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Ability, location and household demand for Internet bandwidth

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This paper examines consumer preferences for Internet bandwidth, focusing on technical ability and urban/rural location as sources of preference heterogeneity. An economic model is outlined that shows that ability decreases the effective price of bandwidth. As a result of this decrease, part of the total effect of an increase in ability will always be an increase in the demand for bandwidth. The implication is empirically investigated with an econometric approach that overcomes the limitations of the aggregated data that is currently available to describe consumer preferences. Results show that high-ability, urban consumers are willing to pay a substantive monthly premium for an improvement in bandwidth relative to rural consumers.

1. Introduction

The U.S. Telecommunications Act of 1996 encouraged the "… reasonable and timely deployment of advanced telecommunications services to all Americans." Recently, several Federal and State subsidy programs have been promoting high-speed Internet access to health-care providers, libraries, and schools. Moreover, there has been some debate about extending these to households to help close the "digital divide."[1] However, much of this debate has taken place without formal economic analysis of consumer preferences for high-speed Internet access. This study examines two questions. What are household valuations for faster Internet access, i.e., bandwidth, and how do valuations of bandwidth vary with technical ability and urban versus rural location?

We address these questions by presenting a simple theory that considers a household's labor–leisure choice along with choices about the consumption of Internet bandwidth and time spent at the computer online. Households combine their technical ability, bandwidth, and time online to produce savings in the time required to do ordinary (but unpaid and necessary) tasks. Improvements in ability reduce the effective price of bandwidth and increase the demand for bandwidth. This possibility is examined empirically by estimating U.S. demand for Internet access. However, a problem with estimating U.S. demand arises from the limited data available to describe consumer preferences. Unlike regulated telephone markets, there is no Federal agency that collects data on prices, products and market sales. The discrete choice methods developed by Berry et al. (1995) cannot be implemented as it is not possible to identify the mean utility of a product without market share data. Moreover, even if these data were available, there is insufficient variation in product characteristics to identify important marginal utility parameters of interest. For example, Internet access service plans are typically structured so that the "always on" feature is bundled with a high-speed connection.

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[1] The digital divide describes the gap between people with access to information technology (IT) and those without, e.g., rich/poor, majority/minority race or urban/rural geographical location.

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We use an econometric approach that overcomes these problems by combining household data, obtained from consumer choices in both a real market and an experimental setting, with a well-specified discrete choice econometric model to identify consumer preferences for bandwidth.

The demand for bandwidth is examined with data collected by household survey. Respondents are presented with eight choice scenarios, and in each scenario, must choose between a pair of Internet access service alternatives that differ by five product attributes. The information in these choices is enriched with market data by having respondents indicate whether they would stay with their current (actual) Internet service or switch to the hypothetical service they had just selected. The parameters of the representative individual's utility function, and willingness-to-pay (WTP), are then estimated from the observed choices. Results show that high-ability, urban consumers are willing to pay a substantive monthly premium for an improvement in bandwidth relative to rural consumers. Given that rural locations have a smaller population, and all things being equal, a lower base of high-ability/high-valuation customers, this finding suggests that the potential for an urban versus rural digital divide in the U.S. may be somewhat overstated.

The paper is organized as follows. Section 2 reviews the recent literature on determinants of the Internet digital divide. Section 3 presents a simple theory of the demand for Internet bandwidth. The data, choice experiment and survey administration are described in Section 4. Section 5 outlines the empirical model and econometric method used to estimate consumer preferences for bandwidth. Empirical results are presented in Section 6, and Section 7 concludes.

2. Review

Several studies have empirically examined the potential for a digital divide in both the deployment and use of high-bandwidth telecommunications infrastructure. Gabe and Abel (2002) count the number of telephone lines in the U.S. with integrated services digital network (ISDN) capability from 1996 to 2000. They find that ISDN is more prevalent in urban areas and suggest that rural demand is insufficient to attract new investments in advanced telecom infrastructure. Prieger (2003) estimates a model that relates the decision by a broadband carrier to enter geographic markets to expected demand, costs and competition. Using data on broadband entry by zip code for 2000, he finds little evidence of unequal broadband availability based on income or on black or Hispanic concentration. He also finds that availability is lower in rural locations, while market size, education and commuting distance increase availability.[2]

Fairlie (2004) uses household data from the 2000 Current Population Survey to examine racial differences in Internet demand. He models the household's decision to purchase Internet access as a function of race and other demographics. Results show that racial differences in education, income and occupation contribute substantially to the race divide in residential access. Fairlie also finds a negative correlation between rural location and Internet access and suggests this may be due to relatively higher subscription prices. Using Forrester's household data at 2001, Goldfarb and Prince (2007) show that while income and education positively correlate with Internet adoption, they negatively correlate with time online. They argue that with fixed connection and near-zero usage fees, low-income people spend more time online due to their lower opportunity costs of time. Prieger and Hu (2008) examine the racial gap in Internet demand in 2000 by estimating the probability that at least one household in the census block subscribes to digital subscriber line (DSL) service. Results show that race matters independently of income, education and location, in the demand for DSL and that rural locations have lower demand. They argue that the lack of price competition may be creating some dimensions of the digital divide.

Chinn and Fairlie (2007) estimate Internet demand for 161 countries from 1999 to 2001. Their results suggest that the Internet divide between countries is mainly due to differences in income, telephone density and the propensity for market-orientated regulatory policies. Curiously, they find a negative correlation between urban population and Internet penetration, which contrasts the results of Fairlie (2004) and Prieger and Hu (2008). They argue that after controlling for telephone density, the Internet substitutes for the benefits that accrue in an urbanized environment. This result is consistent with the "global village" hypothesis of Forman et al. (2005) and implies that rural residents may be willing to pay more for faster Internet access.

In summary, existing studies have typically used aggregate data to estimate the effects of income, education, race, and location on broad measures of Internet penetration. None of these studies explicitly control for Internet prices and other quality attributes.[3] Furthermore, no study has used household-level data to examine how both the technical ability of users and their urban/rural location affect the demand for faster Internet access.

3. Theoretical background

Most empirical specifications of demand recognize that people have different tastes and control for preference heterogeneity with demographics and/or by estimating models with random parameters (Crawford, 2000; Riordan et al., 2003; Petrin and Train, 2004; Beckert, 2005; Lee et al., 2006). For many goods, the treatment of heterogeneity in estimation is clear, e.g., low-income households have less taste for price. However, preference heterogeneity for high-technology goods is less obvious and requires theory to guide the selection of demographics, their interactions with product attributes, and to form *a priori* expectations. We outline a simple theory of optimal choice for the Internet access attribute, bandwidth. The model explains why high-ability consumers value bandwidth differently and suggests that demographic proxies for ability should be included in empirical specifications of Internet demand.

The labor–leisure choice model is extended to include the benefits from using bandwidth (b) and time online (t) for networking, playing games, watching movies, etc., and the indirect benefits from using b and t for household production.[4]

[2] Chen and Savage (2007) find that about one-third of Oregon's cable TV franchises provided cable Internet access at 2006, and that cable Internet provision was more likely in densely populated franchises.

[3] Prieger and Hu (2008) indirectly control for DSL quality with a variable that measures the household's distance from the telephone company's central office.

[4] The model disregards the monetary benefits from using bandwidth and time online, and focuses solely on time savings. While more realistic, explicit consideration of these benefits unnecessarily complicates the results without changing key economic insights.

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The consumer is assumed to maximize a utility function of consumption (c), leisure (L), b and t, subject to monetary and time constraints. The inputs b and t also produce reductions in "essential time" defined as the non-remunerated time lost when participating in the labor market, plus time doing fundamental living activities such as banking, bill-paying, maintaining health, shopping, etc. Essential time is represented by the production function $\bar{T}(h, b, t; a)$, where h is the number of hours worked and a is an efficiency parameter that reflects the technical ability of the household. $\bar{T}$ is convex in b and t, and b and t are complements in production so that increasing b will raise the marginal productivity of t. Similarly, a augments the productivity of b and t, decreasing essential time for a given input level. As such, the partial derivatives $\bar{T}_b$, $\bar{T}_t$, $\bar{T}_a$, $\bar{T}_{bt}$, $\bar{T}_{ba}$, $\bar{T}_{ta}$, are negative, and the second partials $\bar{T}_{bb}$, $\bar{T}_{tt}$, are positive. Some of the time costs of work may be fixed. Others, including preparation, recovery, commuting and child care costs, may be concave in the number of hours worked so that $\bar{T}_h > 0$ and $\bar{T}_{hh} < 0$ (Heim and Meyer, 2004).

The consumer's maximization problem is:

$$\begin{aligned} &\max_{h,b,t} \quad U(c, L, b, t) \\ &\text{s.t.} \quad c = y + wh - p_b b - p_t t \\ &\qquad\quad L = T - h - t - \bar{T}(h, b, t; a) \end{aligned} \tag{1}$$

where U is utility, y is non-wage income, w is the wage rate, p_b is the per unit price of bandwidth p_t is the per unit price of time online and T is total time available.[5] Utility is concave in c, L, b and t so that U_c, U_L, U_b, $U_t > 0$ and U_{cc}, U_{LL}, U_{bb}, $U_{tt} < 0$, and the desirability of leisure increases with consumption so $U_{cL} > 0$.

First-order conditions with respect to the choice variables h, b, and t are:

$$\begin{aligned} h: &\quad 0 = U_c w - U_L\left(1 + \bar{T}_h\right) \\ b: &\quad 0 = -U_c p_b - U_L \bar{T}_b + U_b \\ t: &\quad 0 = U_c p_t - U_L\left(1 + \bar{T}_t\right) + U_t\,. \end{aligned} \tag{2}$$

The first condition in Eq. (2) equates the effective wage, $\hat{w} = w/(1+\bar{T}_h)$, with the marginal rate of substitution of leisure for consumption, U_L/U_c. Substituting $U_L/U_c = \hat{w}$ into the second condition gives $-(p_b - (U_b/U_c))/\bar{T}_b = \hat{w}$. This result shows that the consumer chooses optimal bandwidth b^* by equating the effective price of bandwidth per unit of time saved, $\hat{p}_b = (p_b - (U_b/U_c))/\bar{T}_b$, with the effective wage. Substituting $U_L/U_c = \hat{w}$ into the last condition gives $-(p_t - (U_t/U_c))/(1+\bar{T}_t) = \hat{w}$. This shows that the consumer chooses optimal time spent online t^* by equating the effective price of time online, $\hat{p}_t = -(p_t - (U_t/U_c))/(1+\bar{T}_t)$, with the effective wage.

The second condition in Eq. (2):

$$\hat{p}_b = -(p_b - (U_b/U_c))/\bar{T}_b = \hat{w} \tag{3}$$

[5] In many countries, consumers pay a fixed fee per month for Internet access and a usage fee per unit of time online. In the U.S., consumers typically pay nothing for usage, although usage fees are charged when a gigabyte threshold is reached in some markets. For e.g., see cable Internet service plans provided by BendBroadband Oregon at http://www.bendcable.com/residentialservices_08.cfm.

Table 1
Internet access price and attribute levels

Price/attribute	Levels		
COST (p)	\$10 to \$85 per month (in multiples of \$5)		
ALWAYS ON	1. Always on	2. Not always on	
INSTALL	1. Immediately	2. Within one week	3. Within several weeks
RELIABLE	1. Very reliable	2. Less reliable	
SPEED (b)	1. Very fast	2. Fast	3. Slow (same as dial up)

provides useful information about the effects of technical ability on the demand for Internet bandwidth, $\partial b^*/\partial a$. All other things being equal, an increase in ability, or "technical progress," permits the household to produce time savings more efficiently through $\bar{T}_b < 0$, which lowers the effective price of bandwidth p_b. As a result of this price decrease, part of the total effect of an increase in ability will always be an increase in the demand for bandwidth so that $\partial b^*/\partial a > 0$.[6] Condition (3) also provides a plausible explanation of how location affects demand. All other things being equal, location should not affect U_b; rural and urban households should obtain the same satisfaction from using bandwidth for networking, gaming, watching video, etc. However, because they would be required to travel longer distances to physically participate in these activities, the marginal time savings from Internet bandwidth through T_b are possibly larger for rural households, and they may have stronger demand for faster Internet access than urban households. In contrast, when their marginal time savings are small, rural demand may be relatively weak.

4. Data

4.1. Choice experiment

We examine the demand for bandwidth empirically with data from a mail questionnaire employing repeated discrete choice experiments. Respondents answer eight choice questions. In each choice occasion a pair of Internet access alternatives is presented. The two alternatives differ by five attributes. Respondents indicate their preference for choice alternative 1 or 2. Table 1 describes the Internet access price and quality attributes. COST (p) is the fixed monthly price for Internet access with unlimited usage. Access is ALWAYS ON when no dial up is required for Internet connection and respondents can use the Internet and place telephone calls at the same time. INSTALL reflects the time, cost, and complexity of ordering and installing a new Internet connection. Installation of an Internet service can be immediate, within one week, or within several weeks. Very RELIABLE Internet access is never disrupted, however, with less reliable Internet access users may occasionally experience slower speed, outages that require customer support, and their account may be transferred from one company to another. SPEED (b) is the time it takes to receive and send information to and from the home computer.

[6] This analysis does not consider the second-order "income effect" contained in comparative static results. When the second-order effect runs opposite to the effect described above, and has a relatively large magnitude, it is possible that $\partial b^*/\partial a \leq 0$.

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In addition, the information in these choices is enriched with market data by having respondents indicate whether they would stay with their current (actual) Internet service, the "status quo," or switch to the hypothetical service they had just selected, or if they would adopt the service selected if they did not already have service. The parameters of the representative individual's utility function are then estimated from the observed choices.

The experimental approach is useful because it exogenously determines the attributes and prices of each Internet access alternative offered and avoids collinearity problems by offering non-existing alternatives. For example, the values for the always on and bandwidth attributes change independently in hypothetical alternatives, as opposed to market data, where they often move together perfectly. By asking eight choice questions, we are able to generalize the model by identifying an additional variance parameter, increase parameter estimation precision and reduce sampling costs by obtaining more information on preferences for each respondent, and facilitate the fitting of random random-parameters models.

Our hypothetical choice data are enriched with revealed-preference information on each respondent's status quo alternative, chosen in the market for Internet access. While the use of market data in our experimental design helps alleviate any biases in the hypothetical choice setting, it may introduce an endogeneity problem concerning the positive correlation between market price and quality attributes observed by the consumer but not the econometrician (Berry et al., 1995). We address this potential problem empirically in Section 6.4.

The Internet access choice experiment was administered by household survey questionnaire. The questionnaire begins with 23 questions about the respondent's current use of information technology (IT). In this section respondents are provided with information about the Internet access attributes described in Table 1. This is followed by the choice task where each respondent is presented with eight questions that describe a pair of Internet access options, 1 and 2, that differ by the five attributes.[7] Respondents indicate their preferred choice. They then indicate whether they would switch to the service they had selected, or if they would adopt the service selected if they had none. Appendix A displays a choice question example. Finally, respondents are asked their age, employment status, household size, education level, wage rate, gender, zip code and race.

4.2. Survey and data

The gross sample consisted of 1240 addresses. These were randomly drawn from a database of households collected from all U.S. white-page telephone directories and proprietary sources of non-listed telephone households. Advance postcards were mailed on September 3, 2002 informing households that they would receive a survey in the mail in a few days and requesting their cooperation in completing the survey. The initial package with questionnaire, a $2 bill as an incentive, and postage-paid return envelope was mailed on September 6. Of the 1240 surveys sent out, 54 were undeliverable and four were deceased, reducing the gross sample to 1182. By the end of October 397 complete questionnaires were obtained with a unit response rate of 33.6%. Of these 397 completed questionnaires, 357

Table 2
Sample demographics (percent)

	U.S. census	Mail sample
Census region		
Northeast	19.1	16.5
Midwest	22.9	34.6
South	35.6	33.6
West	22.4	15.2
Sample size	–	381
Age		
18–24 years	13.3	3.9
25–34 years	18.1	15.0
35–44 years	21.8	19.4
45–54 years	18.9	23.9
55–64 years	11.9	20.7
65 years and over	16.1	17.1
Sample size	–	381
Race		
Black	11.9	4.4
White	83.2	91.2
Other	4.9	2.9
Sample size	–	385
Gender		
Male	48.0	55.9
Female	52.0	44.1
Sample size	–	392
Education		
Less than high school	15.8	4.6
High school	33.0	16.2
Some college	19.3	27.4
Associate degree	7.8	11.8
Bachelors degree and beyond	24.1	40.0
Sample size	–	390
Household income		
Under $10,000	7.4	2.6
$10,000–$24,999	18.4	8.3
$25,000–$49,999	28.5	21.5
$50,000–$74,999	20.0	29.7
$75,000 or more	25.7	38.3
Sample size	–	312
Years online		
Fewer than one year	n.a.	4.6
One to three years	n.a.	19.3
Three to five years	n.a.	23.9
More than five years	n.a.	42.6
Never been online	n.a.	9.6
Sample size	–	394
Employment status		
In labor force	65.3	68.9
Not in labor force	34.7	31.1
Sample size	–	351
Location		
Urban	34.7	42.7
Rural	65.3	57.3
Sample size	–	316

Notes: Years online is "years using the Internet to go online at home, school, work, and other locations."

[7] Measures developed by Zwerina et al. (1996) and Huber and Zwerina (1996) generate an efficient non-linear optimal design. A fractional factorial design created 64 paired descriptions of Internet service that were grouped into eight sets of eight questions, and randomly distributed across respondents.

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respondents answered all eight Internet access choice questions for an item response rate of 90%. The median completion time for each mail questionnaire was about 20 min.

A selection of sample demographics, along with similar data from the U.S. Census Bureau (2003), is presented in Table 2. The sample covers 44 states. The typical respondent is a white, 50 year old male with either some college (no degree), who resides in a household with 1.7 other members. He was employed last month at a location outside of the home, and has average annual household income $65,095. The sample is similar to the U.S. population with respect to geographic coverage, respondent's age, gender, employment status and urban/rural location. However, the sample has a higher percentage of both white and male respondents, and sample respondents are more educated and wealthier than the population.

4.3. Technical ability

We employ two indicators of technical ability in our empirical analysis. The first indicator is specific to the Internet task as it captures the relationship between Internet experience and the productivity of the individual when using the Internet. EXP_i equals 1 when the number of years the respondent has been using the Internet to go online at home, school, work, and other locations is less than one year; 2 for one to three years; 3 for three to five years; and 4 for over five years. The second indicator is more general in that it captures the relationship between education (i.e., years of schooling) and the productivity of the individual when using the Internet. EDUC_i equals 1 when the highest level of school completed is eighth grade or less; equals 2 for some high school; equals 3 for high school diploma or equivalent; equals 4 for some college, no degree; equals 5 for two-year degree or technical school; equals 6 for four-year college degree; equals 7 for some graduate training, no degree; and equals 8 for graduate degree.

There may also be other, unobservable indicators of ability, such as family background, motivation and propensity to be an early-adopter of IT, as well as tastes for bandwidth that are not measured in EXP and EDUC. We have information on these indicators and tastes, in the form of the respondent's status quo decision on the type of Internet access (i.e., no Internet access, dial up or high-speed) actually purchased for their home. This decision was made in the past and hence is exogenous to the choices of Internet access alternative 1 or 2 made in the choice experiments.[8] To control for unobservable indicators of ability and tastes for bandwidth, we use $\text{HS}_i=1$ if the household has high-speed Internet access and $\text{HS}_i=0$ if not.

Table 3 presents descriptive statistics for ability for the full sample and for the urban and rural subsamples. The full-sample mean value for EXP of 3.29 corresponds approximately to three to five years Internet experience. The full-sample mean value for EDUC of 5.04 corresponds closely to a two-year or technical school degree. About 22% of our full sample have (actual) high-speed Internet access in the home at October, 2002 (27% in urban areas and 17% in rural areas).

Table 3
Descriptive statistics

	Mean	S.D.	Min	Max
Full sample				
EXP	3.29	1.02	1	5
EDUC	5.04	1.75	1	8
HS	0.22	0.41	0	1
$n=357$				
Urban subsample				
EXP	3.30	1.00	1	5
EDUC	5.27	1.78	1	8
HS	0.27	0.44	0	1
$n=135$				
Rural subsample				
EXP	3.36	0.96	1	5
EDUC	4.90	1.77	1	8
HS	0.17	0.38	0	1
$n=181$				

Note. S.D. is standard deviation. Urban versus rural samples are measured by respondent's zip code and the Census Bureau's "rural region" definition (i.e., respondent resides in a zip code with population density less than 1000 persons per square miles).

5. Empirical model and econometric methodology

Our theoretical model shows that individual consumers may have heterogeneous preferences toward bandwidth. For the *i*-th respondent facing the *j*-th choice experiment, let the empirical model of the conditional utility for Internet access alternative 1 be:

$$U^1_{ij} = \beta_z' \boldsymbol{z}^1_{ij} + (\beta_s + \boldsymbol{a}_i'\delta) b^1_{ij} + \beta_p p^1_{ij} + \varepsilon^1_{ij}, \tag{4}$$

and similarly for alternative 2 (indicated by superscript), where $\boldsymbol{z}_{ij}$ is a vector of quality attributes, $\boldsymbol{a}_i$ is an $m\times1$ vector of indicators for an individual's technical ability (EXP_i, EDUC_i, and HS_i), b_{ij} is bandwidth, p_{ij} is the price of Internet access, and the elements of $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are preference parameters. For notational simplicity define:

$$\boldsymbol{x}_{ij} = \begin{pmatrix} \boldsymbol{z}_{ij} \\ \boldsymbol{b}_{ij} \\ \boldsymbol{a}_i\boldsymbol{b}_{ij} \\ p_{ij} \end{pmatrix}, \beta = \begin{pmatrix} \beta_z \\ \beta_s \\ \delta \\ \beta_p \end{pmatrix}, \tag{5}$$

so that Eq. (4) can be written

$$U^1_{ij} = \beta' \boldsymbol{x}^1_{ij} + \varepsilon^1_{ij}. \tag{6}$$

The unobserved, random errors ε^1_{ij} and ε^2_{ij} are assumed to be independent and identically distributed, mean zero, normal random variables, uncorrelated with the independent variables, with constant unknown variance σ^2.[9] The parameters

[8] This is similar to the lagged dependent variable argument. The decision to adopt high-speed access was made in the past, once. Now the respondent is faced with a questionnaire, and the fact that she adopted high-speed service in the past can be taken as pre-determined in our empirical model.

[9] We allow for correlation of errors for an individual when it comes to choices involving the status quo. For the hypothetical choices, there is no question of correlation since the effective errors that enter the likelihood are the *difference* in the two errors for any choice occasion, and the attribute sets are randomly assigned to choice "A" or choice "B". That is, the relevant distribution theory for forming the likelihood is based on $\varepsilon^1_{i1} - \varepsilon^2_{i1}$, for example (person *i*, first choice occasion–see Eq. (6)). In addition, any additive systematic component of the error is then eliminated. This is similar to the arguments of Heckman and Robb (1985) in their evaluation of social interventions.

of interest, β_s, β_p and $\boldsymbol{\delta}$, determine WTP for bandwidth, and indicate how price and technical ability affect the demand for bandwidth. Specifically, WTP is implicitly defined here as the amount the individual would be willing to pay for a one-unit increase in bandwidth, from b_{ij} to $b_{ij}+1$:

$$\begin{aligned} U_{|b} &= \beta_z' \boldsymbol{z}_{ij} + (\beta_s + \boldsymbol{a}_i'\delta) b_{ij} + \beta_p p_{ij} \\ &= \beta_z' \boldsymbol{z}_{ij}' + (\beta_s + \boldsymbol{a}_i'\delta)(b_{ij}+1) + \beta_p (p_{ij} - WTP) = U_{|b+1} \end{aligned} \tag{7}$$

which implies $\mathrm{WTP}_b = (\beta_s + \boldsymbol{a}_i'\boldsymbol{\delta})/\beta_p$. This means that $-\boldsymbol{\delta}/\beta_p$ provides estimates of $\partial \mathrm{WTP}_b / \partial \boldsymbol{a}$, i.e., how WTP varies with indicators of an individual's technical ability.

Utility for the (current) status quo Internet access service, U_i^0 under the model assumption (Eq. (6)) is given by:

$$U_i^0 = \beta_z' \boldsymbol{z}_i^0 + (\beta_s + \boldsymbol{a}_i'\delta) b_i + \beta_p p_i + \varepsilon_i^0 = \beta' \boldsymbol{x}_i^0 + \varepsilon_i^0, \tag{8}$$

where ε_i^0 are disturbances and $\boldsymbol{x}_i^0$ are the attributes of the individual's current Internet access. The attributes of the status quo vary over individuals, but not over choice occasions, so it is assumed that the utility of the status quo is evaluated only once by each individual (U_i^0 and ε_i^0 are subscripted with i only). The ε_i^0 are assumed to be independent, identically distributed normal random variables with zero expectation uncorrelated with ε_{ij}^1 and ε_{ij}^2. Because the question comparing the status quo with a hypothetical choice is asked separately and for each choice occasion, it is possible to econometrically identify the variance of these status quo errors. This is an advantage of our survey design, as there is no reason to assume these errors have the same variance as the ε_{ij}. We denote this variance by σ_0^2.

As in any discrete choice model, a normalization is required. Let $\sigma_\varepsilon^2 = 1/2$. Define $\lambda^2 = \sigma_0^2/\sigma^2 = 2\sigma_0^2$. When $\lambda = 1$, $\sigma^2 = \sigma_0^2$ and the choice 1 versus choice 2 question and the question comparing choice 1 or choice 2 to the status quo have equal weight in the likelihood. When $\lambda < 1$ the question relating to the status quo contains more information, as there is more variability in the errors for the 1 versus 2 question ($\sigma^2 > \sigma_0^2$), and conversely.

The probability of choosing alternative 1 over alternative 2 and then choosing alternative 1 over the status quo is the bivariate probability:

$$\begin{aligned} &P\left(U_{ij}^1 > U_{ij}^2, U_{ij}^1 > U_i^0\right) \\ &= \Phi_2\left[-\beta V\left(\boldsymbol{x}_{ij}^2 - \boldsymbol{x}_{ij}^1\right), -\beta V\left(\boldsymbol{x}_i^0 - \boldsymbol{x}_{ij}^1\right) / \sqrt{\left(1+\lambda^2\right)/2}; \rho\right] \end{aligned} \tag{9}$$

where ρ is the correlation between $\varepsilon_{ij}^2 - \varepsilon_{ij}^1$ and $\varepsilon_i^0 - \varepsilon_{ij}^1$,

$$\rho = \frac{\sigma_\varepsilon^2}{\sqrt{2\sigma_\varepsilon^2(\sigma_0^2 + \sigma_\varepsilon^2)}} = \frac{\sigma_\varepsilon}{\sqrt{2(\sigma_0^2 + \sigma_\varepsilon^2)}} = \frac{1}{\sqrt{2\left(1+\lambda^2\right)}}, \tag{10}$$

and Φ_2 is the standard bivariate normal cumulative distribution function. Similar expressions apply to choosing alternative 2 over alternative 1, and to choosing the status quo over either alternative (see Savage and Waldman, 2008). The likelihood is the product of probabilities like Eq. (9).

This analysis does not take into consideration the fact that the formation of that part of the likelihood involving the comparison of the chosen alternative to the status quo involves the error difference $\varepsilon_i^0 - \varepsilon_{ij}^1$ or $\varepsilon_i^0 - \varepsilon_{ij}^2$ (depending upon the choice), and from choice occasion to choice occasion these error differences are correlated. This correlation is induced by the common occurrence of ε_i^0, since respondents evaluate their utility of the status quo only once. This point is generally missed in other analyses of repeated choice experiments. Instead, we treat the person, and not the person-choice occasion, as the unit of observation, so that we may explicitly model this correlation. This is difficult, as a multiple integration of the multinormal density is required, and for eight choice occasions this would be computationally intractable. Fortunately, as the correlation between $\varepsilon_i^0 - \varepsilon_{ij}^1$ and $\varepsilon_i^0 - \varepsilon_{ij}^2$, for example, is a result of the common occurrence of ε_i^0, we can follow a familiar conditioning argument to express the probability of all eight choices of an individual as the integral of the product of eight, independent bivariate probabilities, integrated against the univariate normal density (see Waldman, 1985; Savage and Waldman, 2008). The cost of this generality is in programming and computer time, as the likelihood must be maximized by simulation or with quadrature methods. We used Hermite polynomial quadrature with 20 evaluation points (see Abramowitz and Stegun, 1964, p. 890).

6. Empirical results

The data from Section 4 are used to estimate U.S. Internet demand. We estimate the marginal utility of Internet access price and quality attributes, the WTP for improvements in these attributes, and how the WTP for bandwidth varies with ability and with urban/rural location. We also estimate λ, the ratio of the standard deviation of the errors in evaluating the status quo alternative to the errors in evaluating the hypothetical alternatives.

6.1. Marginal utility, willingness-to-pay and $\partial b^*/\partial a > 0$

The first panel of Table 4 contains maximum likelihood estimates of the model without the bandwidth-experience (SPEED × EXP), bandwidth-education (SPEED × EDUC), and bandwidth-high-speed (SPEED × HS) interactions. Except for INSTALL, all marginal utility parameters have signs predicted by theory and are statistically significant. Negative signs for these attributes imply that an individual's relative utility increases when Internet access is always on, price is decreased, access is improved from less to very reliable, and speed (bandwidth) is increased. Reliability and speed are important Internet access attributes. Estimates from this parsimonious model show that consumers are willing to pay \$15.25 per month for more reliable service and \$10.92 for an incremental improvement in speed. Consumers are also willing to pay \$5.70 for and Internet connection that is always on.[10]

[10] Note also that the estimates of λ, i.e., the ratio of the standard deviation of the errors in evaluating the status quo alternative to the errors in evaluating the hypothetical alternatives, are large enough so that the null hypothesis $\lambda = 1$ is rejected at the one percent level (t-ratio of about 6). A value of λ greater than one implies $\sigma_0^2/\sigma_\varepsilon^2 > 1$, i.e., that the variance of the error in evaluating the status quo is greater than the error in valuing a hypothetical alternative. One explanation for this finding is that experience with an actual Internet service is more multidimensional than is portrayed by our set of attributes, while the hypothetical choice presented by the survey instrument highlights the attributes in a cleaner manner.

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The second panel of Table 4 reports maximum likelihood estimates of the model including the observed bandwidth-experience (SPEED × EXP) and bandwidth-education (SPEED × EDUC) interactions, as well as the control for an unobservable indicator of ability, (SPEED × HS). The estimates for price and the quality attributes are close to those reported in the first panel. Consumers are willing to pay $15.52 per month for more reliable service and $5.63 for always on functionality. The estimated coefficients on the interactions indicate that the range of bandwidth valuations for individuals with different abilities can be quite large. For example, let us define low-, average- and high-ability consumers by the vectors $\boldsymbol{\alpha}_{Li}$ = [EXP_{Li}, $EDUC_{Li}$], $\boldsymbol{\alpha}_{Hi}$ = [EXP_{Hi}, $EDUC_{Hi}$] and $\boldsymbol{\alpha}_{Ai}$ = [EXP_{Ai}, $EDUC_{Ai}$], where the subscript L (H) indicates values of Internet experience and education one one-standard deviation below (above) their sample means, and the subscript A indicates mean values of Internet experience and education. Table 5 shows that when evaluated at the mean values for EXP and EDUC, consumers with no high-speed Internet access to their home are willing to pay $7.83 for an improvement in bandwidth while consumers with high-speed Internet access are willing to pay $24.14. Moreover, an increase in ability, measured by a one-standard deviation increase in both experience and education, translates into a $3.61 increase in WTP for bandwidth per month. This finding is consistent with $\partial b^* / \partial a > 0$ from our theoretical model.

Table 4
Maximum likelihood estimates of utility

	Without ability		With ability and bandwidth/speed interactions	
	Estimates	WTP	Estimates	WTP
	(t-ratios)	(t-ratios)	(t-ratios)	(t-ratios)
Attributes				
ALWAYS ON	−0.106	$5.70	−0.105	$5.63
	(5.20)[a]	(1.87)	(5.44)	(1.87)
SPEED (b)	−0.203	$10.92	0.062	$7.83/$24.14
	(10.88)	(1.89)	(1.11)	(1.05/1.56)[b]
COST (p)	−0.019	n.a.	−0.019	n.a
	(17.44)		(17.07)	
INSTALL	0.051	n.a.	0.059	n.a
	(3.00)		(3.74)	
RELIABILITY	−0.284	$15.25	−0.291	$15.52
	(12.24)	(1.86)	(13.40)	(1.78)
Interactions				
SPEED × EXP			−0.033	
			(2.57)	
SPEED × EDUC			−0.020	
			(2.63)	
SPEED × HS			−0.306	
			(8.23)	
Variance ratio				
λ	1.529[c]		1.693	
	(5.99)		(6.74)	
Mean Log-L	−9.307		−9.173	

n = 357, J = 8.
[a] t-ratios for coefficients of attributes are for tests of H_0: $\beta = 0$.
[b] WTP and t-ratio for HS = 0 / 1.
[c] t-ratios for λ are for tests of H_0: $\lambda = 1$.

Table 5
Full Full-sample estimates of WTP for bandwidth

Ability	HS = 0	HS = 1
Low (L)	$4.22	$20.53
Average (A)	$7.83	$24.14
High (H)	$11.44	$27.75

Notes: Low- and high-ability consumers are defined by the vectors $\boldsymbol{\alpha}_{Li}$ = [EXP_{Li}, $EDUC_{Li}$], $\boldsymbol{\alpha}_{Hi}$ = [EXP_{Hi}, $EDUC_{Hi}$], where L(H) indicates values of Internet experience and education one one-standard deviation below (above) their sample means. Average-ability consumer is defined by the vector $\boldsymbol{\alpha}_{Ai}$ = [EXP_{Ai}, $EDUC_{Ai}$], where A indicates mean values of Internet experience and education. HS = 0 indicates the household does not have actual high-speed Internet access. HS = 1 indicates the household has high-speed Internet access.

6.2. Urban versus rural location

To examine variation in bandwidth valuations by location, we use zip zip-code data and the “rural region” definition from the U.S. Census Bureau (i.e., respondent resides in a zip code with population density less than 1000 persons per square miles) to measure each respondent's urban/rural location. Because some respondents did not provide zip zip-code information in the survey, the sum of observations for the urban (n = 135) and rural (n = 181) subsamples is less than the full sample (n = 357). The mean population density for the urban sample is 3620 persons per square miles and the mean population density for the rural sample is 278 persons per square miles.

Maximum likelihood estimates of the model for the urban and rural subsamples are reported in Table 6, in the columns marked “Fixed β_s.” Again, estimates for price and the quality attributes are qualitatively similar to those reported for the full sample in Table 4. Urban consumers are willing to pay $19.04 per month for more reliable service, and $3.70 for an always on connection. Rural consumers are willing to pay $18.02 per month for more reliable service, and $7.76 for an always on connection. Table 7 shows that urban consumers with average ability and no high-speed Internet access to their home are willing to pay $8.09 for an improvement in bandwidth while corresponding consumers with high-speed Internet access are willing to pay $25.45. Rural consumers with average ability and no high-speed Internet access to their home are willing to pay $9.44 for an improvement in bandwidth while corresponding consumers with high-speed Internet access are willing to pay $24.45. The effect of ability on WTP for bandwidth is higher for urban consumers. An increase in ability now translates into a $3.07 increase in WTP for bandwidth per month for urban consumers compared to $1.15 for rural consumers.[11]

[11] Our WTP measures are reported the conventional way, in dollars and cents, e.g. $25.45, although they are not so accurately estimated. The relatively large standard errors on these estimates are due in part to the fact that they are nonlinear combinations of parameters (in particular involving a ratio of estimated coefficients), as in the discussion below Eq. (7). While we can fairly accurately estimate the effects on the valuation of bandwidth in the consumer's utility function, the complexity of the WTP calculation, compounded by the need to approximate standard errors with the delta method, necessarily means that WTP estimates will be imprecise.

Table 6
Urban and rural subsamples with and without a random bandwidth parameter

	Urban $n=135$				Rural $n=181$			
	Fixed β_s		Random β_s		Fixed β_s		Random β_s	
	Estimates (t-ratios)[a]	WTP (t-ratios)[b]	Estimates (t-ratios)	WTP (t-ratios)	Estimates (t-ratios)	WTP (t-ratios)	Estimates (t-ratios)	WTP (t-ratios)
Attributes (β's)								
ALWAYS ON	−0.069	$3.70	−0.106	$5.01	−0.150	$7.76	−0.224	$7.93
	(1.79)	(1.09)	(2.14)	(0.54)	(5.04)	(1.43)	(5.42)	(0.78)
SPEED (b)	0.023	$8.09/$25.45	0.224	$8.60/$28.80	−0.106	$9.44/$24.45	−0.227	$8.66/$25.05
	(0.41)	(0.82/1.07)	(1.19)	(0.58/0.56)	(1.12)	(1.20/1.25)	(1.32)	(0.83/0.78)
COST (p)	−0.019	n. a.	−0.021	n. a.	−0.019	n. a.	−0.028	n. a.
	(10.43)		(5.69)		(12.16)		(7.79)	
INSTALL	0.031	n. a.	0.043	n. a.	0.018	n. a.	−0.012	n. a.
	(1.18)		(1.48)		(0.88)		(0.45)	
RELIABILITY	−0.355	$19.04	−0.380	$17.41	−0.347	$18.02	−0.517	$18.32
	(8.73)	(1.08)	(5.11)	(0.58)	(10.38)	(1.35)	(8.38)	(0.80)
Interactions (δ's)								
SPEED × EXP	−0.005		−0.038		−0.021		−0.049	
	(0.27)		(0.80)		(1.09)		(1.13)	
SPEED × EDUC	−0.030		−0.054		−0.001		0.030	
	(2.51)		(2.07)		(0.12)		(1.34)	
SPEED × HS	−0.323		−0.429		−0.289		−0.462	
	(5.68)		(3.94)		(14.70)		(4.03)	
Random-parameter standard deviation								
σ_u			0.447				0.457	
			(7.08)				(7.81)	
Variance ratio								
λ	1.498		1.875		1.487		2.034	
	(13.02)[c]		(1.76)		(14.70)		(3.15)	
Mean Log-L	−9.177		−10.165		−9.072		−9.981	

[a] t-ratios for coefficients of attributes are for tests of H_0: $\beta=0$.
[b] WTP and t-ratio for HS = 0 / 1.
[c] t-ratios for λ are for tests of H_0: $\lambda=1$.

6.3. A random random-parameters model

Another way to model the relationship between the marginal utility of bandwidth and ability is to write:

$$\beta_{si} = \delta_0 + \delta' \boldsymbol{a}_i + u_i \tag{11}$$

where the $\boldsymbol{\beta}_{si}$, $i=1,\ldots,n$ are the individual marginal utilities of bandwidth, $\boldsymbol{\alpha}_i=[\text{EDUC}_i, \text{EXP}_i, \text{HS}_i]$, δ_0 and the elements of δ are unknown parameters, and u_i is a random disturbance with mean zero and variance σ_u^2, assumed to be uncorrelated with the ε_{ij}'s.[12] Substituting Eq. (11) into Eq. (4) yields

$$U_{ij}^1 = \beta_z' \boldsymbol{z}_{ij}^1 + (\delta_0 + \delta' \boldsymbol{a}_i + u_i) b_{ij}^1 + \beta_p p_{ij}^1 + \varepsilon_{ij}^1. \tag{12}$$

Operationally, this is a model with bandwidth (δ_0), interactions between the observed indicators of ability and bandwidth ($\boldsymbol{\delta}'\mathbf{a}_i$), and a random parameter (u_i) on bandwidth itself. As a result of this specification, the estimated coefficient on bandwidth now has a probability distribution, with mean $\delta_0+\boldsymbol{\delta}'\mathbf{a}_i$ and variance σ_u^2. The fixed parameter model is a special case of this model, with $\sigma_u^2=0$.

Maximum likelihood estimates of this model are reported in Table 6 in the columns marked “Random β_s” for the urban and rural subsamples. Household valuations for RELIABILITY and ALWAYS ON are similar to those reported above, and are similar between locations: urban consumers are willing to pay $17.41 per month for more reliable service and $5.01 for always on functionality; rural consumers are willing to pay $18.32 per month for more reliable service and $7.93 for always on functionality.

Focusing on the marginal utilities of bandwidth, $\boldsymbol{\beta}_{si}$, we first observe that the estimated standard deviation of the bandwidth parameter, σ_u, is about 0.45 in both subsamples, and it is accurately estimated, with a t-statistic greater than seven. Although the mean WTP is similar in both the fixed- and random-parameter models, the magnitude of the estimate of σ_u indicates considerable individual variation in the valuation of bandwidth. The variation can be best seen by scaling by the cost parameter estimate, that is, with respect to WTP. For either the rural or urban subsamples, a one-standard deviation difference in the bandwidth parameter is associated with a difference of approximately $16 in WTP.

The “Random Parameter” panel of Table 7 shows that urban consumers with average ability and no high-speed Internet access to their home are now willing to pay $8.60 for an improvement in bandwidth while corresponding consumers

[12] To estimate the model by maximum likelihood we will assume that the u_i are normally distributed, although in reality the distribution of the u_i must be bounded from below at $-(\delta_0+\delta' a_i)$.

Table 7
Urban and rural estimates of WTP for bandwidth

	Fixed parameter				Random parameter			
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
Ability	HS=0		HS=1		HS=0		HS=1	
Low (*L*)	$5.02	$8.29	$22.38	$23.30	$2.21	$8.88	$22.41	$25.27
Average (*A*)	$8.09	$9.44	$25.45	$24.45	$8.60	$8.66	$28.80	$25.05
High (*H*)	$11.16	$10.59	$28.52	$25.60	$14.99	$8.44	$35.19	$24.83

Notes: Low- and high-ability consumers are defined by the vectors $\boldsymbol{\alpha}_{Li}$=[EXP$_{Li}$, EDUC$_{Li}$], $\boldsymbol{\alpha}_{Hi}$=[EXP$_{Hi}$, EDUC$_{Hi}$], where *L*(*H*) indicates values of Internet experience and education one one-standard deviation below (above) their sample means. Average-ability consumer is defined by the vector $\boldsymbol{\alpha}_{Ai}$=[EXP$_{Ai}$, EDUC$_{Ai}$], where *A* indicates mean values of Internet experience and education. HS=0 indicates the household does not have actual high-speed Internet access. HS=1 indicates the household has high-speed Internet access.

with access are willing to pay $28.80. Rural consumers with average ability and no high-speed Internet access to their home are willing to pay $8.66 for an improvement in bandwidth while the average consumer with access is willing to pay $25.05. The effect of ability on WTP for bandwidth is much higher for urban consumers. The incremental increase in ability now translates into a $6.39 increase in willingness-to pay for bandwidth per month for urban consumers, which is consistent with $\partial b^*/\partial a>0$. In contrast, the impact of an increase in ability for rural consumers' WTP is relatively small and negative. These marginal effects indicate, as highlighted in Table 7, that high-ability, urban consumers are willing to pay a substantial monthly premium for more bandwidth relative to high-ability, rural consumers.

6.4. Endogeneity of status quo price

When unobserved quality and price are positively correlated in the status quo alternative, ε_i^0 will not have constant mean conditional on price and the estimated coefficient on price will be biased toward zero. Because our experimental design exposes different consumers to randomly assigned prices and qualities, error differences are not correlated with prices. To support this claim we investigate whether price for the status quo alternative (i.e., PRICE) is correlated with the respondent's propensity to select the status quo over the 1 *or* 2 alternative (i.e., STATUS_QUO).[13] All other things equal, a positive correlation suggests the higher-priced status quo alternative is chosen with more frequency because price reflects some unobserved quality that is valuable to the respondent. The correlation between PRICE and STATUS_QUO is 0.070 and not statistically significant for all respondents (n=359). When we exclude respondents who do not pay for Internet service, the correlation is −0.053 and not significant (n=278).

6.5. Policy discussion

Our empirical results help shed light on some of the commercial and public policies prevailing in the U.S. First, the estimated large differences in bandwidth valuations between low- and high-ability urban consumers are consistent with price variation in residential Internet plans. Internet access providers typically provide two or more versions of high-speed Internet access, with the monthly subscription price increasing with the downstream speed to the home, and consumers select into the appropriate version according to their preferences. This pricing practice has the potential to increase societal welfare when low-valuation consumers, who otherwise would not be served under uniform pricing, are able to get high-speed Internet access.

Our results also indicate that valuations of bandwidth for rural consumers with average to high ability are relatively low. This finding complements the empirical evidence from Gabe and Abel (2002), Prieger (2003), and Chen and Savage (2007), who show that limited supply of high-speed Internet access to rural areas. Rural locations have lower population, and all things being equal, a lower base of high-ability/high-valuation customers. Although the cost of deploying advanced telecommunications infrastructure can be lowered with policies, such as investment allowances and matching investments from local governments, often, demand is simply not sufficient to justify the costly upgrades to local cable TV and telephone networks. It is in these low-population density markets that we are much more likely to observe the satellite provision of high-speed Internet, a technology that is better able to balance the relatively higher fixed costs of entry against a potentially larger national subscriber base.

Finally we note that although the FCC has the authority to add high-speed Internet to the list of residential telecommunications services supported under federal Universal Service programs, thus far, it has not chosen to do so. Of course, this could be due to, among other things, political considerations and/or a lack of suitable funding mechanisms. However, this decision may also recognize that the potential for a rural Internet divide, as indicated by our demand-side results, is somewhat overstated. For example, our estimated valuations of bandwidth suggest that most rural demand can be adequately met by the market with dial up and satellite technologies, and also with public provision through libraries, schools, etc.

7. Conclusions

This paper examined consumer preferences for Internet bandwidth, focusing on technical ability and urban/rural location as sources of preference heterogeneity. An economic

[13] PRICE is the price for the status quo alternative. STATUS_QUO is the number of times this alternative was chosen over alternative 1 *or* 2 (this variable has range 0 through 8). The mean and standard deviation for STATUS_QUO for respondents that do not pay for home Internet service are 4.14 and 3.09, respectively. The mean and standard deviation for respondents that do pay are 5.12 and 2.52, respectively. The mean and standard deviation for PRICE for respondents that do pay are 15.55 and 16.68.

model is outlined that shows that ability enables more efficient use of the Internet, and decreases the effective price of bandwidth. As a result of this decrease, part of the total effect of an increase in ability will always be an increase in the demand for bandwidth. We investigated this implication empirically on experimental and market data obtained from an Internet access choice survey.

It is important to account for indicators of technical ability, such as family background, motivation and propensity for early IT adoption, as well as tastes for bandwidth that are not measured in conventional indicators such as education and experience. By design, our choice experiment generated information on these indicators, in the form of the respondent's (status quo) decision on the type of Internet access actually purchased for their home, and this information is used in the estimation of the random utility model. We also permit another source of unobserved heterogeneity in consumer preferences for bandwidth by estimating a random random-parameters model.

Our results show that, whereas the estimate of WTP for an incremental improvement in bandwidth from the most parsimonious model is a good measure of the welfare for the *average* individual, we see from the model specifications with bandwidth interactions that the range of estimates for individuals with different abilities is quite large. In fact, urban consumers with relatively high technical ability are willing to pay a substantive monthly premium for an improvement in bandwidth relative to rural consumers. In terms of public policy, this finding suggests that the potential for a rural digital divide in the U.S. may be somewhat overstated.

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Appendix A. Choice question example

Q1a. Check the Internet access option you would prefer (even if you do not view either A or B as ideal, tell us which you would most prefer):

Attribute	A	B
Always on	Always on	Not always on
Speed	Slow	Fast
Cost	$25/month	$45/month
Installation	Immediate	Immediate
Reliability	Less reliable	Very reliable
Mark the option you prefer:	❑	❑

Q1b. If you currently have Internet access at home, consider the always on, speed, cost and reliability features of your service. Would you switch to the access option (A or B) you chose above? (mark one answer)

❑ Yes ❑ No

If you do not currently have Internet access at home, would you adopt the access option (A or B) you chose above? (mark one answer)

❑ Yes ❑ No

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