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Locating digital divides at home, work, and everywhere else

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Abstract

Contributing to previous research that has identified differences in connection speed, user skill, and experience as mechanisms affecting digital divides among Internet users, this paper explores whether location of use should be considered a factor that limits or facilitates individual efforts to apply the Internet toward beneficial activities. At some locations, Internet users enjoy high levels of autonomy, while at others, users may be regulated by restrictions or concerns about surveillance. Results of analyses performed on Current Population Survey (CPS) data suggest that users who have many connection points including home are most likely to conduct four particular activities for which previous research has demonstrated some tangible benefit to users: searching for health and product information online, making purchases online, and banking online. Most broadly, results support the proposition that differences in Internet access point quality can be identified as a previously unexplored digital divide among users, and also that differences in locations of use can partly explain gaps in participation in some beneficial activities by income and education.
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1. Introduction

As flexible communication, information search, entertainment, and transaction tools, Internet-connected devices can be applied to an ever-growing number of online activities. Individuals who go online can search for health, product, or consumer information, submit forms to government or private organizations and receive information in return, play computer games, listen to music, shop, communicate, and apply for jobs (Fig. 1). While a statement might be made in favor of all online activities, some uses of the Internet may enable individuals to acquire human, social, or cultural capital more efficiently and effectively than they might otherwise (Dimaggio et al., 2004). To the extent that certain capital-enhancing activities are becoming mainstream, non-participants may find themselves excluded from major cultural phenomena that will become increasingly important to the way people live and work. While the Internet is still a far cry from

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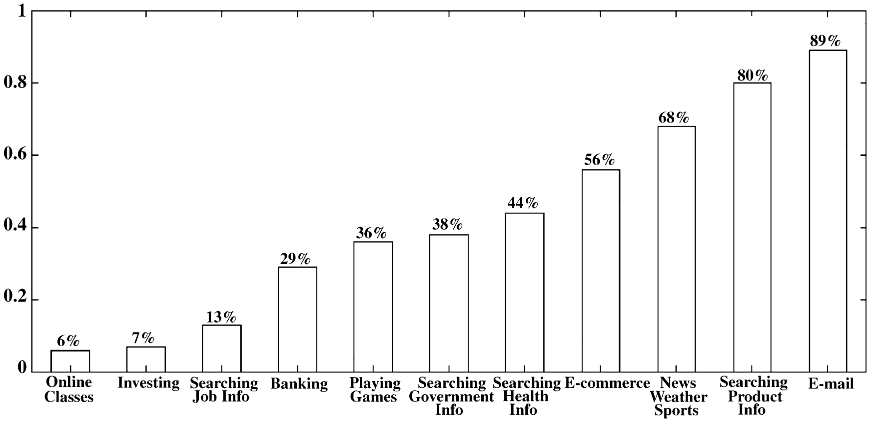

Source: CPS, October 2003 School Enrollment and Computer Use Supplement.

Fig. 1. Percent of Internet users age 18 and over performing various activities, $N = 60{,}593$.

the fingertips of all members of the population in both developed and less developed countries – its current high level of diffusion in some places has prompted interest in understanding second-level digital divides: the reasons for and consequences of the varying ability of Internet users to take full advantage of Internet technology to enhance their social, human, or economic capital (DiMaggio and Hargittai, 2001; Hargittai, 2002). This paper engages with previous research on digital inequality and considers whether variation in the quality of locations people use to connect – such as home, work, school, and public places – should be identified as a contributing factor to inequality among Internet users. Data are drawn from the U.S. case, an appropriate but only one of many possible research sites that could be used to examine second-level digital divides: in the U.S., Internet users now constitute two-thirds of the population (Pew, 2005a).

The locations people rely upon to connect to the Internet vary according to the autonomy people feel they permit and the autonomy that locations actually permit. For example, users may constrain their online activities if they feel that their actions are monitored by workplace Internet tracking software or they may experience low autonomy at the library if they must complete all their activities within a limited time frame. The analysis described in this paper focuses on four Internet activities: searching for product information online, making purchases online, doing one's banking online, and searching for health information online. While there are myriad ends to which people apply the Internet, this paper is limited to a small subset of popular online activities that existing research suggests may offer some tangible benefit to users. Morton et al. (2001) and Brown and Goolsbee (2002) explore the connection between Internet use and prices paid by consumers. The findings in their respective studies on the automobile and insurance industries suggest that applying the Internet toward product information searches and transactions can result in cost savings to consumers. The reason may be that the accessibility of information over the Internet may help reduce information asymmetry between consumers and providers of goods and services. In terms of non-economic benefits, some existing research shows that searching for health information online gives individuals a sense of being informed, empowered, and in control of their health (Baker et al., 2003; Eysenbach, 2003). The benefits of online banking can be inferred from its popularity: of all online activities, online banking has maintained the highest rate of growth during the past few years (Madden and Rainie, 2003). The prevalence of banking online, especially among the wealthiest and most educated, suggests that users must be deriving some utility from making transactions online, even if only convenience and efficiency. Conducting product and health information searches, making purchases online, and doing one's banking online seem to provide opportunities for individuals to enhance their economic wellbeing through savings of time and money and emotional wellbeing through having access to valued information.

Understanding the Internet's potential to bring other kinds of community-level or individual benefits are no less important. Internet technology may also enable greater political participation (Polat, 2005), opportunities for community connectedness and sociability (Quan-Haase et al., 2002; Robinson et al., 2002; Howard et al., 2002), and learning benefits (Kazmer, 2005). Space limitations prevent analysis of a greater number of activities than those considered here; the purpose of considering more than one activity in this paper is to explore the robustness of any identified effect of access point location on the propensity to make productive use of Internet technology. Can the quality of locations where individuals connect to the Internet be seen as contributing to patterns of advantage and disadvantage across the population of Internet users? If location matters, which locations are best?

Results of the analysis contained in this paper support the following key conclusions: (a) despite a strong U.S. policy focus on bringing Internet connectivity into private homes, having an Internet connection at home is an important but insufficient measure of how access locations may relatively enable and constrain individuals in online pursuits; (b) users who utilize many access points have a higher propensity to do the online activities considered in this paper, but access points are not substitutable: some locations offer more freedom and privacy than others; and (c) a large part of the effect of having a particular income and education level on propensity to do the online activities considered here may be explained by the locations at which users go online. Thus, location can be considered a mechanism by which education and income operate to produce differences in the ability of Internet users to marshal the flexible power of the Internet for personal benefit and enrichment.

This paper begins with a review of some existing research on the digital divide. The first section discusses the digital divide – as identified as trends in the differences between the Internet 'haves' and 'have-nots' – and the second addresses multiple digital divides among users such as connection speed, user skill, and experience. Then, the possible role of location of use in present patterns of digital inequality is discussed.

2. A nation digitally divided

Previous research on unequal access to the Internet has contributed a fairly clear picture of how the most digitally deprived – no access from any location – are distributed across sociodemographic categories, and how that distribution has changed over time. The focus of research and data collection on the so-called "digital divide" has been on the diffusion of Internet-connected computer ownership across households (NTIA, 1995) or of Internet use at any location across individuals (NTIA, 2000). Inequality, in these studies, tends to be expressed as the difference between the Internet "haves" and "have-nots," no matter how "having" the Internet is defined. In an important departure from looking purely at growth and diffusion, some research has focused on the spread of Internet non-use and has found that a small minority of individuals – most commonly individuals who by demographic characteristics are least likely to use the Internet in the first place – stop using the Internet, or "drop out" every year (Katz and Rice, 2002; Katz and Aspden, 1997). Incidences of dropping out notwithstanding, Internet use increased across all segments of the U.S. population over the past decade, albeit at different rates.

Differences in adoption rates have led some demographic differences to largely disappear while others have persisted. The basic access gap by gender has drastically declined: men and women had significant differences in their rate of Internet use through the 1990s but those differences have largely disappeared (Ono and Zavodny, 2003). Differences between urban and rural dwellers have also declined (Bikson and Panis, 2000). Some trends have been interpreted in conflicting ways depending upon which measurement conventions analyses employ (Martin, 2003). The trend in inequality by race is one example of a trend that has been interpreted in different ways: the rate of percentage increase in the proportion online is greater for blacks than it is for whites, but at the same time the rate of absolute increase in the percentage of the population online is larger for whites (Dimaggio et al., 2004). Despite different interpretations of how differences by race will fare over time, at present blacks are still less likely to use the Internet than whites. Additionally, younger, better educated, and richer people are significantly more likely to use the Internet than their older and less socioeconomically advantaged counterparts (Pew, 2005b).

3. Inequality among users

Dimaggio et al. (2004) and Warschauer (2003) can be credited for helping to move discussion of inequality beyond the use and non-use dichotomy to the notion of inequality as a spectrum shaped by many factors. Warschauer (2003) argues that these factors can be grouped into the following categories: the physical, digital, human, and social resources upon which individuals draw as they engage with technology. These factors are not mutually exclusive: factors of one type can be strongly related to others. For example, there are at least two possible ways in which low-income status – lack of financial resources – may influence Internet use. Low-income persons are less likely than their high-income counterparts to make purchases online (e-commerce), which can be partially explained as the direct effect of having little money with which to shop. It may also be true that with higher frequency than people with large incomes, low-income Internet users use slower connections and old equipment, which can inhibit them from visiting graphically complex sites. The former explanation of differences in e-commerce behavior inheres in the experience of being low-income while the latter explanation offers a mechanism by which low-income status may operate: by shaping available digital resources. Dimaggio et al. (2004) offer a specific framework for understanding how variations in conditions of use may influence differences in returns to time spent online. Patterns of "digital inequality," are shaped by five conditions: (1) variation in the technical means by which individuals connect to the Internet; (2) the degree of autonomy users enjoy (time, freedom); (3) level of skill; (4) nature, type, and amount of social support (someone to go to for help); and (5) the purposes to which people apply their Internet use (activities). Hargittai (2003b) adds "experience" to this list. The central proposition of this work is that individuals are differently enabled to extract benefits from Internet technology based on a constellation of factors that affect the conditions of their use. These factors can be shaped by resources such as income, education, the quality of equipment, skill of the user, as well as aspects of the social context of use. In this perspective, users are arrayed along a spectrum of ability to take full advantage of what the Internet has to offer, which casts the old digital divide literature in a new light: individuals who do not use the Internet at all simply receive zero benefit.

One approach to examining inequality among users has been to determine how differences in connection speeds, a digital resource, is associated with Internet use. In particular, studies have explored how home users who connect at high speeds using broadband connections differ in their patterns of use from home users with dial-up connections. Generally speaking, broadband enables a higher level of use because it involves an always-on connection as well as rapid page loading and file downloading. In its most recent report, The National Telecommunications Information Agency (NTIA) finds that home broadband users are more likely to log on frequently and to use the Internet for a wide variety of purposes, especially for obtaining information and banking online (NTIA, 2004). Similarly, Horrigan and Rainie (2002b) find that the average home broadband user undertakes seven types of activities online per day while the home dial-up user carries out three types of activities.[1] Home broadband users are also more likely than dial-up users to go online on any given day, undertake financial transactions online, and produce online content (Horrigan and Rainie, 2002b).

Users who have more experience with the Internet and who use it frequently differ significantly in their patterns of Internet use from individuals to whom the Internet is relatively new and who connect less often. Horrigan and Rainie (2002a) find that after users gain experience, they participate in a larger number of activities per online session even as the length of their average session becomes shorter. Wasserman and Richmond-Abbott (2005) show that differences in web knowledge between men and women are at least partially attributable to gender differences in frequency of use. Howard et al. (2002) suggest that frequency of use and length of experience with the Internet are the two most important predictors of the uses to which individuals put the Internet. Hargittai (2003a) concludes that time spent online is related to level of skill, which she defines as the level of efficiency and effectiveness with which individuals locate information online.

The role that social context may play in shaping use has been examined in a limited number of studies. Attewell (2001) concludes that supervision is essential for helping students use the computer for learning rather than purely for entertainment. In a study that addresses the location of computer use, Attewell and Battle (1999) find that eighth-grade students with home computers perform better on math and English exams than do students who do not have home computers. Though the study did not address the extent to which students relied on school computers and it did not collect data on Internet use, it does suggest that using a computer at home is measurably beneficial. In another approach to social context, Kling (1998) argues that social support is essential for users to take full advantage of the Internet: without adequate numbers of technical support staff at institution-based access points, users may be constrained by technical challenges.

Demographic characteristics are also associated with particular patterns of Internet use. In a study based in Switzerland, Bonfadelli (2002) finds that people with high education tend to use the Internet more for education and service-related purposes while people with low education are more likely to undertake entertainment activities online. Furthermore, men express greater interest than women in using the Internet for education-related activity and online banking, while younger users are more interested in chatting, online games, and listening to music online. Broos (2005) finds that gender is significant even despite gains made in some countries toward closing the gender digital divide: though women may be using the Internet now with greater frequency than they used to, women experience greater computer anxiety than men even when computer experience and self-perceived computer and Internet experience are held constant. This pattern suggests that among users, existing gender differences may persist and preclude more equitable access to benefits Internet use can afford.

[1] This report draws its data from the Pew Internet and American Life Project, which has gathered data on 31 different types of online activity that are classified under the following headings: communications, information seeking, information producing, downloading, media streaming, transactions, and entertainment.

4. Locating autonomous use

Dimaggio et al. (2004) suggest three "increasingly demanding" definitions of access: the first is using the Internet from any location, the second is using the Internet at home with a dial-up connection, and the third is using the Internet from home with a high-speed broadband connection. Including home as a feature of the two most demanding definitions of access suggests that – of all locations one could use to log on to the Internet – home is best. A host of reasons support the proposition that aspects of access points outside the home may limit users in their efforts to search, communicate, or transact online. At work, users may be limited in their ability to undertake online activities due to the prevalence of surveillance technologies that are designed to monitor employee Internet activity. In 2001, the American Management Association (2001) concluded that 63% of large employers monitored employee Internet connections. In a follow-up study, the AMA (2003) reported that over half of managers in a sample of 1100 indicate that their organization engages in some form of email monitoring. At public places like libraries, there may be time limits on use, getting there may be more inconvenient than going home or to work, and if users cannot provide their own portable computing devices, they are limited to the quality of equipment and connections public places provide. Even if formal time or use regulations are absent at public places, users may be concerned about the privacy of their activities online – especially if activities involve personal information that could remain on public computers after a session is over. Due to the absence of regulation and high level of privacy, home may allow Internet users the greatest ease of access as well as the greatest freedom of use. In other words, home may provide users with the highest level of autonomy. Work may offer the next highest level of autonomy: ease of access is high, but freedom may be low due to regulation or surveillance. Schools, cafes, libraries, and other public places may offer users the lowest level of autonomy: users may have low ease of access as well as regulation of scope or amount of use.

While home may be the most enabling location of Internet use, failing to consider the many combinations of locations people use to connect to the Internet may prevent gaining a clear picture of how the locations people use to connect may relate to the scope of the activities they pursue online. Some home users connect to the Internet only at home, some home users connect to the Internet at work, and other home users also use the Internet at public places. If logging on at places outside the home provides little added value to users with home connections, there would be little difference in use patterns between individuals with only home access and those with home access who also log on at other places. If this were the case, the only relevant distinction among users would be whether or not users have home access. Recent studies suggest that even if home is the best location of use, there may be value added to having locations of use outside the home. More specifically, the quality of access points outside the home may not be as low – in terms of freedom and convenience – as previous research implies. The speed of connection, the availability of computers, and the presence of technical support have improved at institution-based access points across the country. Broadband has diffused widely across institutions including libraries, schools, coffee shops, and other public access points. The National Center for Education Statistics (2002) estimates that 85% of public schools offered broadband Internet connections in 2001, with 93% of schools with high minority enrollments offering broadband. About 50% of library outlets provide T1 or faster connection speeds, with 47% of libraries in high poverty areas providing broadband.[2] Libraries have increased the number of Internet connections

[2] From fastest to slowest, popular methods of connection are T3, T1, cable, DSL, ISDN, and dial-up.

available to patrons: in 2000, an average of 8.3 connections were designated for patron use; by 2002, that number increased to 10.8 (Bertot, 2002). At libraries around the nation, outreach programs geared toward teaching Internet search and online transaction skills are offered regularly; some even include training in how to engage in e-commerce (McClure et al., 2002). To serve a wider array of patrons and to provide an additional level of convenience, many public and private places are increasingly offering wireless connections to patrons who can provide their own computing equipment. Even if some individuals are unable to take advantage of this service, general use of wireless or plug-in connections by other patrons may in some instances free up time at computers provided at the premises. The institutional resources that patrons may access and the convenience of multiple access locations may contribute to greater autonomy among users who log on outside the home than was previously the case. Public places may still offer less autonomy than home, however due to time limits on use and/or concerns about privacy.

On the spectrum of autonomy, work may provide users with an environment that largely facilitates personal online activity. Though monitoring of employee computer use appears to be widespread, the extent to which surveillance influences actual employee behavior is unclear. In a 2000 Vault.com survey of employees, about 47% of respondents indicated that they spend 30 or more minutes surfing non-work related sites while at work; just 10% say that they never do so. A similar Vault.com survey of employers shows that about 80% of respondents indicated that they had caught an employee surfing the web on company time. Despite methodological shortcomings, Vault.com's survey provides limited evidence that personal use of the Internet is widespread at work even despite the threat of being observed.[3] It may seem that controlling this ''cyberslacking'' would increase worker productivity, however, cracking down on personal use at work may have a negative impact on morale and thus, productivity (Wallace, 2004). Despite evidence of surveillance and prevalence of technologies that facilitate it, work may actually be a place where individuals do act autonomously, and perhaps, largely with connections that are easy to access and that are faster than dial-up. Home use may be more autonomous, but perhaps only to the extent that work users are regulated in their use or modify their behavior out of concerns about surveillance.

As the previous discussion highlights, even if home users enjoy the highest level of autonomy, it would be a mistake to treat the difference between having home access and not having home access as the only distinction of interest. Though users who connect at home may have advantages over those who do not; the strength of this advantage could be exaggerated if home users are more likely than others to have many access points outside the home as well. The bottom line is that the number of access points and the level of autonomy particular access points provide should be explored in tandem as sources of variation in online pursuits. My research aims to specify further the sets of locations that are associated with the greatest advantages. Which location combinations are associated with the highest odds of doing search and transaction activities? Will location matter differently for those activities that are seemingly more risky or sensitive – such as online banking or e-commerce – than it will for those activities for which there may be less perceived risk – such as looking for product information? Does location of use mediate observed differences in use by race, gender, income, education, and age? It is essential to understand whether access point quality may contribute to demographic differences in the ability of individuals to take full advantage of the Internet.

[3] The web page that hosts the results of Vault.com's survey does not provide any information about how the sample was selected.

5. Data and methods

I use data from the School Enrollment and Computer Use Supplement to the October 2003 Current Population Survey (CPS). The CPS is a monthly survey of the noninstitutionalized U.S. population that collects demographic and economic information on households and individuals, and which occasionally includes questions on special topics. Questions in the supplement ask respondents where civilian household members use the Internet and what they use the Internet to do. In particular, respondents are asked whether they use the Internet at home, at work, at school, at the homes of friends or family members, while traveling, as well as at places like libraries or ‘‘Internet cafes.’’[4] Individuals who report logging on at home are asked whether they use a mobile device to connect, but those who do not connect at home are not asked about mobile devices at all. If individuals report using the Internet at one or more locations, they are asked whether they have participated in particular activities during the past year. These activities include: searching for health, product, job, or government information, banking, purchasing goods or services, investing, viewing news and weather information, playing games, and emailing. Questions about activities are not tied to questions about location of access, which prevents inference about whether individuals with many access points use those access points differently (i.e. if an individual who searches for job information online has access at home and work, it is not possible to determine whether she looks for job information only at work, only at home, or at both locations). In the October 2003 CPS sample, there are 60,593 individuals age 18 and over who use the Internet anywhere at all, which is 58% of the sample that is both civilian and over 18.

6. Recoded variables

The seven different locations of Internet use included in CPS data make $2^7 - 1 = 27$ possible combinations of locations that individuals who log on the Internet at all may use. This number would produce a prohibitively large set of dummy predictor variables, so I recoded location into nine categories (Table 1). It might be argued that nine categories are too large; however, collapsing categories on the basis of empirical similarity could obscure meaningful theoretical differences in the contexts of use at locations. I treat ‘‘only school’’ as a separate category from ‘‘only other’’ so that students might be observed more clearly; however, any category with ‘‘others’’ (plural) in its name includes school because combining school with every other location of use produces a table that is too sparse in some cells (i.e. work and school as well as work, school, and others have very few observations). Grouping all locations besides home and work into ‘‘others’’ makes sense on theoretical grounds in that all such locations are public.[5] The unique status of work as a location at which individuals have more hours of access on average than other places besides home and the high speed of most workplace connections warrants distinguishing work from ‘‘others.’’ About 15% of Internet users age 18 and over lacked data on income. To determine whether missing data on income is systematically associated with the odds of doing various activities, I coded an extra dummy variable distinguishing those cases and included it in all models.

[4] In the past few years, there has been a shift from dedicated ‘‘Internet cafes’’ where patrons pay to use an Internet-connected computer on the premises to coffee shops that provide free wireless to customers who purchase drinks. My use of ‘‘Internet café’’ reflects question wording in the CPS School and Computer Use Supplement.

[5] The homes of family and friends may not be formally public, but it probably offers a similar level of privacy and autonomy to users as public places.

Table 1
Location recode, CPS October 2003

Label	Respondent uses the Internet ...
Only home	Only at home
Only work	Only at work
Only school	Only at school
One other	Only at one of the following places: library, Internet cafe, home of friends or family, while traveling
Home and others	At home plus one or more of: library, Internet cafe, home of friends or family, while traveling, school
Work and others	At work plus one or more of: library, Internet cafe, home of friends or family, while traveling, school
Home and work	At home and at work
Home, work, others	At home, work plus one or more of: library, Internet cafe, home of friends or family, traveling, school
Just others	At two or more of: library, Internet cafe, home of friends or family, while traveling, school

7. Control variables

Many studies of digital inequality have found that education, age, and gender are associated with Internet use (Bonfadelli, 2002; Leigh and Atkinson, 2001; Robinson et al., 2003). I include these variables in all models as possible sources of variation in activity patterns. Furthermore, I include employment status and student status in all models because using the Internet at work and using it at school are conditioned upon being employed and being a student. Income has been shown to be associated with Internet use (Lenhart and Horrigan, 2003), so I include family income as a control variable as well. I also include race, Hispanic ethnicity, and metropolitan status, which have been found to be influential in previous research on digital divides (Bikson and Panis, 2000). It seems likely that these characteristics may also be associated with differences in the likelihood of participating in online activities.

8. Descriptive statistics

The following four online activities are dependent variables: searching for health information, searching for product information, purchasing goods or services (e-commerce), and online banking. Participation rates in these activities vary by demographic characteristics (Table 2). Adults in the sample who are employed, highly educated, and have high family incomes engage in all four activities at higher rates than their unemployed, lower income, and less educated counterparts. The middle age groups – users in the sample age 25–54 – do all activities at about the same rate. White users in the sample participate in the four activities at higher rates than individuals of other races, with one exception: more Asians in the sample participate in online banking than do all other racial groups. In addition, young users in the sample are more likely to bank online than users in all other age groups. The only significant difference in online activity between men and women is ‘searching for health information’: women in the sample search for health information online at higher rates than men. Rates of participating in online activities vary across location combinations as well (Table 3). Users in the sample who log on at home, work and at one or more other locations have the highest rates of doing all four activities. Individuals in the sample who log on only at school and those who log on only at one ‘other’ place, by and large have the lowest rates of doing all online activities. Among people in the sample, users who

Table 2
Internet users 18 and older who do online activities, by characteristics, $N = 60{,}593$

Variable	Searches product information	Searches health information	E-commerce	Online banking	*N*
Total	79.5	44.4	55.6	29.5	60,593
Age (%)					
18–24	72.2	24.8	44.9	23.2	8,267
25–34	82.5	45.1	60.9	39.4	12,194
35–54	81.8	47.5	58.8	31.0	28,024
55–80	76.2	50.1	50.2	20.3	12,108
Sex (%)					
Male	80.6	38.3	56.3	30.1	28,350
Female	78.6	49.8	55.0	28.9	32,243
Education (%)					
Less than high school	63.8	28.3	31.5	14.5	2,765
High school	73.5	36.2	44.2	20.9	15,445
Some college	78.0	40.3	52.8	28.6	13,834
2-year degree	80.9	46.2	55.6	29.7	6,007
Bachelors degree	85.9	52.6	67.5	38.6	14,868
Advanced degree	86.6	57.2	69.3	35.8	7,674
Employment status (%)					
Employed	81.1	44.4	58.0	31.5	46,551
Unemployed	75.5	39.4	43.7	25.7	1,922
Not in labor Force	74.2	45.4	48.5	22.2	12,120
Income (%)					
<$20,000	71.2	39.7	41.9	22.1	4,675
$20,000–$34,999	74.1	41.4	45.1	25.2	7,734
$35,000–$49,999	77.9	42.0	52.2	27.3	8,363
$50,000–$74,999	80.8	44.6	56.5	30.1	12,581
$75,000–$149,999	84.9	48.2	65.7	36.2	14,364
$150,000 or above	88.7	52.6	73.0	38.1	3,826
Missing on Income	75.7	42.1	50.2	23.9	9,050
Race (%)					
White, non-Hispanic	81.3	45.4	58.0	29.7	49,637
Black, non-Hispanic	69.9	41.2	39.7	23.7	4,038
Asian	76.2	42.9	53.5	35.7	2,160
Hispanic	68.0	36.6	43.0	29.8	3,515
Other	77.6	41.5	50.3	27.4	1,243
Student status (%)					
Non-student	80.0	45.9	56.2	29.6	53,346
Student	76.1	33.7	51.6	28.5	7,247
Metropolitan status (%)					
Non-metropolitan	78.7	40.6	52.5	22.4	13,541
Metropolitan	79.8	45.5	56.5	31.5	47,052

Source: CPS, October 2003 School Enrollment and Computer Use Supplement.

connect only at home have about the same rates of doing activities as users who log on at home and at places outside work.

The demographic characteristics that are associated with low relative rates of doing online activities tend also to be the same demographic characteristics that are associated with location

Table 3
Percent of Internet users 18 and older who do online activities, by locations of use, $N = 60{,}593$

	Searches product information	Searches health information	E-commerce	Online banking	*N*
Only home	74.3	39.5	47.3	21.8	22,266
Only work	65.8	35.8	41.0	19.6	5,534
Only school	55.1	19.2	27.3	9.8	510
One other	59.2	24.7	22.4	6.2	1,573
Home and others	80.8	41.9	55.6	29.3	6,918
Work and others	80.8	46.1	49.4	26.3	1,476
Home and work	88.5	51.7	68.4	38.7	15,732
Home, work, others	94.6	63.0	82.5	53.9	5,914
Just others	71.6	31.6	30.6	13.7	670

Source: CPS, October 2003 School Enrollment and Computer Use Supplement.

combinations where the rate of doing online activities is low. A greater proportion of people with 'just others' or at 'one other place' access are Black, Hispanic, a student, young, unemployed, and have less than a high school education than are people with other location combinations. Individuals with demographic characteristics that are associated with high rates of participation in online activities tend also to have the Internet at 'home and work' and at 'home, work and others' more often than do individuals with lower education and income (Table A.1 in the Appendix A).

9. Analysis

For each activity – searching for health information, searching for product information, e-commerce, and banking online – I run two different models that have directly comparable coefficients. The first model for each activity is a logistic regression on demographic variables. The second model for each activity includes location of use as an independent variable and is not a logistic regression, but rather, is a modified logistic distribution to which I apply maximum likelihood estimation. Logistic regression is not performed on the second model for each activity because it would likely result in biased parameter estimates due to an endogeneity bias. In this analysis, endogeneity bias would occur if an unobserved variable influences both a person's propensity to use certain location combinations and his or her propensity to undertake a particular activity online. One label for this unobserved variable is what could be called a person's "level of desire to do activity *x*." Someone who values health information highly may go online at many places in order to satisfy his or her desire for health information, making him or her both more likely to search for health information online and more likely to have many locations of access. The modified logistic distribution eliminates the possibility of endogeneity bias. The model is given by the equation:

$$P(a_{ij}|\mathbf{L}_i \quad \text{and} \quad \mathbf{X}_i \quad \text{and} \quad d_{rj}) = \frac{\exp(\mathbf{A}_j\mathbf{X}_i + \mathbf{B}_j\mathbf{L}_i + \rho_j d_{rj})^{a_{ij}}}{1 + \exp(\mathbf{A}_j\mathbf{X}_i + \mathbf{B}_j\mathbf{L}_i + \rho_j d_{rj})} \tag{1}$$

Eq. (1) gives the probability of doing a particular activity a_{ij} for person *i* and activity *j* given a person's set of access points $\mathbf{L}_i$, demographic characteristics $\mathbf{X}_i$, and level of desire to do a particular activity d_{rj}. $\mathbf{A}_j$, $\mathbf{B}_j$, and ρ_j label the coefficients for each variable.

Eq. (1) is basically a logit model. To address endogeneity, I adapt a technique previously developed by Mroz (1999) and implemented by others (Seiber et al., 2005; Van Ours, 2004).

I construct a joint likelihood function that expresses the probability of doing a particular activity online while at a particular location online. I assume that location combinations are distributed according to the multinomial logit distribution. Furthermore, following Mroz (1999), the unknown levels of desire d_{rj} are assumed to be distributed discretely. This likelihood function is then maximized to obtain unbiased parameter estimates. Results from logistic regression do not largely depart from results obtained from the modified MLE I employ in this analysis. The differences that do exist are consistent with the interpretation that the adapted MLE corrects bias in the location coefficients while minimally affecting demographic coefficients. For an empirical comparison to logistic regression results, and a detailed discussion of the method, please consult the Appendix A.

10. Results

Table 4 reports odds ratios for online banking and e-commerce. Table 5 displays odds ratios for health information and product information seeking. The results from the logistic regressions on activities (Models B1, E1, H1, and P1) show that, in general, whites of either gender between the ages of 25–54, who are highly educated, and who earn over \$75K a year are most likely to participate in the majority of activities considered in this analysis. One exception is the practice of health information seeking: female whites over the age of 55, who are highly educated, and who have either low or high incomes are most likely to participate.

Comparing demographic coefficients in the first models (Models B1, E1, H1, and P1) to coefficients in the second models (Models B2, E2, H2, and P2) reveals that location mediates the effects of income and education but not race and age. Users with high income and high levels of education have high relative odds of participating in activities, but these odds decrease significantly when location coefficients are added. Similarly, the relative odds that low-income individuals will participate in a particular activity increase significantly when location coefficients are added. Internet access points explain 30–60% of the differences in odds of undertaking online activities between individuals with low education and income and those with high education and income. Identifying location of use as one mechanism by which differences in income and education produces unequal ability among users to make beneficial use of the Internet is an important finding.

The second key finding is that connecting to the Internet from home does not, by itself, describe those users who are most likely to participate in activities. By a large margin, users who connect at home, work, and at one or more other places have the greatest odds of searching for health information, searching for product information, banking, and making purchases online (Models B2, E2, H2, and P2 in Tables 4 and 5). Overall, users who access the Internet at more than one place – even if home is not included – are more likely to participate in activities than users who utilize only one access point. These findings support the proposition that using an Internet connection at home is only one dimension of the best form of access: there is value added to having multiple access points. Results of this analysis also confirm that the home is a prime location of access. Among people who use roughly the same number of access points, those who count their home as among the places they connect are across the board more likely to participate in the activities considered here. These results indicate that policy research that examines only the binary difference between home users and those users who connect only outside the home fail to fully capture the relationship between the locations people use to connect and their ability to make use of the Internet for personal benefit.

Table 4
Odds ratios for participating in online transaction activities, $N = 60,593$

Variable	Banking				E-Commerce			
	Model B1		Model B2		Model E1		Model E2	
	e^{β}	z-value	e^{β}	z-value	e^{β}	z-value	e^{β}	z-value
Age (25–34 omitted)								
18–24	0.57	−15.63	0.62	−12.70	0.66	−12.67	0.71	−9.77
35–54	0.67	−16.93	0.65	−17.67	0.84	−7.57	0.82	−8.27
55 and up	0.41	−28.41	0.41	−28.15	0.62	−17.06	0.62	−16.54
Female	0.98	−1.04	0.99	−0.37	1.00	0.19	1.01	0.72
Education (high school omitted)								
Less than high school	0.70	−6.14	0.73	−5.23	0.69	−8.34	0.71	−7.40
Some college, no degree	1.48	13.77	1.36	10.79	1.40	13.73	1.30	10.50
Two-year degree	1.48	11.06	1.35	8.33	1.44	11.68	1.32	8.77
Bachelors degree or above	1.98	26.75	1.56	16.81	2.26	35.70	1.82	25.19
Other demographic								
Unemployed	0.89	−2.22	1.24	3.72	0.75	−5.75	0.97	−0.57
Not in labor force	0.82	−7.53	1.15	4.48	0.89	−5.33	1.14	5.05
Student	1.03	0.97	0.79	−6.17	1.05	1.60	0.78	−6.94
Metropolitan (Yes = 1)	1.43	14.95	1.38	13.16	1.06	2.64	1.01	0.44
Race (White omitted)								
Black	0.72	−8.28	0.77	−6.55	0.51	−19.46	0.53	−17.61
Asian	1.05	0.97	1.09	1.68	0.67	−8.65	0.68	−8.03
Hispanic	1.04	1.03	1.11	2.59	0.64	−11.90	0.67	−10.40
Other race	0.98	−0.23	1.00	−0.06	0.85	−2.70	0.86	−2.53
Income ($35,000–$49,999 omitted)								
Less than $20,000	0.85	−3.57	0.94	−1.30	0.78	−6.44	0.85	−3.98
$20,000 to $34,999	0.96	−1.17	1.01	0.34	0.82	−6.17	0.86	−4.63
$50,000 to $74,999	1.07	2.01	1.02	0.67	1.09	3.08	1.05	1.55
$75,000 to $149,999	1.26	7.47	1.15	4.27	1.43	12.24	1.30	8.65
$150,000 or above	1.30	6.04	1.14	2.87	1.84	13.75	1.61	10.52
Missing on income	0.84	−4.72	0.89	−3.20	0.92	−2.83	0.97	−0.93
Location of use (only home omitted)								
Only work	–	–	0.85	−4.13	–	–	0.74	−8.99
Only school	–	–	0.49	−4.62	–	–	0.65	−4.04
One other place	–	–	0.24	−13.35	–	–	0.39	−14.79
Home and others	–	–	1.49	11.26	–	–	1.57	13.73
Work and others	–	–	1.14	2.02	–	–	1.07	1.18
Home and work	–	–	1.93	24.45	–	–	1.90	25.80
Home, work, and others	–	–	3.41	34.89	–	–	4.11	35.22
Just other places	–	–	0.62	−4.16	–	–	0.70	−4.02
Intercept	0.33	−27.61	0.27	−30.70	1.07	1.84	0.91	−2.37
Nagelkerke R^2	0.06		0.09		0.08		0.12	

Source: CPS, October 2003 School Enrollment and Computer Use Supplement.

The four online activities considered in this paper – searching for health information, searching for product information, banking, and making purchases online (e-commerce) – were selected because previous research suggests that these activities offer some tangible benefit to users. Users may perceive the risks intrinsic to transaction activities differently from risks

Table 5
Odds ratios for participating in online information search activities, $N = 60{,}593$

Variable	Health information				Product information			
	Model H1		Model P1		Model P1		Model P2	
	e^{β}	z-value	e^{β}	z-value	e^{β}	z-value	e^{β}	z-value
Age (25–34 omitted)								
18–24	0.47	−21.32	0.49	−27.76	0.68	−10.08	0.70	−13.91
35–54	1.10	4.39	1.11	8.72	0.88	−4.41	0.87	−8.44
55 and up	1.23	7.40	1.27	13.01	0.66	−12.10	0.68	−17.48
Female	1.67	29.73	1.71	46.39	0.93	−3.54	0.94	−4.15
Education (high school omitted)								
Less than high school	0.83	−4.06	0.85	−3.66	0.76	−6.13	0.78	−6.05
Some college, no degree	1.30	10.52	1.23	11.46	1.28	8.76	1.19	8.40
Two-year degree	1.43	11.23	1.34	11.02	1.40	8.86	1.29	7.61
Bachelors degree or above	1.94	29.05	1.65	36.48	1.91	23.19	1.57	22.73
Other demographic								
Unemployed	1.03	0.63	1.22	4.00	0.95	−0.92	1.07	1.16
Not in labor force	1.09	3.74	1.30	13.79	0.86	−5.75	0.97	−1.25
Student	0.97	−0.81	0.72	−12.49	1.02	0.53	0.69	−12.67
Metropolitan (Yes = 1)	1.19	8.21	1.15	14.68	1.01	0.36	0.97	−-2.43
Race (White omitted)								
Black	0.87	−4.11	0.90	−3.13	0.57	−14.85	0.60	−14.09
Asian	0.82	−4.39	0.84	−3.87	0.63	−8.53	0.65	−8.04
Hispanic	0.84	−4.46	0.88	−3.47	0.56	−14.56	0.59	−14.12
Other race	0.97	−0.42	0.97	−0.58	0.90	−1.55	0.90	−1.42
Income ($35,000–$49,999 omitted)								
Less than $20,000	1.10	2.36	1.15	4.32	0.83	−4.36	0.88	−3.93
$20,000 to $34,999	1.05	1.34	1.07	2.97	0.89	−3.22	0.92	−3.03
$50,000 to $74,999	1.06	2.00	1.03	1.82	1.11	2.91	1.07	2.72
$75,000 to $149,999	1.10	3.39	1.03	1.95	1.33	7.77	1.20	7.63
$150,000 or above	1.18	4.10	1.07	2.13	1.71	9.12	1.50	7.73
Missing on income	0.95	−1.53	1.00	0.21	0.89	−3.19	0.96	−1.50
Location of use (only home omitted)								
Only work	–	–	0.84	−6.26	–	–	0.57	−19.74
Only school	–	–	0.97	−0.22	–	–	0.89	−1.23
One other place	–	–	0.59	−8.72	–	–	0.57	−10.78
Home and others	–	–	1.62	18.6	–	–	1.77	18.44
Work and others	–	–	1.45	6.87	–	–	1.36	4.59
Home and work	–	–	1.52	25.94	–	–	1.90	25.58
Home, work, and others	–	–	2.74	36.44	–	–	4.49	25.96
Just other places	–	–	1.24	2.53	–	–	1.44	4.15
Intercept	0.36	−27.38	0.28	−149.9	4.00	31.71	3.77	126.6
Nagelkerke R^2	0.06		0.09		0.04		0.08	

Source: CPS, October 2003 School Enrollment and Computer Use Supplement.

associated with searching for information online. In the former case, personal financial information is typically entered onto web pages or displayed on screen while in the latter case, users are not necessarily required to display or enter sensitive information. Do users appear to be more willing to use access points that would seem to offer little privacy for information search activities than they are for transaction activities? Though data used in this analysis does not permit a direct test of whether it is concern for privacy that limits certain activities at public places, results are consistent with this interpretation. Relative to all other users, individuals who connect just at one public place or at many public places ('one other place' and 'just other places') are significantly less likely to conduct transaction activities than they are to participate in information search activities.

Though the mediating effect of location of access on income and education is a general pattern that is robust across all four activities, the greatest mediating role of location on income and education occurs with online banking (Models B1 and B2 in Table 4). The gap in the odds of banking online between individuals with high school education and those with a bachelors degree or above is reduced by 38% when location coefficients are included; between individuals with the lowest family income and those with family incomes at or above $150K, the gap in the odds of online banking is reduced by a full 60%. This finding is consistent with the interpretation that the advantage of having a high income stems from the fact that a high income facilitates a person's use of a large number of high-quality Internet access points. The case of online banking perhaps most clearly illustrates that location of Internet use can be considered a mechanism through which differences in income and education operate to produce unequal ability to benefit from time spent online.

Results from the analysis of health information seeking (Models H1 and H2 in Table 5) are least consistent with results from analyses of the other three activities. Compared to the power of income to predict participation in the three other online activities, income is a relatively poor predictor of health information seeking. Internet users who make $150K or more per year have only 18% greater odds than do users who are the least likely to search health information online (those users whose family incomes fall between $35K and nearly $50K). Adding location coefficients to the health information seeking model results in only a small and ambiguous mediating effect: the income coefficients change in different directions. One possible explanation for the deviation of these results from the other three activities is that users with low family income may be more motivated than their more affluent counterparts to search for health information online. Low-income users may be in poorer health relative to richer users and thus, demand a high level of health information. In addition, low-income users may be more motivated to seek health information online than individuals with larger family incomes, especially if relatively poor users substitute online health information for expensive visits to medical professionals.

11. Discussion

Previous research on the U.S. case has suggested that Internet users who connect from home are better able to take full advantage of the Internet than users who do not. The purpose of this analysis was to evaluate claims about the importance of home access while broadening the inquiry to consider the possibility that connecting to the Internet from many locations may also benefit users. The theoretical basis for exploring the relationship between locations of Internet use and particular online activities can be summarized as follows: (1) as a flexible communications tool, the Internet can be applied to ends that enhance human, social, or financial capital to greater or lesser degrees; (2) the resources users possess may relatively enable or constrain them from taking full advantage of Internet technology for personal benefit; (3) previous research has identified a number of resources that influence Internet use including the speed at which users connect, their level of experience, and the quality of their equipment; (4) other research has identified how use varies by demographic characteristics; (5) given that access points provide different levels of privacy, freedom, and connection qualities, perhaps the locations where individuals use the Internet may be understood as a resource which relatively enables or constrains online pursuits; and (6) if location of Internet use does indeed influence online activity, then perhaps it is also one causally proximate mechanism that can help explain why users with different demographic characteristics apply Internet technology differently.

The results of this analysis confirm that the locations where individuals use the Internet shape their online pursuits and that having access at home is a key factor that is strongly associated with applying the Internet toward ends that enhance individual wellbeing. The results also suggest that having access at home is not sufficient to explain how location of use matters: individuals who have many connections – especially if those connections are high speed, offer privacy and freedom from felt or actual constraint – are most likely to take advantage of Internet technology for personal benefit. Finally, part of the differences in use between users with high education and income and those with low education and income may be explained by the set of locations that these groups tend to use in their efforts to connect to the Internet. While it is true that individuals access the Internet by choice and ‘‘select into’’ various access points, it is also true that these access points are situated in broader institutional settings. One must be employed to have Internet access at work; one must be a student to access the Internet at school; and one must be proximate to public places of connection in order to utilize them.

In the U.S., policy research on Internet access has tended to focus on how Internet connections in general or high-speed connections in particular can be brought into a greater number and wider array of households. The results of the analysis considered here suggest that efforts to bring high-speed Internet access into the home might also be complemented by efforts to make the Internet as available as possible in daily life, which could mean making high-quality public Internet access more of a reality for users of all income and education levels. In the last five years especially, many places of business including coffee shops, airports, and shopping malls, have made wireless Internet access available to patrons who bring Internet-capable portable devices. The trend toward providing greater wi-fi access at public places is not limited to the U.S. case: a wi-fi network launched in 2003 across the UK, Sweden, and Germany called ‘‘The Cloud’’ opens more than 100 new hotspot locations every week.[6] Some wi-fi devices are as small as cellular phones, while other devices include large screens and full keyboards. How these devices limit or enable online activity given their features and cost is an important area of future research. As Agre (1995) points out, technical features of media technologies condition the way they can be used, creating affordances for some kinds of uses but not necessarily for others.

Rather than creating wholly new activities, in the short term, technological innovations are often pressed into the service of existing patterns of life (Fischer, 1992). To the extent that the Internet enables users to economize on transaction costs associated with daily activities such as researching potential consumption decisions, submitting forms to regulatory bodies, making purchases without traveling to a store, and communicating – users who can bend the Internet to their purposes are able to do more in less time and with less expense. As with many resources, however, the benefits the Internet can bring are not yet distributed equitably. Barriers that inhibit

[6] Information provided at ‘‘The Cloud’’ website: http://www.thecloud.net/about/what_we_do.asp. Last accessed May 3, 2006.

online activities for some users – whether those barriers be cognitive or structural in nature – ought to be addressed if Internet use is to become a mainstream medium to which all have equal qualities of access.

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Appendix A

A.1. Correcting endogeneity bias

See Tables A.1 and A.2.

In this analysis, I assume that the propensity a^*_{ij} for a person i to do activity j online is given by

$$a^*_{ij} = \mathbf{X}_i\mathbf{A}_j + \mathbf{L}_i\mathbf{B}_j - \varepsilon_{ij} \tag{A.1}$$

where $\mathbf{X}_i$ denotes demographic parameters such as race, gender, and age, and $\mathbf{L}_i = (w_{i1}, w_{i2}, \ldots, w_{ik}, \ldots, w_{im})$ denotes the location combinations at which a person does (or does not perform) activity j. $\mathbf{L}_i$ is an m dimensional vector, where m denotes the number of different possible location combinations (in this paper, nine), at which individuals may use the Internet. The kth component w_{ij} of the vector $\mathbf{L}_i$ is equal to 1 if an individual uses the Internet at the kth location, and 0 if she does not. Essentially, this equation describes the constellation of factors, including unobserved factors in ε_{ij}, that provide the conditions and impetus for doing particular online activities. If the propensity for doing an activity is large enough, an individual will participate in the activity. Mathematically, a person does activity j, a situation that I denote as $a_{ij} = 1$, when $a^*_{ij} > 0$. Conversely, a person abstains from activity j when $a^*_{ij} > 0$, and I write this condition as $a_{ij} = 0$.

The goal of this analysis is to determine consistent estimates of the coefficients $\mathbf{A}_j$ and $\mathbf{B}_j$ using sample data. I employ maximum likelihood estimation to accomplish this task. Using MLE requires specifying $\prod_i P(a_{ij} \text{ and } \mathbf{L}_i \text{ and } \mathbf{X}_i)$ as a likelihood function with its dependence on $\mathbf{A}_j$ and $\mathbf{B}_j$ made explicit.[7] One way to find $P(a_{ij}$ and $\mathbf{L}_i$ and $\mathbf{X}_i)$ is to write it as a product of three probability functions:

$$P(a_{ij} \text{ and } \mathbf{L}_i \text{ and } \mathbf{X}_i) = P(a_{ij}|\mathbf{L}_i \text{ and } \mathbf{X}_i) \times P(\mathbf{L}_i|\mathbf{X}_i) \times P(\mathbf{X}_i) \tag{A.2}$$

It is also essential to make assumptions about the correlation between $P(a_{ij}|\mathbf{L}_i$ and $\mathbf{X}_i)$ and $P(\mathbf{L}_i|\mathbf{X}_i)$ because any correlations between these functions will influence estimates of the coefficients $\mathbf{A}_j$ and $\mathbf{B}_j$. In order to identify the relationship between these functions, it is helpful

[7] In other words, $P(a_{ij}$ and $\mathbf{L}_i$ and $\mathbf{X}_i)$ is the joint probability of person i doing activity j or not, who has particular demographic characteristics $\mathbf{X}_i$, and who uses the location $\mathbf{L}_i$. The likelihood function is the product of all individual probabilities.

Table A.1
Percent of internet users age 18 and older who use various sets of locations, $N = 60{,}593$

	Only home	Only work	Only school	Only other	Home others	Work others	Home work	Home work others	Just others	*N*
Age										
18–24	26.1	3.6	5.2	5.2	37.9	3.3	7.2	7.1	4.5	8,267
25–34	32.1	9.1	0.5	3.8	9.7	3.6	26.7	13.3	1.2	12,194
35–54	35.2	10.6	0.1	1.5	6.0	2.2	33.5	10.5	0.4	28,024
55–80	52.3	9.6	0.0	2.1	7.7	1.2	20.6	6.1	0.3	12,108
Sex										
Male	35.8	8.6	0.8	2.5	11.1	2.0	27.1	11.1	1.0	28,350
Female	37.6	9.6	0.9	2.7	11.7	2.8	25.0	8.6	1.2	32,243
Education										
Less than high school	53.4	7.5	2.7	7.2	16.5	1.2	7.5	1.2	2.8	2,765
High school	50.5	10.8	0.7	4.3	9.4	1.9	18.1	3.1	1.1	15,445
Some college	35.4	7.6	1.9	2.5	19.8	2.7	19.8	8.2	2.0	13,834
2-year degree	39.5	9.4	0.3	2.3	9.4	2.8	27.3	8.2	0.9	6,007
Bachelors degree	26.8	9.3	0.2	1.1	7.8	2.9	35.8	15.6	0.5	14,868
Advanced degree	22.5	8.5	0.1	0.7	7.0	2.4	39.5	19.0	0.2	7,674
Employment status										
Employed	28.1	11.9	0.4	2.0	7.2	3.2	33.8	12.7	0.7	46,551
Unemployed	56.2	0.0	0.9	10.5	27.5	0.0	0.0	0.0	4.9	1,922
Not in labor force	66.9	0.0	2.4	3.8	24.9	0.0	0.0	0.0	2.1	12,120
Income										
<$20,000	37.3	6.1	2.8	10.4	19.4	3.7	8.3	6.4	5.5	4,675
$20,000–$34,999	42.4	10.2	1.1	5.7	12.5	4.3	15.5	6.3	2.0	7,734
$35,000–$49,999	42.0	9.4	0.5	2.7	11.7	3.2	21.6	8.0	0.8	8,363
$50,000–$74,999	37.2	8.6	0.5	1.4	11.0	2.2	28.4	10.0	0.6	12,581
$75,000–$149,999	29.6	6.9	0.3	0.5	10.0	1.5	36.7	14.2	0.3	14,364
$150,000 or above	25.8	5.7	0.5	0.2	10.9	1.4	36.7	18.6	0.1	3,826
Missing on Income	42.0	15.2	1.3	1.8	9.1	1.7	23.0	5.0	0.7	9,050
Race/ethnicity										
White, Non-Hispanic	37.2	8.6	0.7	2.3	10.9	2.2	27.2	10.0	0.9	49,637
Black, Non-Hispanic	32.6	12.8	2.1	4.4	13.7	3.9	19.2	8.2	3.1	4,038
Asian	32.2	10.2	1.5	1.0	14.2	2.2	27.7	10.5	0.5	2,160
Hispanic	39.0	11.1	1.1	4.6	13.1	4.0	18.0	7.1	2.2	3,515
Other	32.4	9.8	2.0	5.4	14.4	3.7	18.7	10.7	2.8	1,243
Student status										
Student	11.6	1.3	7.0	0.5	48.4	4.0	4.4	17.7	5.0	7,247
Non-Student	40.2	10.2	0.0	2.9	6.4	2.2	28.9	8.7	0.6	53,346
Metropolitan status										
Metropolitan	35.3	9.1	0.8	2.3	11.7	2.5	26.6	10.7	1.1	47,052
Non-metropolitan	41.7	9.2	1.1	3.8	10.5	2.4	23.6	6.5	1.3	13,541

Source: Current Population Survey, October 2003 School Enrollment and Computer Use Supplement. *Note:* ‘Others’ includes using the Internet at a library, Internet cafe, someone else’s home, school, and while traveling, while ‘Only Other’ means that a person uses the Internet at any ONE of these places not including school.

Table A.2
Comparing logistic regression and MLE method: searching for product information, $N = 60{,}593$

Variable	Logistic regression		Adapted MLE	
	e^{β}	z-value	e^{β}	z-value
Age (25–34 omitted)				
18–24	0.71	−8.43	0.70	−13.91
35–54	0.87	−4.62	0.87	−8.44
55 and up	0.68	−11.04	0.68	−17.48
Female	0.93	−3.17	0.94	−4.15
Education (high school omitted)				
Less than high school	0.79	-5.30	0.78	-6.05
Some college, no degree	1.18	5.81	1.19	8.40
Two-year degree	1.28	6.32	1.29	7.61
Bachelors degree or above	1.52	14.29	1.57	22.73
Other demographic				
Unemployed	1.13	2.13	1.07	1.16
Not in labor force	1.04	1.40	0.97	−1.25
Student	0.70	−8.04	0.69	−12.67
Metropolitan (Yes = 1)	0.97	−1.35	0.97	−2.43
Race (White omitted)				
Black	0.61	−13.04	0.60	−14.09
Asian	0.65	−7.75	0.65	−8.04
Hispanic	0.59	−13.15	0.59	−14.12
Other Race	0.90	−1.43	0.90	−1.42
Income ($35,000–$49,999 omitted)				
Less than $20,000	0.88	−2.87	0.88	−3.93
$20,000 to $34,999	0.92	−2.12	0.92	−3.03
$50,000 to $74,999	1.06	1.70	1.07	2.72
$75,000 to $149,999	1.19	4.72	1.20	7.63
$150,000 or above	1.48	6.55	1.50	7.73
Missing on Income	0.96	−1.05	0.96	−1.50
Location of use (only home omitted)				
Only work	0.64	−12.77	0.57	−19.74
Only school	0.76	−2.73	0.89	−1.23
One other place	0.58	−9.63	0.57	−10.78
Home and others	1.82	14.52	1.77	18.44
Work and others	1.53	6.02	1.36	4.59
Home and work	2.16	23.74	1.90	25.58
Home, work, and others	5.12	26.03	4.49	25.96
Just other places	1.33	3.12	1.44	4.15
Intercept	3.45	27.05	3.77	126.6
Nagelkerke R^2	0.12		0.08	

Source: CPS, October 2003 School Enrollment and Computer Use Supplement.

to specify an equation that governs the dynamics that propel individuals to use the Internet at particular location combinations:

$$w_{ik}^{*} = f_k(\mathbf{X}_i) + \gamma_{ik} \tag{A.3}$$

The latent variable, w_{ik}^{*}, describes the propensity for individual i to use the Internet at a particular location combination k. For now, f_k is an arbitrary function of demographic characteristics.

Like a^*_{ij}, the propensity w^*_{ik} is a continuous variable, which requires a convention to reduce its continuous values to discrete outcomes. To this end, I assume that $w_{ik} = 1$ where $w^*_{ik} = \max(w_{i1}, w_{i2}, \ldots, w_{ik}, \ldots, w_{im})$ and $w_{ik} = 0$ otherwise. Essentially, a person's location of use is the location for which she has the greatest propensity. The error term, γ_{ik}, contains all unobserved factors that may influence where people connect to the Internet.

It is possible to express the probability $P(\mathbf{L}_i|\mathbf{X}_i)$ using the distribution of γ_{ik}. If ε_{ij} is not correlated with γ_{ik}, then any particular value of ε_{ij} would have no effect on the probability of obtaining a particular value of γ_{ik}. In this case, if the probability function $P(a_{ij}|\mathbf{L}_i$ and $\mathbf{X}_i)$ is some function $g_i(\mathbf{A}_j, \mathbf{B}_j, \mathbf{C}_j)$ where $\mathbf{C}_j$ is some set of other parameters upon which this probability depends, then $P(\mathbf{L}_i|\mathbf{X}_i)$ is some other function $h_i(\mathbf{D}_k)$ that does not depend on any of these same parameters, $\mathbf{A}_j$, $\mathbf{B}_j$, and $\mathbf{C}_j$.

In this analysis, there are grounds to assume that ε_{ij} and γ_{ik} are correlated. The hypothesized factors in my model that explain online activity include demographic characteristics and locations of use. While I argue that these factors can mainly explain trends, one important factor has not yet been explicitly included in my model due to its unobserved status. An unobserved variable – a person's level of desire to do activity j – may influence the location combination an individual uses to connect to the Internet as well as the propensity for that individual to do the activity in question. In other words, an individual who values seeking health information highly may go online at many locations in order to search health information. Throughout the rest of this discussion, level of desire to do activity j will be referred to as d_j, where j indexes the four activities considered in this analysis. The path diagram in Fig. A.1 expresses the full model.

To proceed with finding the coefficients for the demographic and location variables in Eq. (1) – $\mathbf{A}_j$ and $\mathbf{B}_j$ – it is necessary to write the relationships expressed in Fig. A.1 explicitly. The assumptions I make about these relationships are as follows:

(1) In Eq. (A.2), $w^*_{ik} = f_k(\mathbf{X}_i) + \gamma_{ik}$ is linear in $\mathbf{X}_i$:

$$w^*_{ik} = \mathbf{D}_k\mathbf{X}_i + \gamma_{ik} \tag{A.4}$$

(2) To simplify the analysis, I assume that an arbitrary level of desire d_j, which I label d_{rj} takes n possible discrete values. The probability associated with obtaining a particular d_{rj} I designate as P_{rj}.

(3) In Eq. (1) and (A.7), the error terms ε_{ij} and γ_{ik} are linear in the unobserved desire variable d_{rj}:

$$\varepsilon_{ij} = \rho_j d_{rj} + \alpha_{ij}, \qquad \gamma_{ik} = \rho_k d_{rj} + \beta_{rj} \tag{A.5}$$

(4) α_{ij} and β_{ik} are not correlated. Desire d_{rj} is the only factor upon which ε_{ij} and γ_{ik} are correlated.

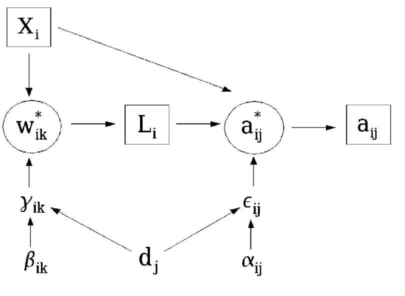

Fig. A.1.

(5) α_{ij} and β_{ik} are distributed according to the extreme value distribution.

For a given desire d_{rj}, the above assumptions imply that:

$$P(a_{ij}|\mathbf{L}_i \text{ and } \mathbf{X}_\text{i} \text{ and } d_{rj}) = \frac{\exp(\mathbf{A}_j\mathbf{X}_i + \mathbf{B}_j\mathbf{L}_i + \rho_j d_{rj})^{a_{ij}}}{1 + \exp(\mathbf{A}_j\mathbf{X}_i + \mathbf{B}_j\mathbf{L}_i + \rho_j d_{rj})} \tag{A.6}$$

It also follows from the above conditions that for a given d_{rj}, $P(\mathbf{L}_i|\mathbf{X}_i$ and $d_{rj})$ follows the multinomial logit distribution:

$$P(\mathbf{L}_i|\mathbf{X}_i \text{ and } d_{rj}) = \frac{\prod_k \exp(\mathbf{D}_k\mathbf{X}_i + \rho_k d_{rj})^{w_{ik}}}{\sum_k \exp(\mathbf{D}_k\mathbf{X}_i + \rho_k d_{rj})}, \quad D_m = 0 \tag{A.7}$$

Then,

$$\begin{aligned} &P(a_{ij} \text{ and } \mathbf{L}_i \text{ and } \mathbf{X}_i|d_{rj}) \\ &\quad = \frac{\exp(\mathbf{A}_j\mathbf{X}_i + \mathbf{B}_j\mathbf{L}_i + \rho_j d_{rj})^{a_{ij}}}{1 + \exp(\mathbf{A}_j\mathbf{X}_i + \mathbf{B}_j\mathbf{L}_i + \rho_j d_{rj})} \frac{\prod_k \exp(\mathbf{D}_k\mathbf{X}_i + \rho_k d_{rj})^{w_{ik}}}{\sum_k \exp(\mathbf{D}_k\mathbf{X}_i + \rho_k d_{rj})} \times P(X_i) \end{aligned} \tag{A.8}$$

Summing over all levels of the unknown desire variable d_{rj}, weighted by their associated probabilities P_{rj} and taking the product over all individuals, gives the likelihood function used in this analysis:

$$\begin{aligned} \prod_i P(a_{ij} \text{ and } \mathbf{L}_i \text{ and } \mathbf{X}_i) &= \prod_i \sum_r P(a_{ij} \text{ and } \mathbf{L}_i \text{ and } \mathbf{X}_i|d_{rj}) \times P_{rj} \\ &= \prod_i \sum_r P_{rj} \times \frac{\exp(\mathbf{A}_j\mathbf{X}_i + \mathbf{B}_j\mathbf{L}_i + \rho_j d_{rj})^{a_{ij}}}{1 + \exp(\mathbf{A}_j\mathbf{X}_i + \mathbf{B}_j\mathbf{L}_i + \rho_j d_{rj})} \frac{\prod_k \exp(\mathbf{D}_k\mathbf{X}_i + \rho_k d_{rj})^{w_{ik}}}{\sum_k \exp(\mathbf{D}_k\mathbf{X}_i + \rho_k d_{rj})} \times P(X_i) \end{aligned} \tag{A.9}$$

In my particular analysis, I allow three possible values of desire d_{rj}. Given that d_{rj} is an unobserved variable, I simultaneously fit for its values, for its probabilities P_{rj}, and for general model coefficients.

Table A.1 compares results from a logistic regression analysis of the full product information model to the adapted MLE approach I have used in this analysis. From this table, it is clear that the largest corrections the adapted MLE makes are to the location variables, which is consistent with the proposition that those variables are most subject to endogeneity bias.

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