0.89 [0.813,0.944]	0.11 [0.059,0.178]
901	901	White, Black, AI/AN	0.86 [0.822,0.891]	0.14 [0.106,0.173]
902	902	White, Black, Asian	0.92 [0.878,0.951]	0.08 [0.053,0.119]
904	904	White, Black, Other Race (W.I.)	0.89 [0.807,0.943]	0.11 [0.058,0.190]
905	905	White, AI/AN, Asian	0.90 [0.840,0.946]	0.09 [0.051,0.145]
907	907	White, AI/AN, Other Race (W.I.)	0.85 [0.702,0.927]	0.14 [0.070,0.260]
911	911	White, Chinese, Hawaiian	0.87 [0.799,0.923]	0.13 [0.075,0.196]
912	912	White, Chinese, Filipino, Hawaiian	0.89 [0.796,0.942]	0.11 [0.060,0.180]
913	913	White, Japanese, Hawaiian	0.87 [0.780,0.927]	0.13 [0.071,0.212]
914	914	White, Filipino, Hawaiian	0.88 [0.812,0.930]	0.12 [0.066,0.188]
916	916	White, AI/AN and Filipino	0.85 [0.759,0.916]	0.14 [0.082,0.226]
917	917	White, Black, and Filipino	0.88 [0.802,0.932]	0.11 [0.062,0.177]
920	920	White, Asian, Other Race (W.I.)	0.86 [0.755,0.932]	0.13 [0.064,0.232]
921	921	White, Filipino, Other Race (W.I.)	0.91 [0.852,0.948]	0.09 [0.048,0.159]
922	922	White, Asian (W.I.), Other Race (W.I.)	0.89 [0.813,0.941]	0.11 [0.059,0.184]
925	925	White, PI, Other Race (W.I.)	0.88 [0.801,0.930]	0.12 [0.070,0.194]
943	943	Asian, PI, Other Race (W.I.)	0.92 [0.863,0.960]	0.08 [0.045,0.128]
944	944	Asian, NH/PI, and Other Race	0.90 [0.839,0.938]	0.10 [0.062,0.160]
950	950	White, Black, AI/AN, Asian	0.89 [0.818,0.937]	0.11 [0.061,0.178]
960	960	White, AI/AN, Asian, PI	0.89 [0.818,0.940]	0.11 [0.059,0.178]
963	963	White, Asian, PI, Other Race (W.I.)	0.88 [0.846,0.917]	0.11 [0.079,0.149]
964	964	White, Chinese, Japanese, Native Hawaiian	0.88 [0.788,0.933]	0.12 [0.068,0.198]
973	973	Black, Asian, PI, Other Race (W.I.)	0.87 [0.774,0.930]	0.13 [0.072,0.211]
974	974	AI/AN, Asian, PI, Other Race (W.I.)	0.81 [0.717,0.884]	0.17 [0.098,0.258]
976	976	Two Specified Asian, NH/PI, and Other Race	0.87 [0.806,0.914]	0.13 [0.083,0.191]
982	982	White, Black, AI/AN, PI, Other Race (W.I.)	0.86 [0.735,0.929]	0.14 [0.075,0.245]
983	983	White, Black, Asian, PI, Other Race (W.I.)	0.88 [0.802,0.934]	0.12 [0.067,0.193]
985	985	Black, AI/AN, Asian, PI, Other Race (W.I.)	0.81 [0.691,0.890]	0.18 [0.109,0.288]
990	990	White, Black, AI/AN, Asian, PI, Other Race (W.I.)	0.86 [0.775,0.913]	0.14 [0.083,0.216]
100	1100	Mexican	0.83 [0.821,0.829]	0.17 [0.163,0.171]
200	1200	Puerto Rican	0.86 [0.852,0.870]	0.13 [0.126,0.144]
300	1300	Cuban	0.86 [0.848,0.874]	0.13 [0.119,0.144]
411	1411	Costa Rican	0.89 [0.853,0.920]	0.11 [0.081,0.146]
412	1412	Guatemalan	0.83 [0.814,0.853]	0.16 [0.142,0.179]
413	1413	Honduran	0.81 [0.785,0.836]	0.18 [0.157,0.206]
414	1414	Nicaraguan	0.88 [0.861,0.904]	0.11 [0.086,0.128]

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...table A3 continued

Code			Women	
Census	Figure	Label	Broadband in home	Mobile only
415	1415	Panamanian	0.88 [0.840,0.906]	0.12 [0.091,0.152]
416	1416	Salvadoran	0.83 [0.820,0.849]	0.16 [0.145,0.174]
417	1417	Central American (N.E.C.)	0.78 [0.685,0.853]	0.19 [0.125,0.279]
420	1420	Argentinean	0.89 [0.860,0.916]	0.11 [0.082,0.140]
421	1421	Bolivian	0.90 [0.863,0.929]	0.10 [0.070,0.133]
422	1422	Chilean	0.88 [0.847,0.911]	0.12 [0.086,0.153]
423	1423	Colombian	0.88 [0.860,0.889]	0.12 [0.110,0.137]
424	1424	Ecuadorian	0.87 [0.849,0.888]	0.12 [0.106,0.143]
425	1425	Paraguayan	0.91 [0.849,0.949]	0.09 [0.050,0.138]
426	1426	Peruvian	0.87 [0.848,0.885]	0.12 [0.107,0.144]
427	1427	Uruguayan	0.89 [0.826,0.933]	0.11 [0.070,0.166]
428	1428	Venezuelan	0.90 [0.874,0.915]	0.10 [0.083,0.123]
431	1431	South American (N.E.C.)	0.88 [0.806,0.928]	0.10 [0.057,0.170]
450	1450	Spaniard	0.87 [0.847,0.885]	0.13 [0.107,0.145]
460	1460	Dominican	0.85 [0.835,0.864]	0.15 [0.134,0.162]
498	1498	Other (N.S.)	0.78 [0.758,0.791]	0.21 [0.198,0.230]

Notes. Census codes (column 1), adjusted codes for figure with all racial/ethnic groups (column 2) and labels (column 3) from the Integrated Public Use Microdata System. We show racial/ethnic labels as they are reported by the census. *W.I.*: write in; *N.E.C.*: not otherwise coded; *N.S.*: not specified. Median posterior estimates with 95% credible intervals in brackets.

Table A4: Estimates of in-home broadband access for Hispanic populations in California, Florida, and Texas

Code				Broadband in the home	
Census	Figure	State	Label	Men	Women
100	1100	California	Mexican	0.85 [0.844,0.856]	0.83 [0.828,0.840]
200	1200	California	Puerto Rican	0.89 [0.863,0.905]	0.86 [0.833,0.886]
300	1300	California	Cuban	0.89 [0.856,0.910]	0.87 [0.832,0.897]
411	1411	California	Costa Rican	0.90 [0.853,0.931]	0.88 [0.831,0.921]
412	1412	California	Guatemalan	0.85 [0.821,0.866]	0.83 [0.803,0.855]
413	1413	California	Honduran	0.83 [0.790,0.865]	0.80 [0.757,0.845]
414	1414	California	Nicaraguan	0.90 [0.869,0.921]	0.89 [0.855,0.911]
415	1415	California	Panamanian	0.90 [0.864,0.934]	0.88 [0.837,0.920]
416	1416	California	Salvadoran	0.84 [0.826,0.863]	0.83 [0.806,0.845]
417	1417	California	Central American (N.E.C.)	0.78 [0.678,0.861]	0.75 [0.640,0.839]
420	1420	California	Argentinean	0.90 [0.862,0.929]	0.88 [0.842,0.919]
421	1421	California	Bolivian	0.90 [0.861,0.938]	0.89 [0.838,0.929]
422	1422	California	Chilean	0.89 [0.844,0.922]	0.87 [0.818,0.909]
423	1423	California	Colombian	0.89 [0.868,0.917]	0.88 [0.846,0.904]
424	1424	California	Ecuadorian	0.88 [0.842,0.912]	0.86 [0.822,0.898]
425	1425	California	Paraguayan	0.90 [0.822,0.944]	0.90 [0.819,0.945]
426	1426	California	Peruvian	0.88 [0.852,0.906]	0.87 [0.836,0.894]
427	1427	California	Uruguayan	0.91 [0.852,0.953]	0.90 [0.825,0.943]
428	1428	California	Venezuelan	0.90 [0.865,0.931]	0.89 [0.852,0.924]
431	1431	California	South American (N.E.C.)	0.88 [0.806,0.933]	0.87 [0.792,0.929]
450	1450	California	Spaniard	0.89 [0.860,0.908]	0.88 [0.845,0.900]
460	1460	California	Dominican	0.88 [0.842,0.907]	0.85 [0.807,0.890]
498	1498	California	Other (N.S.)	0.81 [0.781,0.829]	0.78 [0.749,0.803]
100	1100	Florida	Mexican	0.86 [0.837,0.876]	0.83 [0.809,0.855]
200	1200	Florida	Puerto Rican	0.89 [0.879,0.908]	0.88 [0.861,0.892]
300	1300	Florida	Cuban	0.88 [0.868,0.897]	0.86 [0.846,0.877]
411	1411	Florida	Costa Rican	0.92 [0.888,0.948]	0.91 [0.869,0.940]
412	1412	Florida	Guatemalan	0.88 [0.849,0.911]	0.87 [0.824,0.898]
413	1413	Florida	Honduran	0.86 [0.819,0.889]	0.84 [0.791,0.873]
414	1414	Florida	Nicaraguan	0.90 [0.876,0.925]	0.88 [0.850,0.911]
415	1415	Florida	Panamanian	0.91 [0.866,0.934]	0.90 [0.863,0.935]
416	1416	Florida	Salvadoran	0.86 [0.820,0.892]	0.84 [0.799,0.880]
417	1417	Florida	Central American (N.E.C.)	0.81 [0.696,0.885]	0.77 [0.657,0.864]
420	1420	Florida	Argentinean	0.92 [0.883,0.943]	0.90 [0.862,0.931]
421	1421	Florida	Bolivian	0.92 [0.879,0.948]	0.91 [0.863,0.941]
422	1422	Florida	Chilean	0.91 [0.879,0.942]	0.89 [0.851,0.928]
423	1423	Florida	Colombian	0.91 [0.890,0.922]	0.89 [0.869,0.909]
424	1424	Florida	Ecuadorian	0.89 [0.859,0.918]	0.88 [0.849,0.914]
425	1425	Florida	Paraguayan	0.92 [0.849,0.956]	0.92 [0.861,0.962]
426	1426	Florida	Peruvian	0.90 [0.877,0.926]	0.89 [0.858,0.913]
427	1427	Florida	Uruguayan	0.92 [0.865,0.952]	0.89 [0.822,0.940]
428	1428	Florida	Venezuelan	0.92 [0.896,0.938]	0.91 [0.881,0.928]
431	1431	Florida	South American (N.E.C.)	0.91 [0.850,0.953]	0.90 [0.821,0.947]
450	1450	Florida	Spaniard	0.91 [0.884,0.935]	0.90 [0.865,0.926]
460	1460	Florida	Dominican	0.87 [0.846,0.895]	0.85 [0.823,0.877]
498	1498	Florida	Other (N.S.)	0.85 [0.811,0.874]	0.82 [0.782,0.854]
100	1100	Texas	Mexican	0.83 [0.818,0.834]	0.81 [0.800,0.816]
200	1200	Texas	Puerto Rican	0.88 [0.848,0.901]	0.85 [0.819,0.883]

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...table A4 continued

Code				Broadband in the home	
Census	Figure	State	Label	Men	Women
300	1300	Texas	Cuban	0.87 [0.829,0.900]	0.85 [0.804,0.886]
411	1411	Texas	Costa Rican	0.87 [0.813,0.915]	0.87 [0.807,0.913]
412	1412	Texas	Guatemalan	0.82 [0.775,0.858]	0.81 [0.759,0.852]
413	1413	Texas	Honduran	0.81 [0.758,0.853]	0.78 [0.729,0.834]
414	1414	Texas	Nicaraguan	0.87 [0.824,0.910]	0.88 [0.835,0.918]
415	1415	Texas	Panamanian	0.89 [0.848,0.927]	0.86 [0.797,0.903]
416	1416	Texas	Salvadoran	0.85 [0.822,0.878]	0.84 [0.804,0.867]
417	1417	Texas	Central American (N.E.C.)	0.74 [0.612,0.843]	0.00 [0.000,0.000]
420	1420	Texas	Argentinean	0.89 [0.842,0.925]	0.86 [0.803,0.904]
421	1421	Texas	Bolivian	0.90 [0.855,0.938]	0.89 [0.831,0.929]
422	1422	Texas	Chilean	0.85 [0.785,0.898]	0.86 [0.800,0.907]
423	1423	Texas	Colombian	0.87 [0.831,0.896]	0.86 [0.822,0.891]
424	1424	Texas	Ecuadorian	0.86 [0.816,0.900]	0.85 [0.805,0.893]
425	1425	Texas	Paraguayan	0.00 [0.000,0.000]	0.91 [0.845,0.956]
426	1426	Texas	Peruvian	0.88 [0.841,0.907]	0.85 [0.811,0.890]
427	1427	Texas	Uruguayan	0.92 [0.868,0.957]	0.89 [0.825,0.939]
428	1428	Texas	Venezuelan	0.89 [0.854,0.922]	0.87 [0.821,0.904]
431	1431	Texas	South American (N.E.C.)	0.86 [0.759,0.919]	0.83 [0.724,0.907]
450	1450	Texas	Spaniard	0.86 [0.823,0.896]	0.84 [0.798,0.879]
460	1460	Texas	Dominican	0.86 [0.820,0.896]	0.81 [0.748,0.851]
498	1498	Texas	Other (N.S.)	0.77 [0.742,0.803]	0.74 [0.705,0.770]

Notes. Census codes (column 1), adjusted codes for figure with Hispanic groups (column 2), state name (column 3), and labels (column 3) from the Integrated Public Use Microdata System. We show racial/ethnic labels as they are reported by the census. *N.E.C.*: not otherwise coded; *N.S.*: not specified. Median posterior estimates with 95% credible intervals in brackets.

Table A5: Estimates of mobile only broadband access for Hispanic populations in California, Florida, and Texas

Code				Mobile only	
Census	Figure	State	Label	Men	Women
100	1100	California	Mexican	0.14 [0.138,0.149]	0.16 [0.153,0.163]
200	1200	California	Puerto Rican	0.11 [0.089,0.129]	0.13 [0.107,0.157]
300	1300	California	Cuban	0.11 [0.086,0.142]	0.13 [0.101,0.163]
411	1411	California	Costa Rican	0.10 [0.069,0.145]	0.11 [0.077,0.164]
412	1412	California	Guatemalan	0.15 [0.126,0.173]	0.16 [0.139,0.187]
413	1413	California	Honduran	0.17 [0.133,0.206]	0.19 [0.152,0.235]
414	1414	California	Nicaraguan	0.09 [0.071,0.121]	0.10 [0.077,0.134]
415	1415	California	Panamanian	0.09 [0.064,0.128]	0.11 [0.076,0.155]
416	1416	California	Salvadoran	0.15 [0.131,0.168]	0.17 [0.147,0.185]
417	1417	California	Central American (N.E.C.)	0.19 [0.119,0.272]	0.21 [0.136,0.314]
420	1420	California	Argentinean	0.10 [0.071,0.135]	0.11 [0.080,0.155]
421	1421	California	Bolivian	0.09 [0.060,0.131]	0.11 [0.068,0.155]
422	1422	California	Chilean	0.11 [0.076,0.154]	0.13 [0.087,0.181]
423	1423	California	Colombian	0.10 [0.083,0.131]	0.12 [0.095,0.151]
424	1424	California	Ecuadorian	0.11 [0.084,0.142]	0.12 [0.094,0.162]
425	1425	California	Paraguayan	0.10 [0.052,0.162]	0.09 [0.050,0.161]
426	1426	California	Peruvian	0.11 [0.090,0.138]	0.12 [0.099,0.154]
427	1427	California	Uruguayan	0.09 [0.050,0.141]	0.10 [0.059,0.169]
428	1428	California	Venezuelan	0.10 [0.067,0.134]	0.10 [0.072,0.146]
431	1431	California	South American (N.E.C.)	0.10 [0.053,0.168]	0.10 [0.055,0.178]
450	1450	California	Spaniard	0.11 [0.086,0.136]	0.12 [0.095,0.150]
460	1460	California	Dominican	0.12 [0.087,0.154]	0.14 [0.106,0.187]
498	1498	California	Other (N.S.)	0.18 [0.160,0.209]	0.21 [0.183,0.237]
100	1100	Florida	Mexican	0.13 [0.115,0.154]	0.16 [0.135,0.178]
200	1200	Florida	Puerto Rican	0.10 [0.089,0.116]	0.12 [0.104,0.134]
300	1300	Florida	Cuban	0.11 [0.098,0.125]	0.13 [0.116,0.146]
411	1411	Florida	Costa Rican	0.08 [0.053,0.113]	0.09 [0.061,0.130]
412	1412	Florida	Guatemalan	0.11 [0.085,0.146]	0.13 [0.098,0.165]
413	1413	Florida	Honduran	0.14 [0.107,0.169]	0.15 [0.122,0.194]
414	1414	Florida	Nicaraguan	0.09 [0.067,0.114]	0.10 [0.080,0.133]
415	1415	Florida	Panamanian	0.09 [0.062,0.126]	0.09 [0.063,0.129]
416	1416	Florida	Salvadoran	0.14 [0.104,0.173]	0.15 [0.112,0.193]
417	1417	Florida	Central American (N.E.C.)	0.17 [0.103,0.264]	0.20 [0.118,0.304]
420	1420	Florida	Argentinean	0.08 [0.059,0.116]	0.10 [0.069,0.138]
421	1421	Florida	Bolivian	0.08 [0.050,0.115]	0.09 [0.056,0.135]
422	1422	Florida	Chilean	0.09 [0.058,0.120]	0.10 [0.071,0.144]
423	1423	Florida	Colombian	0.09 [0.076,0.108]	0.11 [0.089,0.128]
424	1424	Florida	Ecuadorian	0.11 [0.081,0.137]	0.11 [0.084,0.142]
425	1425	Florida	Paraguayan	0.08 [0.043,0.133]	0.07 [0.038,0.124]
426	1426	Florida	Peruvian	0.09 [0.070,0.117]	0.10 [0.080,0.135]
427	1427	Florida	Uruguayan	0.08 [0.049,0.132]	0.11 [0.064,0.172]
428	1428	Florida	Venezuelan	0.08 [0.061,0.100]	0.09 [0.070,0.115]
431	1431	Florida	South American (N.E.C.)	0.07 [0.038,0.133]	0.09 [0.043,0.156]
450	1450	Florida	Spaniard	0.08 [0.063,0.112]	0.10 [0.073,0.128]
460	1460	Florida	Dominican	0.12 [0.102,0.150]	0.14 [0.119,0.173]
498	1498	Florida	Other (N.S.)	0.15 [0.121,0.186]	0.17 [0.140,0.214]

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...table A5 continued

Code		State	Label	Mobile only	
Census	Figure			Men	Women
100	1100	Texas	Mexican	0.17 [0.158,0.175]	0.18 [0.176,0.192]
200	1200	Texas	Puerto Rican	0.12 [0.097,0.147]	0.14 [0.115,0.172]
300	1300	Texas	Cuban	0.13 [0.098,0.162]	0.14 [0.110,0.186]
411	1411	Texas	Costa Rican	0.13 [0.087,0.184]	0.13 [0.088,0.188]
412	1412	Texas	Guatemalan	0.18 [0.140,0.218]	0.19 [0.149,0.236]
413	1413	Texas	Honduran	0.19 [0.146,0.234]	0.21 [0.163,0.262]
414	1414	Texas	Nicaraguan	0.12 [0.087,0.160]	0.11 [0.078,0.152]
415	1415	Texas	Panamanian	0.10 [0.071,0.145]	0.14 [0.096,0.191]
416	1416	Texas	Salvadoran	0.15 [0.120,0.179]	0.16 [0.130,0.193]
417	1417	Texas	Central American (N.E.C.)	0.23 [0.142,0.345]	0.00 [0.000,0.000]
420	1420	Texas	Argentinean	0.11 [0.079,0.160]	0.14 [0.097,0.196]
421	1421	Texas	Bolivian	0.09 [0.061,0.140]	0.11 [0.070,0.161]
422	1422	Texas	Chilean	0.14 [0.094,0.205]	0.14 [0.092,0.200]
423	1423	Texas	Colombian	0.13 [0.103,0.167]	0.14 [0.107,0.178]
424	1424	Texas	Ecuadorian	0.13 [0.098,0.171]	0.14 [0.102,0.186]
425	1425	Texas	Paraguayan	0.00 [0.000,0.000]	0.08 [0.045,0.141]
426	1426	Texas	Peruvian	0.12 [0.089,0.158]	0.14 [0.104,0.185]
427	1427	Texas	Uruguayan	0.08 [0.046,0.126]	0.11 [0.061,0.171]
428	1428	Texas	Venezuelan	0.11 [0.079,0.145]	0.13 [0.096,0.178]
431	1431	Texas	South American (N.E.C.)	0.12 [0.067,0.211]	0.14 [0.078,0.242]
450	1450	Texas	Spaniard	0.13 [0.102,0.169]	0.15 [0.116,0.194]
460	1460	Texas	Dominican	0.13 [0.103,0.176]	0.19 [0.145,0.244]
498	1498	Texas	Other (N.S.)	0.21 [0.186,0.245]	0.25 [0.217,0.281]

Notes. Census codes (column 1), adjusted codes for figure with Hispanic groups (column 2), state name (column 3), and labels (column 3) from the Integrated Public Use Microdata System. We show racial/ethnic labels as they are reported by the census. *N.E.C.*: not otherwise coded; *N.S.*: not specified. Median posterior estimates with 95% credible intervals in brackets.