1-1-2010

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PEER-REVIEWED JOURNAL ON THE INTERNET

The digital divide in Internet information searching: A double-hurdle model analysis of household data from Vermont

by Guangxuan Zhang, Qingbin Wang, and Jane Kolodinsky

Abstract

While most studies on the digital divide in the United States focus on disparities in access to computers and the Internet, this study examines the digital divide in Internet information searching. With data from 476 Vermont households surveyed in 2009, a double–hurdle model is used to identify the factors that impact the likelihood and frequency of using the Internet for information searching. Empirical results suggest that there are significant disparities in both the likelihood and frequency of online information searching in Vermont and that these disparities are closely associated with several socioeconomic and demographic factors such as education level, income, and age. Also, the impacts of some variables on the likelihood to use the Internet to search for information are different from their impacts on the frequency of using the Internet for information searching. These research findings are expected to be useful when developing programs and policies for reducing the digital divide.

Contents

Introduction

The digital divide, a term introduced in the mid–1990s, generally refers to the gap between people with effective access to digital information and communication technologies (ICTs) and those with limited or no access at all. The U.S. Department of Commerce (USDC) first defined it in 1995 as the separation between information “haves” and information “have–nots” with a focus on the gap between people in their physical access to computers and the Internet. The Organisation for Economic Co–operation and Development (OECD) generalized the concept as the gap between individuals, households, businesses and geographic areas at different socioeconomic levels with regard both to their opportunities to access ICTs and to their use of ICTs for a wide range of activities (OECD, 2001). In other words, the digital divide now includes imbalances in

physical access to ICTs, resources and skills needed to effectively use ICTs, as well as imbalances in the actual use of ICTs.

As computers and the Internet have become widely available to American households in recent years, concerns about the digital divide have shifted from physical access to computers and the Internet to imbalances in the effective use of and benefits from ICTs. The percentage of American households with Internet connection reached 70 percent in 2007 and, by the end of 2008, 57 percent had broadband Internet connections (Technology Policy Institute, 2009). In 2003, van Dijk and Hacker identified four distinct stages of ICT access: motivation access, material access, skills access, and usage access. Of these four, the final stage — usage access — has received most attention in recent years in explaining disparities between households with respect to the digital divide (Quibria, *et al.*, 2002; Ono and Zavodny, 2008; Valadez and Durán, 2007; Morey, 2007). James (2008) finds that physical access to ICTs is only a potential problem with actual use of ICTs being the real issue that defines the digital divide.

Despite all these studies, many questions persist regarding the sources and socioeconomic impacts of the digital divide and viable options for reducing it. This study contributes to the literature by analyzing the factors associated with imbalance in actual use of the Internet for information search. With data from 476 Vermont households surveyed in 2009, the study uses a double–hurdle model to identify the factors that affect the likelihood and frequency of using the Internet for information search.

Related work on the digital divide

Since the "digital divide" was first formally recognized in the mid–1990s, the USDC has published a series of reports on its status (USDC, 2000; 1999; 1998; 1995). These reports identify significant gaps in physical access to ICTs along the lines of race, gender, age, economic status, education level, household composition and geographic location. Other studies (Servon, 2002; Compaine, 2001; Warschauer, 2003) support the findings in the USDC reports. In general, people with less income, lower education, senior age and living in rural areas are less likely to adopt or have adopted ICTs later than their counterparts. Also, households with children are more likely to have computer and Internet connection, presumably because parents want to introduce computers and the Internet to their children at an early age.

Although frequently mentioned, in the literature, there are relatively limited empirical studies regarding the digital divide in the actual use of ICTs. This may be attributed to data limitations and the lack of standardized measures of effective ICT uses for a wide range of activities (Vehovar, *et al.*, 2006). Among the limited studies available, Kolodinsky, *et al.* (2004) and Hogarth, *et al.* (2008) analyzed the use of e-banking by U.S. consumers. Their findings revealed that socioeconomic and demographic factors such as income, education, gender and age affect not only the adoption but also the intention to adopt e–banking applications.

Unlike traditional information and communication media, the Internet is dynamic, heterogeneous, and less structured, and has unique navigational properties (Bilal, 2001). As a result, the ability to efficiently and effectively find information on the Internet has been one of critical indices of effective use of the Internet (Hargittai, 2002). There is a growing breadth and depth in research concerning online information search and interest in a variety of issues from interactions, cognitive processes, to search strategies (Jansena and Spink, 2006; Wang, *et al.*, 2000; Teevan, *et al.*, 2004). However, these studies have paid more attention to the general issues in the process of using Internet search tools, but shed less light on the differences between individuals.

Hargittai (2002) estimated the disparity in online search skills based on in–person observations and interviews with a random sample of 54 Internet users. The estimation results showed that there was a large variance across users in both the ability to find the information and the time needed to find the information. The study identified age and experiences with the technology as significant factors contributed to the variance. In another study, Teo, *et al.* (1999) suggested that the actual use of ICTs not only relied on online search skills but also depended on personal motivation to use the Internet.

In another study, Cheong (2007) examined the digital divide in Internet use at home and at work in Singapore and found that single, higher income and better educated individuals are more likely to use the Internet and use it more frequently. Also, females tend to use the Internet less intensively than males. Wodjao (2007) employed a double–hurdle model to estimate two levels of the digital divide among U.S. households simultaneously: the decision to own computers and have Internet connection at home, and the decision on the intent to use them. The study revealed that demographic factors such as age, education, income, race, and disability of the respondents explained a large percentage of the variation in the time spent using computer at home but had limited explanatory power regarding the likelihood of owning a computer and Internet connection.

This study contributes to the literature by examining the likelihood and frequency of using the Internet for information search. It focuses on the disparity in actual Internet use for information search among Vermont households. Specifically, the study identifies the factors that affect the likelihood and frequency of using the Internet for information search in Vermont, and also examines the impacts of identified factors.

The model

This section presents the econometric model and describes the data set with summary statistics. Different econometric models such as binary logistic, multinomial, ordered probit, Tobit, and double–hurdle models have been used to analyze the likelihood and frequency of consumer purchase of commodities or participation in recreation activities (Cragg, 1971; Wang, *et al.*, 1996; Ewing, *et al.*, 2004). Examples of double–hurdle model applications include Cragg (1971) who developed a double–hurdle model to study the demand for durable goods, Jones (1989) who used one to examine the behavior of cigarette consumption, and Wang, *et al.* (1996) who developed a double–hurdle model to examine the impact of cholesterol information on egg consumption in the United States.

This study uses a double–hurdle model to identify the factors that affect the probability for a survey respondent to use the Internet for information search and the factors that affect the frequency of the Internet use. The double–hurdle model includes a binary logistic regression (BLR) model for the first hurdle and an ordered logistic model (OLR) for the second hurdle. The BLR for the first hurdle analyzes the decision to use the Internet for information search, and the OLR for the second hurdle addresses the question: “for respondents who have used the Internet for information search, what are the factors that contribute to variation in the frequency of searching information online?”

In modeling the likelihood of using the Internet for information search, the dependent variable (Y) is limited to only two possibilities (Y=1 for individuals who have used the Internet for information search and Y=0 otherwise). In this case, a BLR can be used to examine the impacts of a set of independent variables (X_1, X_2, …, X_n) on the logistic function of the probability (P)

for Y=1 (*i.e.*, P is the probability for Y=1). Estimation results of a logistic model can be used to identify factors that significantly contribute to the probability for Y=1 and examine the marginal impact of each significant independent variable on the odds ratio for Y=1. A BLR model is represented by the following function:

$$Logistic\,(P) = \ln\left\{P/(1-P)\right\} = a + \sum_{1}^{n} b_i X_i + e \quad (1)$$

where P, X_1, X_2, …, and X_n are as defined above, a, b_1, b_2, …, and b_n are the coefficients to be estimated, and e is the error term. This BLR is used to identify the factors that contribute to "the probability of using the Internet for information searching" and to examine the marginal impacts of each significant independent variable on the odds ratio for Y=1.

In addition to the BLR models, an OLR model is used to identify the factors that determine the frequency of using the Internet for information search for the individuals who have used the Internet for information searching. This second hurdle is for only those respondents who pass the first hurdle or have used the Internet for information search. In this case, the dependent variable Y ranges from 1 to 6, corresponding to six levels of use frequency: (1) less than once a month, (2) about once a month, (3) 2–3 times a month, (4) about once a week, (5) a few times a week, and (6) daily. If P_i is the probability for Y = i, and $P(Y \le j) = P_1 + P_2 + \ldots + P_j$ represents the probability that a respondent falls in a category less than or equal to the jth category (j = 1, 2, …, 5), then we have a collection of cumulative probabilities for each case. The final category $P(Y \le 6)$ has a cumulative probability of 1. The OLR model based on the cumulative probability can be specified as:

$$Logistic\left[P(Y \le 1)\right] = \ln\left[\frac{P_1}{1-P_1}\right] = \alpha_1 - \sum_{1}^{n} \beta_i X_i + e$$

$$Logistic\left[P(Y \le 2)\right] = \ln\left[\frac{P_1 + P_2}{1-(P_1+P_2)}\right] = \alpha_2 - \sum_{1}^{n} \beta_i X_i + e$$

(3)

$$Logistic\left[P(Y \le 5)\right] = \ln\left[\frac{P_1 + P_2 + P_3 + P_4 + P_5}{1 - (P_1 + P_2 + P_3 + P_4 + P_5)}\right] = \alpha_5 - \sum_1^n \beta_i X_i + e$$

and $$P(Y \le 6) = 1$$

where α_1, α_2, … and α_5 are the intercepts, β_1, β_2, …, and β_n are the coefficients to be estimated, and e is the error term. The cumulative model constrains the coefficients in these models to be the same but allows the intercepts to vary (Allison, 1999; O'Connell, 2006).

Models (1) and (2) together form a simple double hurdle model. As discussed by Tsekeris and Dimitriou (2008), model (1) and (2) can be estimated simultaneously when the error terms in the two models are assumed to be correlated, or separately when they are assumed to be independent. Also, many studies have used the same set of independent variables in the two models (hurdles), especially when data are limited (*e.g.*, Wang, *et al.*, 1996). In this study, we use the same set of independent variables in the BLR and OLR models and estimate the two models separately. While the choice of the same set of independent variables for the BLR and OLR is largely due to data limitation (the statewide household survey covered a very wide range of topics and the Internet use was only a small part of the survey), the choice of estimating the two models separately was due to the computer programming challenge for estimating the BLR and OLR simultaneously.

The data and descriptive statistics

Data employed in our analysis are from the 2009 Vermont Poll conducted in February 2009. The poll as a statewide survey covered a variety of issues related to public concerns within Vermont and has been conducted annually by the Center for Rural Studies (CRS) at the University of Vermont for more than a decade. The telephone survey was conducted using a computer–aided telephone interviewing (CATI) software. A random sample for the poll was drawn from a list of Vermont telephone numbers, which is updated quarterly and included listed and unlisted telephone numbers. Cellular phone numbers were not included in the sampling frame and this may not cause serious problems because Vermont has the lowest percentage of "wireless–only" households in the country. Only Vermont residents over the age of eighteen were interviewed. While there were 615 respondents in the 2009 Vermont Poll, 139 of them are not included in this study due to missing data.

The personal characteristics of the sample are summarized in Table 1. Compared to the Vermont data collected by the U.S. Census Bureau, respondents of the 2009 Vermont Poll have higher education and income. The difference is likely due to the fact that the Census Bureau data

included the whole population and the survey included only one adult from each selected household. In addition, 64.5 percent of the respondents reside in rural areas and 70.0 percent of the respondents have no child under 18. The percentages of male and female are almost equal. The median age of the sample is 55, and about half of the respondents are between 46 and 55. These sample statistics are similar to that from the census.

Table 1: Descriptive statistics of the sample in comparison with census data.

	VT Poll 2009 (percent)	VT data (2005–2007) (percent)
Education		
Less than high school	5.3	10.3
High school	17.1	57.0
College	77.6	32.7
Household income ($US)		
<25,000	14.8	23.7
25,000–50,000	25.5	26.8
50,000–75,000	23.6	20.3
>75,000	36.1	29.1
Residence		
Rural	64.5	NA
Suburban	20.6	NA
Urban	14.9	NA
Family composition		
Without child	71.0	70.9
With children	29.0	29.1
Gender		
Male	49.3	49.1
Female	50.7	50.9
Age		
20–45	21.5	32.5*
46–65	52.4	29.4*
>65	26.1	13.2*

Data source: Vermont Poll 2009; 2005–2007 American Community Survey 3–Year Estimates (U.S. Census Bureau).

NA: Not available.

* The sum is not equal to 100 because of the exclusion of population under the age of 20.

Figure 1 presents the percentages of households with computer and the Internet connection in Vermont since 1999. Between 1999 and 2009, the percentage of households with computer increased significantly from 1999 to 2002 and then has been steady around 80 percent. Household Internet connectivity has risen to nearly match computer ownership and reached 81.7 percent in 2009. Recently, broadband Internet connection has grown quickly in Vermont, reaching 66.8 percent of households in 2009. Data presented in Figure 1 are from the Vermont Pool conducted by the University of Vermont.

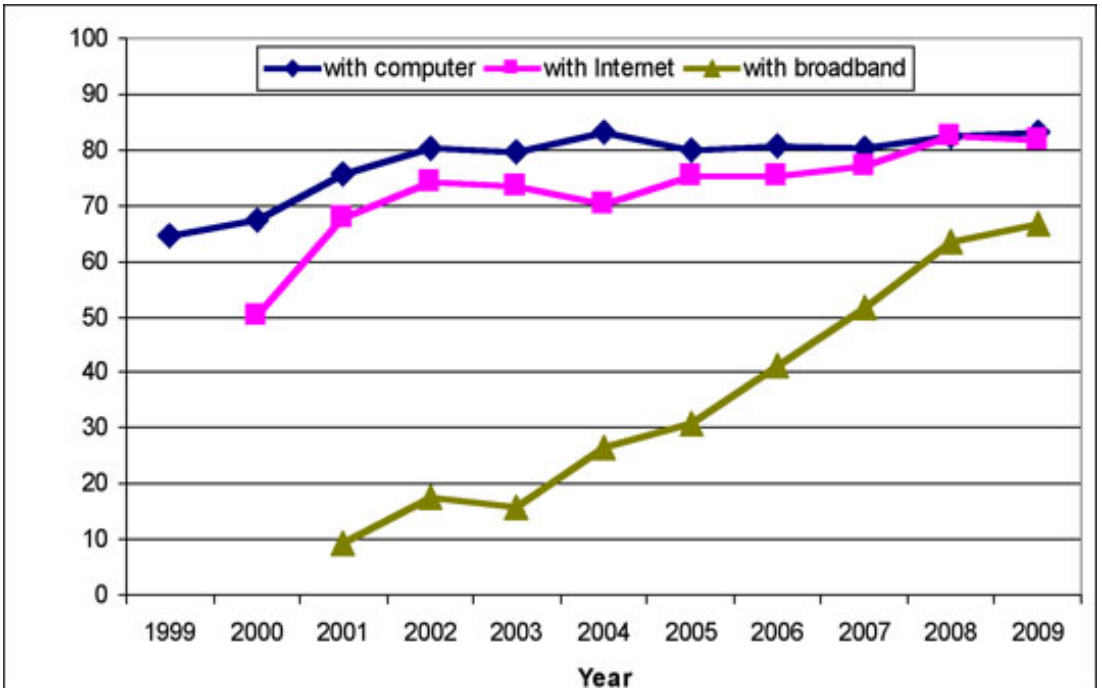

Figure 1: Vermont household computer ownership and the Internet connection. Data source: Vermont Poll 1999–2009.

With computers and the Internet becoming widely available in Vermont, the differences in the frequency of actual use of the Internet become apparent. As shown in Figure 2, there is a gap between those who have used the Internet for information search and those who have not. 12.2 percent of respondents have never used search engines. Among those who are already users, the frequency of searching through the Internet varies widely, with 56.1 percent of respondents using search engines to search for information daily.

Estimation results and discussion

Empirical results are summarized in Table 2. In general, the two regression models fit the data well according to the overall tests. One notable difference is that most of the variables have a significant impact on the likelihood of searching for information online, but only three variables have significant effects on the frequency of use.

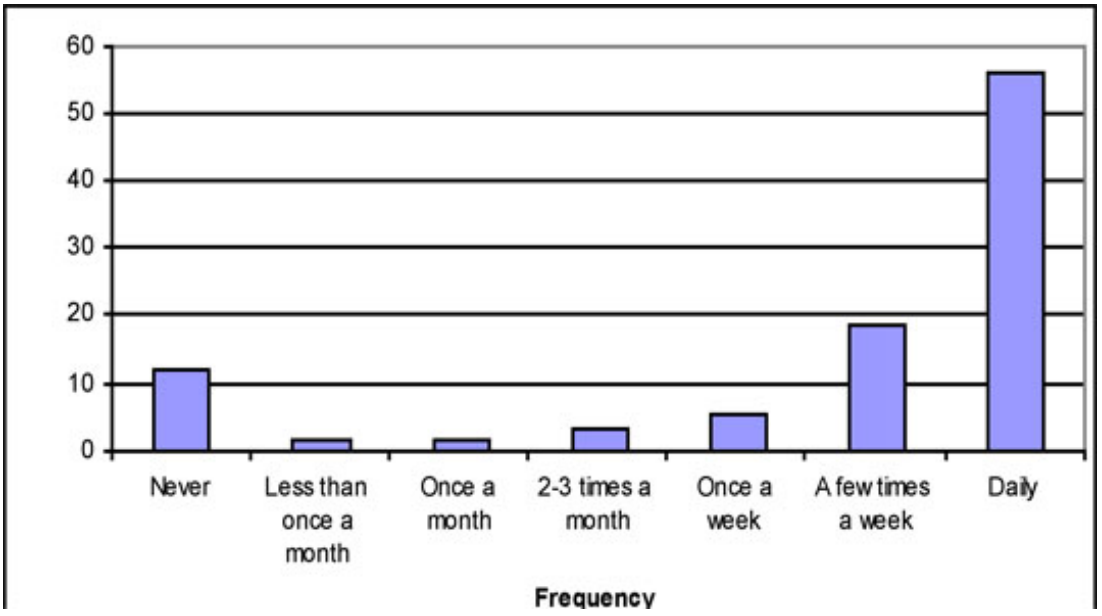

Figure 2: Frequency of using the Internet for information searching.
Data source: 2009 Vermont Poll.

Empirical results of the BLR model for the first hurdle indicate that six socioeconomic and demographic variables have significant influence on the likelihood of using the Internet to search for information. Education has the most influential impact. Compared to those with less than high school education, the odds of searching for information online increases 12.84 times for those with a high school diploma, and 34.64 times for those who have college education. Household income also shows a positive and significant impact on the likelihood of using the Internet to search for information. Those who come from households with US$50,000–US$75,000 or more than US$75,000 income, are increasingly likely to use the Internet to search for information (OR = 4.63 and OR = 6.34, respectively) in comparison to those whose household incomes are less than US$25,000.

Table 2: Estimation results of the double–hurdle model for online information searching.

	Information searching			
Education	Participation		Frequency	
Variables	b	OR[a]	β	OR[a]
Education (reference: less than high school)				
High school	2.63***	13.84	-0.16	

College	3.57***	35.64	0.25	
Household income (reference: <$US25,000)				
25,000–50,000	0.10		0.44	
50,000–75,000	1.53***	4.63	0.84**	2.31
>75,000	1.85***	6.34	0.78**	2.17
Home composition (reference: without child)				
With children	-0.13		0.00	
Residence (reference: rural)				
Suburban	-0.46		0.27	
Urban	-0.97**	0.38	-0.01	
Gender (reference: male)				
Female	0.28		-0.34*	
Age (continuous)	-0.07***	0.94	-0.01	
N	476		418	
Prediction power	90.8%			
-2LL χ^2 (P–value)			18.53 (0.047)	
Significant level: * .1, ** .05, *** .01.				
a. The odds ratio (OR) is reported for only the variables with significant impact.				

Urban residents in Vermont are less likely to use the Internet to search for information than those who live in rural areas (OR = 0.38) when other variables are controlled, while there is no significant difference between rural and suburban residents. This finding is opposite to previous national results related to physical access. One possible reason is that a large portion of Vermonters reside in rural areas. The percentage of rural residents is 62.6 in Vermont while the average level in the U.S. is 21.0 (U.S. Census Bureau, 2000). Another potential reason is that Vermont's government has made a lot of efforts promoting the diffusion of ICTs in rural areas. For example, Act 79 established a Vermont telecommunications authority to facilitate the establishment and delivery of broadband infrastructure and services for residents throughout the state in 2007. Age has a negative impact on the likelihood of using the Internet to search for information. The odds decrease by six percent when age increases by one year. Gender and whether there are children at home are not significant.

While the OLR model fits the data well as a whole, only three variables show significant impacts on the use frequency of searching for information through the Internet. Although tests reveal no significant correlations between the included independent variables, it is possible that the frequency of using the Internet for information search could be associated with some variables we did not have data to measure.

Two factors, income and gender, affect the frequency of using the Internet for information search given one has used it. Individuals in households earning more than US$50,000 use search engines more frequently than those who come from the lowest income households. Being female decreases the odds of being in a higher frequency category by 29 percent. The impacts of education level, region of residence, and age are insignificant.

Conclusions

While previous studies on the digital divide in the United States have focused on disparities in physical access to ICTs, this study contributes to the literature by analyzing the factors associated with the imbalance in actual Internet use. With a dataset of 476 Vermont households surveyed in 2009, a double–hurdle model is used to identify the factors and examine their impacts on the likelihood and frequency of use the Internet for information searching.

Empirical results suggest three conclusions: First, when computer and the Internet become widely available to Vermont households, there are significant disparities in both the likelihood and frequency of making effective use of the Internet. The disparities are closely associated with socioeconomic and demographic factors. Second, considering the likelihood of using the Internet for information search, those who have less education, lower incomes, and are of older age are less likely to use search engines. Particularly, rural residents in Vermont are more likely to use both applications than urban residents. Third, in terms of use frequency, disparities still exist among the respondents who have begun to use the Internet for information searching. Household income positively impacts the frequency of using the Internet for information searching, while being a female decreases the frequency.

The impacts of personal characteristics are more on the likelihood to use the Internet for information search and less on the frequency of use. As shown by Chau (2001), computer attitude and self–efficacy have influences on IT usage behavior. Also, the studies of Kolodinsky, *et al.* (2004), and Hogarth, *et al.* (2008) indicate that besides personal factors, technological characteristics of the ICT also affect adoption. Future studies are needed to reveal the influence of technological factors and other potential factors, which affects the use frequency when one has started to make use of the Internet.

The findings of this paper are useful for developing programs and policies for reducing the digital divide or disparities in Vermont and may apply to other states. While it is still necessary to deploy universal and affordable Internet access to American households, more attention should be given to introducing and assisting individuals to make effective use of ICTs. Previous studies showed that the groups which are less likely to use the Internet, and those who use it less frequently, are also the same groups that get connected to the Internet latter, partly because of a learning or content divide. Therefore, increasing individuals' computer and the Internet literacy should be the focus of the future efforts.

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Editorial history

Received 17 August 2010; accepted 28 October 2010.

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by Guangxuan Zhang, Qingbin Wang, and Jane Kolodinsky.
First Monday, Volume 15, Number 11 - 1 November 2010
https://journals.uic.edu/ojs/index.php/fm/article/download/3118/2649