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**ARE WE STILL DIGITALLY DIVIDED? ANALYSIS OF USES OF THE INTERNET
ACROSS RESIDENCE IN THE UNITED STATES**

A Thesis in

Rural Sociology

by

Tyler Augst

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The thesis of Tyler Augst was reviewed and approved* by the following:

Diane McLaughlin

Professor of Rural Sociology and Demography

Thesis Adviser

Leland Glenna

Associate Professor of Rural Sociology and Science, Technology, and Society

Leif Jensen

Distinguished Professor of Rural Sociology and Demography

Cynthia Hinrichs

Professor of Rural Sociology

Director of Graduate Studies Rural Sociology

*Signatures are on file in the Graduate School.

ABSTRACT

Previous research has shown that the spread and use of information communication technologies (ICTs) and infrastructure have been unequally distributed, both socially and geographically. With the Internet becoming more central to daily life and participation in the world, these inequalities of the information age may have significant impacts on individuals and societies. This study is an analysis of secondary data collected from a nationally representative survey by Pew Research Center completed in October 2013. The survey asked respondents about their online photo and video sharing behaviors as well as a variety of individual characteristics. This study builds on previous digital divides literature that argues for re-conceptualizing those divides in more nuanced ways than traditional access/non-access or use/non-use of the Internet as well as literature on the differences between online content consumers and content creators. The existence of a traditionally conceptualized (access/non-access) digital divide between rural, suburban, and urban areas is examined, while controlling for other socio-demographic characteristics previously shown to be associated with digital divides (race, ethnicity, gender, age, education, and income). The digital divide in specific uses of the internet also was examined. Analyses were conducted to test for the predictive power of residence in explaining individuals' photo/video sharing and posting behaviors online. This analysis is accomplished using multivariate logistic regression. Results vary depending on the type of content and if the shared content is original or was created by someone else. While residence was not a statistically significant predictor of internet use, it was significant in models predicting specific types of internet activities. Some relationships between demographic traits and online behaviors may be mediated by the types of devices used to access the internet, such as smartphone technology.

Table of Contents

List of Tables	v
List of Figures	vi
Introduction.....	1
Literature Review.....	5
Introduction - What are Digital Divides?	5
Early Digital Divides Research	6
New Conceptualizations of the Divide.....	7
Manifestations of the Divide	16
The Rural-Urban Digital Divide	20
Summary	26
Methods.....	29
Sample.....	29
Dependent Variables	32
Independent Variables.....	35
Statistical Methods	42
Results.....	44
Internet Use	44
Who Is More Likely to Engage in Specific Uses of the Internet?	51
Summary	83
Discussion and Conclusions	87
Are We Still Digitally Divided in Terms of Our Internet Use?	87
Do Digital Divides Exist in <i>How</i> People Use the Internet?	89
The Importance of Smartphones	90
Residence-Based Digital Divides	92
Conclusions	93
Limitations	96
Implications.....	97
Final Thoughts.....	100
References.....	102

List of Tables

Table 2.1: Characteristics of Individuals with Home Broadband Connections in 2013.....	27
Table 3.1: Sample Response Rates	30
Table 3.2: Sample Demographic Characteristics (Percentages)	31
Table 3.3: Original Educational Level Response Categories	37
Table 3.4: Recoded Educational Level Response Categories.....	39
Table 3.5: Original Income Response Categories.....	41
Table 3.6: Recoded Income Response Categories	41
Table 4.1: Logistic Regression of Residence on Likelihood of being an Internet User (N=956)	45
Table 4.2: Logistic Regression of Residence and Demographic Traits on Likelihood of being an Internet User (N=956).....	46
Table 4.3: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of being an Internet User (N=956).....	48
Table 4.4: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of being an Internet User (N=956)	50
Table 4.5: Logistic Regression of Residence on Likelihood of Posting Photos Online among Internet Users (N=796)	52
Table 4.6: Logistic Regression Residence and Demographic Traits on Likelihood of being Posting Photos Online among Internet Users (N=796).....	54
Table 4.7: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of Posting Photos Online (N=796).....	55
Table 4.8: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of Posting Photos Online (N=796)	57
Table 4.9: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Posting Own Photos Online (N=796)	59
Table 4.10: Logistic Regression of Residence on Likelihood of Posting Own Videos Online (N=797).....	60
Table 4.11: Logistic Regression Residence and Demographic Traits on Likelihood Posting Own Videos Online (N=797)	61
Table 4.12: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of Posting Own Videos Online (N=797)	63
Table 4.13: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of Posting Own Videos Online (N=797).....	65
Table 4.14: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Posting Own Videos Online (N=797)	67
Table 4.15: Logistic Regression of Residence on Likelihood of Sharing Photos Online (N=795)	68
Table 4.16: Logistic Regression Residence and Demographic Traits on Likelihood Sharing Photos Online (N=795).....	69

Table 4.17: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of Sharing Photos Online (N=795)	71
Table 4.18: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of Sharing Photos Online (N=795).....	73
Table 4.19: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Sharing Photos Online (N=795).....	75
Table 4.20: Logistic Regression of Residence on Likelihood of Sharing Videos Online (N=797)	76
Table 4.21: Logistic Regression Residence and Demographic Traits on Likelihood Sharing Videos Online (N=797)	77
Table 4.22: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of Sharing Videos Online (N=797).....	78
Table 4.23: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of Sharing Videos Online (N=797)	80
Table 4.24: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Sharing Videos Online (N=797)	82
Table 4.25: Demographic Difference across Residence Types	84
Table 4.26: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Posting Photos, Posting Videos, Sharing Photos, and Sharing Videos Online.....	86
Table 5.1: Who is Less Likely to Engage in Each Specific Internet Use	95

List of Figures

Figure 3.1: Recoding Scheme for the Variable Education	38
Figure 3.2 Recoding of Income Categories	40

Introduction

As the United States entered the new millennium, it, along with the rest of the globe, was undergoing a drastic revolution in how people communicate and send information to one another; the age of the Internet was emerging. Advances in information and computer technologies (ICTs), ranging from personal computers and the Internet to digital cable, have reshaped how people interact with one another both locally and globally. ICTs have allowed for information to be shared faster and cheaper than ever before across huge geographic distances. In a matter of seconds an e-mail can be sent across continents and data can be transferred with the click of a button. Having access to and being able to use ICTs is becoming increasingly essential to life in a modern, global, information society (Selwyn 2004). Yet the growth and use of these new technologies has not been spread evenly throughout the country. These inequalities of the information age, or digital divides, are the focus of this research. Specifically, this study examines inequalities between rural and urban places in whether people use the Internet and among users how people use the Internet.

Information age inequalities have been observed along various demographic, socioeconomic, and residential lines. Initially these inequalities were measured dichotomously in terms of those who had access versus those who do or were using these new technologies and non-users (Tsatsou 2011). As ICTs have continued to advance, advances have occurred in how social scientists think about these technologies. For example, with the introduction of broadband and other high speed connections to the Internet, social scientists began looking at access but also the quality, or speed, of that access (Selwyn 2004).

The potential implications of these new information technologies are far reaching. In their strategic plan to spread broadband access across the United States, the Federal Communication Commission (FCC) acknowledged a host of areas for potential benefits of Internet use from the economy to homeland security (2013). Included in these are the benefits to the government and civic activities that come with a digitally connected society. The FCC states that expanding broadband services could lead to more efficient delivery of services (especially to underserved areas), increased communication between representatives and those they represent,

and make government “more open and transparent, creating a robust public media ecosystem and modernizing the democratic process” (FCC 2013:XIV).

Early scholarship was been divided on what impact the increasing use of Internet technologies has had on actual local community participation. Some researchers argued that the increasing use of the Internet has led to a decline in social involvement (Kraut et al. 1998). Turkle (2011) elaborates on this idea that increasing involvement with technology and ICTs has led to a decline in meaningful face-to-face interactions in her book *Alone Together: Why We Expect More from Technology and Less from Each Other*. These arguments seemed to play on larger popular beliefs that as people spend more time in front of screens and in virtual realities their participation in the actual world suffers.

Other studies have argued the opposite, suggesting that increased Internet usage can actually have benefits for community participation. In suburban areas, Hampton and Wellman (2003) found that Internet technology can be seen a way to bolster community participation through discussion of local matters. Stern and Dillman’s (2006) work supported Hampton and Wellman’s claims for Internet users in rural areas as well. The authors distinguish between two types of participation that take place within a community, nominal (membership in a group or attending an event) and active (taking a role in or investing in the success of a group or event). Increased Internet usage was correlated with higher levels of both types of participation. The authors argue that this was because community members had easier access to information about their community, including what events were going on, that allowed them to become more engaged.

In addition to potential impacts on community participation, the digital divide may have implications in the political sphere as well. Using data from the 2007 Pew Internet and American Life Project, Sylvester and McGlynn (2010) examined whether different levels of physical access to Internet technologies across place impacts levels of political participation (anything that directly or indirectly influences government action) and found that higher levels of Internet access and use were positively related to political participation.

If the technology known as the Internet is not equally distributed throughout the population of the United States then it is very possible that these desirable outcomes of increased

Internet use may be accumulating unequally as well. For this reason it is important to understand and work to counteract digital divides, such as the one that has been shown to exist between rural and urban places in the United States. The digital divides also warrant attention from social scientists as the Internet is increasingly recognized as crucial to living and exercising human rights in a modern society, such as the freedom of speech or protest (UN 2011).

Building upon the work of previous digital divides scholars, the purpose of this research is to determine if residential digital divides persist in regards to whether people use the Internet and how when controlling for demographic and socioeconomic characteristics. Previous research has acknowledged the role that place, as well as household and individual traits, plays in Internet habits. Using recent data, this project seeks to readdress that issue and test for place-based inequalities in Internet use. A second purpose of this research is to test for digital divides among those already online in regards to content creation and content sharing, focusing on rural and urban differences. This will be done using 2013 survey data that is publically available from the Pew Research Center. A series of logistic regression models testing the relationship between residence and likelihood of Internet use and controlling for a host of previously established controls are estimated. The thesis is organized as described in the remainder of this chapter.

Chapter two reviews the relevant digital divides literature and examines how inequalities of the information age have been treated by previous scholars. This begins by tracing the historical development of the conceptualizations of digital divides starting with early work in the 1990s exploring inequities in access and use. This research was refined by subsequent scholars to include measures of quality of access, type of use (including content creation and content sharing), and more recent conceptualizations focusing on the integration of the Internet and other ICTs into daily life. Following this primer on the myriad of types of digital divides that have been studied, manifestations of these divides will be reviewed focusing on those segments of the population who are less likely to have access to or use ICTs. These disadvantaged segments of the population include the elderly, racial and ethnic minorities, the less educated, and those with lower incomes. The second chapter will conclude with special consideration of one type of digital divide, the inequalities that exist between rural and urban places in terms of access to and use of the Internet.

Chapter three outlines the data and methodology to be employed in this research, including variable definitions and recoding schemes. The survey data was originally collected by Pew Research Center's Internet Project in October of 2013 and focuses on individual's online pictorial activities. This nationally representative telephone survey data includes measures for residence type, Internet use, engagement with specific Internet uses, and a host of individual and household measures that have been previously shown to be associated with ICT use. This chapter will also lay out the roadmap for the five multivariate logistic regression models estimated for this project.

Chapter four presents the full results from each of the iterations of the logistic regression models for each of the five measures of Internet use. For the first outcome variable, being an at least occasional Internet user, four models are presented. The first model only includes the bivariate relationship between place and likelihood of being an Internet user; the subsequent models add demographic variables, education, and income as controls. For the four specific use outcome variables (posting photos online, posting videos online, sharing photos online, and sharing videos online) a similar approach is taken with one difference. For each outcome a fifth model is included that adds a variable for smartphone ownership as a control.

Chapter five is a discussion of the results obtained from the statistical models. This discussion builds on the in depth analysis from chapter four organized into four key sections. The first section addresses whether digital divides exist in who is likely to be an Internet user. The second answers whether divides exist within Internet users in regards to specific uses (the posting and sharing of photos and videos). This is followed by a discussion of the second order digital divides that exist between those who create content for online audiences and those who share already existing content. Special consideration is also given to the role smartphone ownership plays in increasing the likelihood of posting or sharing content. Chapter five concludes with an analysis of residential-based digital divides that remained when all control variables were included in the models.

The thesis concludes in chapter six with a brief summary of the research project and its findings. In addition to this summary the final chapter also includes a brief discussion of the limitations of this study along with suggestions for future research. Potential policy implications of this, as well as other digital divides research, are also considered.

Literature Review

Introduction - What are Digital Divides?

The concept of a digital divide has grown and developed alongside the information communication technologies that it seeks to describe. As the new technologies of the information age advanced, the adoption of these technologies was not distributed equally. This unequal distribution created a new dimension of inequality in society. These inequalities have come to be known as information age inequalities or the digital divide. Over the years many different conceptualizations of the digital divide have circulated. Some of this variation is a product of the rapidly evolving and shifting field of information communications technology and some is because of differences in how the concept of the divide has been defined. Tsatsou (2011) goes as far as to call the term digital divide itself problematic, instead recognizing that a multitude of digital divides exist and interact with one another. For the purpose of this research digital divides is an umbrella term to represent any inequality in how people access or interact with the Internet and other ICTs.

This chapter will outline the history of digital divides research in the United States through a summary of the various conceptualizations of digital divides that scholars have used since the widespread introduction of the Internet into homes in the 1990s. These conceptualizations span simple dichotomies between users and non-users, which were popular as the technology was still penetrating the country, to more recent measures that seek to understand the multiple ways individuals use the Internet and how much that use is integrated into their daily lived experiences.

Next, the discussion will focus on evidence from the literature of various manifestations that these digital divides have taken. With such a nebulous concept, like digital divides, that has seen multiple definitions over time, the focus of this literature review falls more to general patterns of inequalities that emerge in regards to ICTs. These inequalities span the spectrum of digital divide conceptualizations, but they show relatively persistent patterns of disadvantage based on sex, age, race, ethnicity, educational attainment, and income.

The final section of this literature review focuses on one specific type of digital divide, the one that exists between rural and urban places in the United States. Evidence for this place-based divide will be provided both in terms of infrastructural inequalities and individual variations in use. This divide is important to consider because the access and use of ICTs in rural places lags behind that in urban places, even as nationwide absolute rates of use and access continue to climb each year. This rural-urban divide is also of special consideration because Internet based solutions are often cited as the key to rural America's future. In order for that to be the case, rural America first needs to be fully online.

Early Digital Divides Research

The concept of the digital divide has changed dramatically over time. It has gone from meaning physical access to the infrastructure needed to access the Internet to a more nuanced understanding that explores quality of access, computer literacy, use, and types of use. These new ways of measuring digital divides are increasingly vital as the Internet continues to play an even larger and larger role in society and individual lives.

Early research on Internet and the digital divides was centered on infrastructure and physical access. During this initial period of research, models of technological diffusion developed to explain the spread of telephone and television were adapted in an attempt to explain the lower levels of ICT adoption in rural areas (Agarwal, Animesh, and Prasad 2009). Agarwal and colleagues argued that ICTs were being slow to spread out to rural areas, just as phone or televisions was, because ICTs are still such a new innovation and innovations take time to spread throughout society. Another reason for variation in the spread and adoption of ICTs, according to Grubestic and O'Kelly (2002), is that changes in telecommunications policy in 1996, specifically the deregulation of telecommunications providers, have contributed to the spatially unequal access. Through deregulation the Internet service providers (ISPs) were allowed to let the market forces of supply and demand determine where they would invest in new infrastructure. As a result, rural areas were often overlooked because they did not have the geographically concentrated demand necessary to make infrastructure investments profitable (Grubestic and O'Kelly 2002; Grubestic and Murray 2004).

The combination of lack of infrastructure and a sentiment that those without access to ICTs should have access led much of the initial research to focus on the divide between the technology haves and have-nots. In research, this often manifested as examinations of physical access to the Internet or sometimes as users versus non-users. The divide between having access and not having access has often been framed (and continues to be framed) in terms of demographic characteristics of the individual (Jackson et al. 2008), household (Katz and Aspden 1997; Hampton and Wellman 2003) or communities (Agarwal, Animesh, and Prasad 2009). Selwyn (2004, 2002) argues that the binary distinction between access and non-access defined the problem of digital divides too simplistically, which then enabled policy makers to push for simple and seemingly feasible solutions. By defining the problem in terms of access to ICTs, the digital inequalities could be viewed as being a problem with a concrete solution, such as increasing telecommunications infrastructure or providing more public places to access ICTs.

At the turn of the millennium, the discourse around digital divides began to change. The initial dichotomous conceptualization of the digital divide between those with access and those without was beginning to break down. For example, in 2000 the rates of dial-up access in rural areas were 11% lower than for urban areas but by 2003 the rates actually equalized (Whitacre and Mills 2010). As Tsatsou (2011) notes, simply having the physical access was no longer equated with overcoming the digital divide. Instead, “a more elaborate and realistic understanding of the inequalities of the information age” (Selwyn 2004:346) was needed.

New Conceptualizations of the Divide

This section focuses on some ways that research on issues of the digital divide have expanded and elaborated on the earlier concept of a digital divide to meet that call for “more elaborate and realistic understanding”. While this is not an exhaustive list of all variations that exist within the digital divide literature, what follows are three major conceptualizations that have been particularly useful when investigating digital inequality: Quality of access, Multimodal use models, and Multidimensional approaches.

Quality of Access

The first change in the discourse of the digital divides happened in the early 2000s in response to changes in the way that ICTs were being used. Originally the content available on the Internet was what we now call Web 1.0 applications (in contrast to Web 2.0). Web 1.0 applications, broadly speaking, is the term used to describe web applications where the content being accessed is static and tends to be created by a small group of content creators and the majority of users are content consumers. An example of this would be most corporate websites and news websites (not including comments sections). Around 2003, the term Web 2.0 was brought into the vocabulary to describe the recent growth in web applications and sites that included new features like user-generated content (Wikipedia), social networking (MySpace, Facebook) and other new methods of interacting that were made possible due to advancements in both ICT hardware and infrastructure (Cormode and Krishnamurty 2008).

These new and innovative web applications required faster connection speeds to access and utilize them fully. This caused a shift in digital divides research away from simple access versus non-access towards quality of access, specifically access to high speed or broadband services (200 kilobytes per second) (FCC 2002). Unlike dial-up access, which only requires an existing phone line, these high speed connections involved a much more significant investment in new infrastructure. This higher cost of investment comes from having to install new networks of wire or fiber-optic cable that can handle the amount of information that needs to be transferred, modems or routers in individuals' houses to allow them to connect to those new wires, and hubs that connect local networks to the larger national and global Internet infrastructure.

Prompted by the increased cost to ISPs to provide these high speed services, Grubestic and Murray (2004) sought to explain the variation in high speed access as a function of market demand and competition among providers. Using data from the FCC on high speed ISPs and their subscriber locations (zip codes), Grubestic and Murray created indexes for competition among Internet providers. The authors found that overall from 1999-2001 competition among ISPs increased, but at a slowing rate. They also found that those changes were not seen across all geographic areas. Rural areas continued to lag behind urban areas in competition indexes. In June of 2001, 27.9% of all zip codes in the United States had no high speed ISPs and of those zip

codes 80.4% were rural. Grubestic and Murray (2004) speculate that this is most likely due to the higher cost to establish service in those areas. Some of these initial costs are being circumvented through the growing adoption of satellite and fixed wireless Internet connections. From 2007 to 2009, the percentage of those with home broadband connections that used satellite or fixed wireless connections grew from 8% to 17% (Horrigan 2009a). It is important to note that the decrease in cost for providers that these new connection types provide does not always translate to affordable pricing for users. The high costs of these services and persisting lack of availability leads to lower adoption rates of satellite and fixed wireless connections in rural areas compared to urban (17% v. 19%) (Horrigan 2009a).

Whitacre and Mills (2007) sought to examine the relationship between infrastructure and demographic characteristics for adoption of high speed Internet access in research focusing on the quality of access available. The authors created a novel measure of Digital Communication Technology (DCT) infrastructure from data from *Television and Cable Factbook* and National Exchange Carriers Association. The measure was created for each county (or city) by taking the capabilities of the county (or city) and dividing by the population, creating a sort of speed per capita measure. Using this measure the authors found that when controlling household characteristics, such as income and education, the distribution of infrastructure in the United States is uneven between rural and urban areas showing that the digital divides, in terms of quality of the connection, do exist.

Multimodal Use Models

A second elaboration of the inequalities of the information age goes beyond access to examine how individuals are actually using ICTs. As Selwyn (2004) notes, access does not equate to use and use does not equate to meaningful use. Simply building the infrastructure does not mean that individuals will access and use it equally. In light of that, Wei (2012) proposes a new framework of digital inequalities to replace the binary divide. By using data from the Pew Internet & American Life Project, Wei created a measure of multimodality of use (ranging from 0-11) from respondent's answers to whether or not they used the Internet for 11 different activities. The idea is that the more uses a person engages with, the more integrated the Internet is into their lives. It was found that those respondents who were female, older, poorer, and those

who had less education all engaged in fewer uses of the Internet. As will be shown in the next section these digital divides along demographic characteristics echo those noticed by earlier researchers in terms of access/non-access. Wei also found that respondents who were engaging in fewer uses were more likely to only engage in Web 1.0 technologies and users who expressed higher multimodality used more of the Web 2.0 technologies.

The approach illustrated by Wei (2012) above has been useful as an attempt to measure Internet use in general terms, but a compelling empirical case can be made that different types of uses and goals for using the Internet have differential impacts. We would expect individuals who primarily use the Internet to maintain social connections to have a vastly different experience and outcomes than someone whose primary use was seeking information. In this spirit, Mitchell et al. (2011) sought to untangle the relationships between specific types of uses and personal characteristics. In a survey of undergraduate students at a Midwestern technical school, the authors employed a questionnaire that asked about 30 different specific uses, across six domains (purchasing, information seeking, tasks/services, entertainment, work or school related, and mischief). The relationship between these domain-specific use measures and personal attributes, like happiness, social support, and personal introversion, varied by the type of use being considered. These findings lead the authors to call for “focused research examining specific aspects of Internet use that take into account the dynamic nature of the Internet” (Mitchell et al. 2011: 1860)

These variations based on of type of use have been observed time and time again in the research. From December 2008 to January 2009, Gil de Zúñiga, Jung, and Valenzuela (2012) administered a nationally representative survey that measured general social networking site use, social capital, civic participation, offline political participation, and online political participation. The researchers found that controlling for demographic characteristics, political traits, media use, and characteristics of the participant’s network, using social networking sites to get news was positively associated with social capital, civic participation, offline political participation, and online political participation. Further analysis showed that this relationship was attributable to the use of social networking sites for news and not general social networking sites use.

Those Who Post and Those Who Share

One of the new digital divides that emerged through these use-centered approaches has been the gaps between those who create or those who share content online and those who do not. The focus on this specific use divide has been driven largely by the transformative power ICTs have had on the media landscape of society. In the past, the media landscape was dominated by the traditional forms and mass media. Things like television, newspaper, radio, and print media were the main sources of content for society. What content was available was filtered through what are known as gatekeepers. These gatekeepers are the newspaper editors, news anchors, producers, and so on that have control over the content that is being consumed. The introduction and spread of ICTs, specifically the Internet, has caused a drastic shift in this model of the media landscape.

As the Internet has grown and become more integrated into society, who is a gatekeeper as well as who generates the content to be consumed has been forever altered. With vast amounts of content and information at their fingertips via the Internet, individual users have moved on to being their own gatekeepers. This individual level gatekeeping is driven by the advances in ICT technologies that let the user filter what they see and consume. This is in comparison to the old model where media elites performed this task (Sunstein 2001). In addition to the gatekeeping opportunities afforded to individuals, the Internet has shifted the task of content creation to individual users as well. This shift is a result of the change from Web 1.0 to Web 2.0 applications discussed above. At the same time that individual users were increasingly becoming their own gatekeepers they were becoming the source of new content as well (Hargittai and Walejko 2008). These newer web applications were built on users supplying some content. Initially this content was in response to a static page, such as a comments section, and grew to full pages largely consisting of user generated content. One example of this type of content would be profile pages on social networking sites. As has been observed time and time before, the diffusion and implementation of these new technologies has not been equally distributed across society, which brings us to inequalities in who shares and creates online content.

In an effort to add depth to the understanding of inequalities of the digital age, scholars have begun to consider what have been called second-level digital divides (Hargittai 2002), the participation gap (Jenkins et al. 2006), emerging digital differentiation (Peter and Valkenburg

2006), or the usage gap (van Dijk 2006). All of these terms are attempts to name digital divides that go beyond issues of access or technological qualities, the inequalities that are defined by differential skills, uses, and integration of the Internet and its use into daily life.

Focusing on these types of digital divides is especially important given the tendency for the Internet to be portrayed as a panacea for all manner of social woes, such as participation in civil society and the democratic process. Benkler (2006) makes a compelling argument that with the growth of the Internet creates more opportunities communication for participation outside of the traditional markets. These opportunities allow for more individual autonomy for information gathering and civic participation, regardless of status. In this argument the Internet is seen as a great equalizer. However, as Block (2013) points out a greater number of people seeking information and expressing opinions through the Internet does not necessarily enhance the civic sphere if that participation is unequally distributed.

Previous research has found that engagement with the Internet is unequally distributed among uses, especially in regards to content creation. One would expect the inequalities in specific uses, including content creation and sharing, fall along similar lines as the inequalities in being an Internet user (more on these manifestations later). Age has been found to be negatively associated with specific uses (Blank and Dutton 2013; Block 2013), even among undergraduate students (Hargittai and Walejko 2008). Research has also revealed a sex based divide of content production and sharing, with males sharing more (Hargittai and Walejko 2008). Educational level has been a significant predictor of social/entertainment uses (Schradie 2011) and political uses (Block 2013). These relationships between gender and education disappear though once controls for skills or technological literacy are introduced (Hargittai and Walejko 2008; Block 2013). An interesting result from this line of research has been that higher incomes have been associated with less content production (Block 2013), mirroring results of similar studies of content consumption (Bonfadelli 2002; Beunte and Robbin 2008).

One of the most comprehensive treatments of these digital divides around content creation and sharing has been done by Jen Schradie (2011). Schradie combined the data from a total of 17 different surveys containing questions related to Internet use from Pew Research Center from 2000-2008 into one large data set. This new data set allowed analyses to be done using a variety of predictors such as demographic and socioeconomic traits for 10 different

digital production activities. Schradie characterizes this focus on content production as the next step for digital divides research, building upon the research that has been done on how individuals receive (or cannot receive) information from the Internet because of inequalities of access and uses.

These disparities in content creation begin to have even more apparent ramifications for society when the type of content being created is examined. Hargittai and Walejko (2008) did precisely this in their examination of what they called the production divide. Using a survey of urban undergraduates, the authors asked about the creation, as well as posting online, of music, poetry or fiction, artistic photography, and film or video. By further adding nuance to the measures of posting content through the addition of type of content, the authors were able to observe slightly different relationships between demographic and socioeconomic traits and the production and sharing of various types of content.

This more nuanced analysis of content sharing by type of content was also employed by Blank (2013). Here, the author used responses to survey items about eight types of content creation: writing a blog, maintaining a personal website, posting writing or other creative content, using Social Networking Sites (SNS), posting pictures, uploading video or music files, emailing political content, and commenting on political/social issues as specific uses. A factor analysis of the responses showed these eight items loading into three categories: skilled content, social and entertainment content, and political content. In an additional analysis of the survey responses using these factors, it was found that the relationship of social status and content creation varied for each type of content. Individuals with a lower socioeconomic status were more likely to engage in entertainment or social uses while individuals who had a higher socioeconomic status were more likely to engage in more skilled uses of the technology, such as information seeking.

Multidimensional Approaches

While the focus of this thesis is on specific content creation and sharing activities, a branch of digital divides research goes beyond access and uses and considers the multidimensional nature of the ICT use and to contextualize this use within the users' lives. This

has led researchers to develop some new and exciting frameworks to approach all manners of digital divides. These multidimensional approaches assume that access is a given (an assumption that should be questioned, especially when considering the rural United States) and instead focuses on how individuals use ICTs (much like the multimodal use models) and how that use fits into the context of their lives.

Stern, Adams, and Elsasser (2009) presented one such multidimensional approach to digital divides that centers around three levels of digital inequality:

- 1) Unequal access to Internet and diffusion of new technology
- 2) Unequal proficiencies in usage
- 3) Opportunity divide (how do people use technology to help with day-to-day activities)

Some research attention should be focused on the second and third levels to analyze digital inequalities (without losing sight of the first order inequalities of newer technologies). Specifically for rural areas, the lack of high speed connections is hindering the development of proficiencies that can be transferred into opportunities. This line of research should also examine how rural residents are learning to use new ICTs and potential differences in the diffusion of this IT literacy between rural and urban places.

Research is being done with an eye towards these second and third order inequalities through the frame of skills and literacies. One such effort is the Internet Knowledge measure developed by Denise Potosky (2007). Amusingly shortened to iKnow, this measure seeks to gauge “what people know about the Internet as well as the various kinds of things people are able to do using the Internet” (Potosky 2007: 2761). To capture both these aspects of knowledge Potosky developed a scale of items that asked individuals to self-report their capabilities, Internet use, and familiarity with specific terms.

Similar to the idea of the iKnow, Ferro, Helbig, and Gil-Garcia (2011) included a measure of information technology (IT) literacy in their analysis of digital divides, operationalizing IT literacy as the “ability to use a computer and Internet for information search and e-mail exchange” (p. 4).¹ This information was self-reported as part of a survey on computer

¹ This study was based on data from the Information and Computer Technology Observatory of the Piedmont Region of Italy

and Internet use. In this study IT literacy was seen as a cause for digital divides and a digital divide to be overcome in itself. Ferro et al. (2011) found that IT literacy was statistically significantly related to both a dichotomous model of the digital divide and a more nuanced conceptualization that included usage levels and purpose. The authors categorized users into three categories based on the findings that around 25% of the users were considered “advanced users”, 25% were “basic users” and the remaining half of users were considered “non/sporadic users”. Each of these groups was characterized by differences in their approach to learning new IT skills. The advanced users tended to self-learn IT skills for the inherent reward and the other categories needed more incentives to increase their IT literacy.

Significant research has also been done on ways to measure web-use skills specifically. As opposed to the approach of multimodal use models, the goal in this research was to create a way to measure not *what* individuals were doing online, but rather *how well* they could do it. Toward this goal, Eszter Hargittai (2005) has been developing a survey measure to accurately assess web-use skills after it was observed that individuals’ self-reported measures of skills did not match observed web skills (Hargittai 2009). The initial measure was based on participants’ self-reported familiarity with 27 different Internet terms that represented three levels of Internet understanding, high, medium and low. More recent work by Hargittai and Hsieh (2012) has revisited that measure in an effort to create a more succinct measure that could then be included more easily into a wider variety of research. The researchers were successful eventually creating an index of as few as six items that could measure Internet skills in specific contexts.

The more available and used that the Internet becomes the more important it is to consider the Internet as an integrated aspect of daily life, rather than something in isolation. The focus is placed on the relationship between individuals and the Internet. Loges and Jung summarize this path as an “ecological approach that takes into account the goals, resources, and communication environment” (2001:537) of the individual. Loges and Jung refer to this relationship as Internet connectedness and found it to be useful in developing a more nuanced understanding of some of the digital divides in our society. Näsi, Räsänen, and Lehdonvirta (2011) have also attempted to measure this relationship with the Internet by asking respondents to a survey how connected they feel to a variety of communities, including both offline and online communities.

Manifestations of the Divide

Previous research has found that these digital divides, conceptualized in a variety of different ways, exist across a number of dimensions, just as other forms of inequality in society do. Digital divides have been observed along racial, ethnic, sex, age, and socioeconomic lines. The roots of these inequalities even begin at an early age. For example, Jackson et al. (2008) surveyed 513 children to examine differences in the nature and intensity of information technology (computer, Internet, video games, or cell phones) use across gender and racial lines and found difference across both. The digital divides along these dimensions have also remained relatively stable throughout, which has allowed researchers to identify patterns of inequality when it comes to the digital divides. Of course, given the wide variation in conceptualizations of the divides discussed above, it is difficult to make bold predictions in regard to a specific use of the Internet. What follows is a discussion of how digital divides have manifested themselves across racial and ethnic, gender, age, and socioeconomic lines in an effort to highlight the general patterns of information age inequalities that have been observed. The discussion will be organized by each of these dimensions and includes recent empirical studies focusing on manifestations of the divides followed by a general conclusion regarding the patterns to be expected when these dimensions are considered in relation to new explorations of the divides.

Race and Ethnic Digital Divides

First the digital divides around race and ethnicity will be considered. In the Jackson et al. (2008) study mentioned earlier, the authors found that the nature and intensity of information technology varied by both race and gender. It is important to note that the sample for this study only included African Americans and Caucasians, no other racial or ethnic minorities. African Americans were less likely to use information technology than Caucasians. African American males were the group least likely to use the Internet or computers.

Using the survey results from Pew Research Center (Zickuhr and Smith 2013) it was observed that white, non-Hispanic participants in this nationally representative survey were most likely to have broadband at home followed by Non-Hispanic Blacks respondents and with Hispanics reporting the lowest rates of broadband connection. For both those black, non-

Hispanics and Hispanic respondents the rates of having a broadband connection at home were lower than those for all adults with Hispanics being a full 17% behind total rates and 21% behind white, non-Hispanics.

Sex-Based Digital Divides

Jackson et al. (2008), in their study of the digital divides in children, found the nature of use was found to be gendered. Males were more likely to use information technology for recreation, like video games, while females used the technology to connect and communicate.

Further evidence for a gendered digital divide can be seen in previous research on posting content online. In their survey of “highly wired young adults” (2008: 240) Hargittai and Walejko, found that women were less likely to share creative content on the Internet, even when controlling for the creation of content. In further analyses the authors present user skill as a potential intervening factor. Indeed when user skill was controlled, the gendered inequalities in the sharing of content were no longer observable. The similar pattern of men sharing significantly more than women online was observed among a nationally representative sample of the British (Block 2013). These differences also go away once controls for skills were included. These findings illustrate the importance of how being on the wrong side of one of the lower order divides like access or skills can then have ripple- effects when it comes to taking full advantage of the technology.

Age-Based Digital Divides

A stark digital divide in regards to age has also been observed. Generally it is to be expected that older individuals would be slower to adopt and integrate ICTs into their lives. This pattern is observed in rates of broadband connections between age groups as shown in Pew Research Center data (Zickuhr and Smith 2013). A sharp divide of about 10 percentage points can be seen between respondents who were under 49 years old and those who were 50 or older. This divide seems natural given how recently these technologies have appeared on the scene when placed into the context of seniors’ entire lives. This is different from, for example, the

graduating high school class of 2015 that has always lived in a world where the Internet exists. It is because of the newness of these technologies that digital divide researchers are unsure if the differences in access and use of ICTs based on age are an effect of age itself or some generational effect of not having grown up with these technologies (Abbey and Hyde 2009). Regardless of the cause of an age-based digital divide, this divide has been observed through both quantitative and qualitative studies of Internet access and use.

Most age-based digital divides are normally framed in terms of the younger generations in comparison to older generations. It is in these types of comparison that the differences are most stark, especially considering the relatively low adoption rates observed among those who are 65+. However, age has been shown to be a significant predictor of Internet use, specifically content creation, among first year college students. Even within a population with such a narrow age range, younger participants were more likely to share content online than older participants (Hargittai and Walejko 2008).

In their studies of the digital divide, Loges and Jung (2001) attempt to move from more traditional measures of the divide in terms of access towards multidimensional conceptualizations discussed above. They do so by developing a measure of Internet connectedness, a concept they define as “An ecological approach that takes into account the goals, resources, and communication environment of old and young respondents to a telephone survey” (Loges and Jung 2001:537). This new concept framed the issues of digital divides as one of being concerned with the differential relationships between individuals and ICTs rather than just the individual’s access or use. This relationship between individuals and the Internet was composed of three dimensions: 1) History and Context, or their previous experiences with the Internet and its accessibility, 2) Scope and Intensity of usage, and 3) Centrality, or impact on the individual’s personal life. The authors then tested this new measure of connectedness through a telephone survey of seven areas within 10 miles of Los Angeles. An analysis of the survey results showed that the age-based digital divide is much more than an issue of access. Older respondents used the Internet less and for a narrower range of goals than their younger counterparts and overall had lower scores for connectedness. Even though these older users were less connected they did not report the Internet being any less central their lives. The older users’

lower levels of use may have also been a reflection of their concerns about security and privacy in the newly emerged digital age.

Findings from qualitative added nuances to the age-based digital divide beyond the idea that age has a negative relationship with all measures of engagement with ICTs. Using interviews with 26 politically active seniors (65+), Abbey and Hyde (2009) complicated the age-based digital divide by presenting evidence against the image of seniors as uninterested non-adopters. Using their interviews the authors identified three distinct groups of seniors based on their relationships to ICTs: Cyber-critics, Cyber-neutrals, and cyber-enthusiasts. The Cyber-enthusiasts were the largest group (69%). These seniors were individuals who had largely positive thoughts about ICTs and had adopted them, especially email. Their enthusiasm was not a naïve one though. These seniors were aware of potential disadvantages to ICTs, but saw the benefits as outweighing those risks. The cyber-neutrals were individuals who saw the usefulness of ICTs and were open to them, but some were lacking the skills needed to act on that. The cyber-critics seem to embody that uninterested non-adopter who had no desire to use and saw face-to-face interaction as offering something more than computer-mediated communication. The experience of the cyber-neutrals who may want to use the Internet but are restricted by their lack of skills was also observed in a study that distinguished between Internet or medium skills and content skills and found that while content skills increased with age, the older participants had so few Internet or medium skills that they actually performed worse on Internet search tasks than their younger counterparts (van Deursen, van Dijk, and Peters 2011).

Socio-economic-Based Divides

The positive relationships between income or education and Internet use are particularly clear when examining online political activities/political uses. For example, during the 2008 election in the United States both income and education had strong positive relationships to online political engagement, or in the authors' words "the well-to-do and well-educated are more likely than those less well-off to participate in online political activities" (Smith et al. 2009: 3). Similarly in a national survey of British Internet users it was found that social status was positively related to political content creation (Blank 2013). Similar positive relationships between socioeconomic status and online political participation have been repeatedly shown

(Sylvester and McGlynn 2010; Cohen et al. 2012; Gil de Zúñiga, Jung, and Valenzuela 2012). These positive relationships between income and/or education can be observed in other measures of the digital divide, like skills (van Deursen et al. 2011), variety of uses (Wei 2012) and connection type (Zichuhr and Smith 2012)

Some more recent research that considered more detailed measures of Internet use has yielded some intriguing results that seem to buck the general trend described above. While not based in the United States, one study by Blank (2013) showed that as income of the participants increased their creation of social and entertainment content (using SNSs, posting pictures, and uploading video and music) actually decreased.

The Rural-Urban Digital Divide

While the manifestations of the divides outlined above are important social issues to study and resolve, they are not the focus of this thesis. The research at hand is concerned with digital inequality based on place (rurality) in the United States. Just as the access and use of ICTs was observed to be unequally distributed between various demographic groups, these technologies also are, and have been, unequally distributed spatially throughout the United States.

Since the early days of the Internet, inequalities have existed between the rural and urban United States in regards to access and use of these new technologies. These early inequalities measured in terms of dial up access to the Internet at home were attributed to the slow rate of technological diffusion from urban to rural areas, similar to patterns seen when the telephone and television were new technologies (Agarwal, Animesh, and Prasad 2009). These differences between rural and urban places gained considerable public attention with the publication of a series of documents near the turn of the millennium by governmental agencies that sought to understand who was being excluded from the opportunities afforded by the new ICT revolution (NTIA 1998; NTIA 199a; NTIA 199b; FCC 2000). These early reports found considerable gaps between people in rural and urban areas. Among the reports that found rural areas lagging behind their urban compatriots was a series of reports published by the National Telecommunications &

Information Industry (NTIA) (1998; 1999a; 1999b) known as the *Falling Through the Net* studies.

This series of studies was conducted to assess which segments of the population were “falling through the net” and missing out on the economic benefits that ICTs could offer. The various iterations of this work found a running theme of rural disadvantage in regards to both Internet access and use. The NTIA’s 1999 report found that households in rural areas were less likely to own a home computer than urban households, even controlling for income level. The reports also found that the race, education, and income based divides discussed above were more pronounced in rural places. One example of that trend is that compared to national averages, black households in rural areas were one-third less likely to own a home computer and two-fifths less likely to access the Internet, well below their urban counterparts. These findings from the 1999 report were echoes of similar findings from the 1998 *Falling through the Net* report that rural households were less likely to own a computer or access the Internet. This cycle of inequality is fed by the lower socioeconomic status of rural residents and the less developed ICT infrastructure in those areas.

These inequalities observed by the United States government at the end of the 20th century have continued to be a topic of study and similar patterns of inequality have been observed over the first 15 years of the 21st century. In 2013 the United States Department of Agriculture (USDA) released a new edition of their “Rural Broadband at a Glance” series. This research brief presented findings about the rates of home broadband use based on data from the Internet and Computer Use Supplements to the United States Current Population Survey (August 2000, September 2001, October 2003, October 2007, and October 2010). The USDA found that rural households were almost as likely to use the Internet compared to urban households, but that those rural users were much less likely to have a broad band connection, following the Federal Communications Commission definition of broadband as a connection providing a minimum speed of 200 kilobytes per second. This represents a clear example of a second order digital divide. The rates of Internet access have begun to level out between rural and urban areas (73% versus 62%, respectively), but for rural places the quality of that access is lower than in urban areas (USDA 2013:2). This inequity is represented by the fact that broadband is the connection of choice for 96% of urban Internet users but only 92% of rural subscribers connect via

broadband (USDA 2013: 1). While the exact magnitude of the difference varies by state and regions (Michigan, South Carolina, and Appalachia all have low rural broadband usage rates) the general pattern of rural rates being lower than urban rates holds true across the entire country.

In their brief, the USDA frames this divide in the utilization of broadband between rural and urban places as detrimental to the potential economic development of rural places and an issue worth overcoming. In their efforts to present solutions for the lower rates of broadband use in rural places the authors explored why households stated they did not use the Internet at all, or why households that were active online did not subscribe to a broadband connection. The data showed that for non-Internet users in both rural and urban places the motivations were fairly similar. At the top of the list was lack of interest or desire to have an Internet connection. For those who had Internet connections, but not broadband quality, the differences in reasons varied between rural and urban respondents. Those in rural areas were much more likely than those in urban areas to cite a lack of availability as the reason for not having a broadband connection. For both rural and urban respondents, cost was found to be a major barrier to broadband connections, with the high cost being cited more frequently among rural households and households with lower incomes. The authors concluded by saying while availability is an issue for some rural places, household income was the most significant factor in predicting household broadband use (with other demographic traits such as education and age having an effect).

The Pew Research Center, through their Pew Internet Project, has also explored the rural/urban digital divide, as well as many other manifestations of the digital divide, through their own survey data collected from 2000 to 2013. In 2013 they published their most recent findings on broadband connections in the home (Zickuhr and Smith 2013). Similar to the data from the US Current Population Survey, Pew Research found that rural respondent's home broadband access lagged significantly behind both that in both urban and suburban areas. Suburban respondents had the highest percentage of home broadband connections (72%), followed by urban respondents (70%) then rural respondents (62%). People in rural areas again have lower levels of access.

Whether people access the Internet, as well as how they use that access is one side of the rural-urban digital divide coin, then the flip side of the coin, the availability of services and infrastructure, must also be considered. Due to the infrastructure investment needed to fully

deploy ICTs, the presence of demand for those services does not always translate to infrastructure investments by the telecommunication corporations and Internet Service Providers (ISPs). Building on the findings from government reports a branch of place-based digital divides research developed that focused on the availability of connections in rural places compared to urban.

Strover (2001) in their analysis of Internet connections in rural regions of four states (Texas, Iowa, West Virginia, and Louisiana) sought to explore this rural-urban divide from the supplier perspective. Using a combination of data collection techniques that included secondary statistics and reports, original telephone based surveys of ISPs, and web based investigations of ISP services, Strover found some variation between the four study sites, but observed a running theme that rural places had fewer options for access and the options that were available were of a lower quality than those in more urban areas and charged extra fees.

Strover argued that these inequalities are not because of a lower demand for the Internet in rural places, but rather because of the increased cost to service providers to expand their offerings in non-urban areas. Citing their results from the telephone survey of ISPs, this study found that several rural ISPs were aware that demand was high, but economic realities prevented them from expanding to meet those needs. The high costs for expansion were a direct result of large telecommunications infrastructure providers' lack of investments in rural infrastructure because such investments would not be profitable given the small number of dispersed potential subscribers. Strover places part of the blame for a weak rural ICT infrastructure on national trends towards the deregulation of the communications sector such as the 1996 Communications Act. The argument is that this deregulation trend has led to a rural communications infrastructure that is characterized by near monopolies of existing telephone companies that don't have a profit incentive to upgrade existing infrastructure or any regulations requiring them to upgrade the infrastructure.

In a similar fashion, Tony Grubestic has performed several studies on how broadband providers are spatially distributed throughout the United States. Through this work Grubestic (2006) has developed what he calls the broadband core-periphery framework to characterize the differential availability of broadband between rural and urban places. This theoretical framework

was developed based upon data from FCC documentation of high speed connection providers and spatial analysis.

In another analysis of the availability of Internet services, specifically broadband providers, Grubestic (2008) elaborates on the core-periphery framework and incorporates a longitudinal component to the analysis of broadband providers in order to determine if the inequalities between places were improving or worsening with time. Using data obtained from the Federal Communication Commission on providers of high speed line providers within each zip code as well as supplemental data from the United States Government Accountability Office, Grubestic created a spatial taxonomy of broadband regions (the core and periphery). Changes from 1999 to 2004 within each region were then analyzed.

In the initial statistical determination of broadband regions (December 1999) it was found that 99.78% of the broadband core regions were in census defined metropolitan statistical areas. In comparison, the broadband periphery regions were overwhelmingly rural (87.7%) (Grubestic 2008:217-218). When these regions were revisited using data from December 2004 similar rates of the broadband core were in metropolitan areas and near similar rates of periphery regions were rural, however the broadband periphery regions saw a dramatic increase in zip codes that went from having no providers to at least one broadband provider.

Perhaps a more telling set of findings from Grubestic's work on the nature of the digital divide between rural and urban places relates to the differential competition among broadband providers in the core and in the periphery. As Grubestic (2008: 218) states "while there is a presence of broadband providers in the periphery, the average number of providers for these zip codes is one and the maximum number of providers is also one. Where the broadband core is concerned, the maximum number of providers is 21 and the average is 10." So, while broadband is expanding out from the core to the periphery, it is clear that those residing in the periphery regions are still not able to access that same robust telecommunications infrastructure available in the core. These findings are consistent with the work of other scholars of ICT distribution that find that broadband availability favors urban areas both in the United States and abroad (Kasuske 2005; Marischal 2005; Gebremichael and Jackson 2006; LaRose et al. 2007).

The work of Grubestic (2004) comes to similar conclusions of previous work that the lack of providers in rural places is a product of the much lower returns on infrastructure investments

in rural places. These lower returns on investment are due to the economies of scale at play in sparsely populated areas. Simply put, there are not enough potential customers for the ISPs to justify the initial capital outlay needed for network improvements, especially compared to the returns similar levels of investment could bring in urban places or what Grubestic calls the broadband core. The inherent preference for urban areas based on economies of scale, especially in regards to telecommunication infrastructure, is further supported by Greenstein (2005). Greenstein argues that until new technological developments for providing access emerge that will lower the cost of rural infrastructure, rural places will always lag behind urban places in terms of broadband supply.

These infrastructural inequalities may be one of the key drivers behind the unequal access and use of the Internet between rural and urban areas, but other factors must be considered in order to fully understand the nature of these divides. In an attempt to do exactly that, Mill and Whitacre (2003) utilized data from the 2001 United States Current Population Survey's Internet and Computer Use Supplement to determine if the unequal use of the Internet at home was due to place based differences such as infrastructure or from household member characteristics such as educational level and income. The authors used a logit estimation approach to model the household Internet adoption decision and then decomposed this model into separate metropolitan and non-metropolitan area estimates to determine whether place-based differences or household level differences were driving the divide.

Based on their statistical analyses, Mills and Whitacre (2003) were able to conclude that almost two-thirds of the digital divide, in terms of home Internet use, between rural and urban areas were attributable to differences in metropolitan and non-metropolitan household characteristics, such as income and educational level. The remaining one-third of variation in home adoption was accounted for by place-based differences, such as lower levels of infrastructure in non-metropolitan areas. Mills and Whitacre's (2003) research shows how both sides to the rural-urban digital divide coin, infrastructural inequalities on one side and individual or household level traits influencing the decision to adopt, must be considered simultaneously in order to more completely understand the information age equalities to be considered in this project.

Summary

In summary, the history of digital divides research has gone through several phases, with each subsequent phase adding nuances to the conceptualization and measurement of information age inequalities. Early work on this topic focused purely on the availability or adoption of ICT infrastructure. As ICTs advanced and became more integrated into society it became clear that these binary measures of use or access were not enough to capture the ICT landscape. This realization, as well as the introduction and spread of high speed and broadband connections, lead digital divides researchers to examine not only whether people had access to the Internet, but the quality of that access as well. As the Internet has increasingly become a near ubiquitous feature of modern society, digital divides research turned towards understanding second order digital divides such as differences in how people were using the Internet once they had access instead of the inequalities in access themselves.

No matter which operationalization of the digital divides is considered, the distribution of ICTs and their use has not been evenly distributed socially or spatially. An overview of the segments of the United States who have fallen on the wrong side of the digital divides is represented here by the rates of household broadband Internet access from Pew Research Center (Zickuhr and Smith 2013:3) presented in Table 2.1. These data follow the general patterns of disadvantage that were discussed above from previous digital divides research. Women, racial and ethnic minorities, the elderly, those with lower educational attainment, those with lower incomes, and those in non-metropolitan areas all fall on the wrong side of the digital divide, meaning the they have less access and are less likely to use that access when they do have it.

Table 2.1: Characteristics of Individuals with Home Broadband Connections in 2013

	% with Home Broadband
<i>All Americans (18+) (n=2,252)</i>	70
Men	71
Women	69
<i>Race/Ethnicity</i>	
White, Non-Hispanic (n=1,571)	74
Black, Non-Hispanic (n=252)	64
Hispanic (n=249)	53
<i>Age</i>	
18-29 (n=404)	80
30-49 (n=577)	78
50-64 (n=641)	69
65+ (n=570)	43
<i>Educational Attainment</i>	
No High School Diploma (n=580)	37
High School Grad (n=374)	57
Some College (n=298)	78
College+ (n=582)	89
<i>Household Income</i>	
Less than \$30,000/yr (n=417)	54
\$30,000-\$49,999/yr (n=320)	70
\$50,000-\$74,999/yr (n=279)	84
\$75,000+ (n=559)	89
<i>Residence</i>	
Urban (n=763)	70
Suburban (n=1,037)	73
Rural (n=450)	62

(Zickuhr and Smith 2013:3)

This project will re-examine the already well established digital divide between rural and urban places from two angles: Internet use broadly defined and through the lens of four specific uses of the Internet, posting photos, posting videos, sharing photos, and sharing videos. The first of the two angles, differences in Internet use by place, is focused on examining if place-based differences in even occasional Internet use still persist in the United States and whether any differences continue to persist once factors that previous scholars have cited as important characteristics associated with difference in use (demographic characteristics, education, and income) have been controlled. This line of inquiry in the research seeks to enrich the

understanding of the relationship of place and Internet use through multivariate models, in contrast to the often cited bivariate relationships discussed in the literature, especially with regards to the data from Pew Research Center.

The second angle of this research examines residential differences in the likelihood of Internet users to engage in specific uses of the Internet. This portion of the project is a direct response to scholars' calls for more nuanced understandings of digital divides that go beyond the traditional measures of access or use/non-use. To this end, four specific Internet uses, two that represent content creation and two that represent content sharing, were considered as potential areas for second order digital divides. This research will consist of multivariate regression analysis of the likelihood of engaging in each of these activities. The models will include residence as well as relevant demographic characteristics. This research will test whether residential digital divides in specific uses are present, once other previously established predictors of content creation and sharing are controlled.

This project will add another voice to the conversation occurring in digital divides research regarding if the sources of residential variation in ICT use is due to infrastructural deficits or household and individual characteristics. Much of what has been written on the rural-urban digital divide cites both factors as being important, but results have been mixed on which aspect has greater significance. The trend seems to be towards household and individual differences playing a larger role (USDA 2013) but many rural residents continue to report a lack of availability as a main reason for not having a broadband connection (Zickuhr and Smith 2013). By including both residential and household and individual characteristics into the models this project provides more evidence for the types of policy interventions that can most effectively help level the digital playing field.

Methods

This chapter will begin with a summary of the survey methodology employed by Pew Research Center for the collection of the 2013 Pictorial Activity dataset. This will be followed by a description of the sample that was selected for this survey and an explanation of the variables to be used in the analysis. Finally, the statistical analysis to be employed to answer the following research questions will be described. The main research questions follow:

- Do residential digital divides persist in regards to whether people use the Internet when controlling for demographic traits, educational attainment, and income?
- Among Internet users do residential differences exist in how individuals use the Internet (in terms of posting photos online, posting videos online, sharing photos online, or sharing videos online) when controlling for demographic traits, educational attainment, income, and smartphone ownership?

Sample

Given the level of integration of the Internet into the daily lives of Americans, the data available on Internet use is surprisingly lacking. Pew Research Center's surveys are the only publically available data that measure a wide variety of specific Internet uses. Most other surveys measure basic use (Schradie 2011). Pew Research has been at the fore front of Internet use survey research for years and continues to use a consistent interview and sampling design that has generated a wealth of data on various aspects of Internet use, including the survey pictorial activities used in this study.

The data used in this project were collected by the Princeton Survey Research Associates from October 3-6, 2013 on behalf of the Pew Research Center's Internet Project. The Pew Internet Pictorial Activity survey is a nationally representative sample of 1,000 adults in the United States that was collected via phone (both land lines and cell phones). This sample was obtained through a combination of landline and cellular random digit dialing (RDD). A total of 32,000 landline numbers and 17,500 cellular numbers were dialed to obtain the final sample of 1,000 participants. This translates to a response rate of 6.7% for landlines and 11.4% for cell phones. A complete breakdown of response rates can be seen in Table 3.1.

Each number in the sample was contacted up to three times (including one daytime contact) to attempt to reach participants. For landline numbers that were contacted the interviewer asked to speak with the youngest adult male/female in the household on a random rotation. If the requested gender was not available the interviewer then asked for the youngest adult of the opposite gender. For the cell phone numbers the interviews were conducted with whomever had answered the phone. A survey was then administered over the phone that asked a variety of questions about online photo and video sharing habits. Of the 1000 participants in the sample that completed the survey, there were 835 Internet users and 941 cell phone owners. For a full description of the sample demographic characteristics see Table 3.2.

The data were then weighted using a two-stage weighting procedure to correct sample design and potential non-response bias. The first stage of weighting corrected for the probabilities of selection based on the number of adults in each household and if the household had only a landline, only a cell phone or both. The second stage adjusted sample demographic characteristics to match national population parameters for sex, age, education, race, Hispanic ethnicity, region, population density, and telephone usage. The basic parameters for the adjustment were based on data from the 2011 US Census Bureau’s American Community Survey. Parameters for population density were obtained from 2010 Census data and telephone usage parameters came from the July-December 2012 National Health Interview Survey. A comparison between unweighted and weighted sample and the population parameters can be seen in Table 3.2.

	Landlines	Cells
Total Numbers Dialed	32,000	17,500
Working Numbers	9,298	10,270
<i>Working Rate</i>	29.1%	58.7%
Working Numbers	9,298	10,270
Contacted Numbers	3,841	6,310
<i>Contact Rate</i>	41.3%	61.4%
Contacted Numbers	3,841	6,310
Cooperating Numbers	637	1,200
<i>Cooperation Rates</i>	16.6%	19.0%
Cooperating Numbers	637	1,200
Eligible Numbers	512	514
<i>Eligibility Rate</i>	80.4%	42.8%
Eligible Numbers	512	514
Completes	500	500
<i>Completion Rates</i>	97.7%	97.3%
<i>Response Rate</i>	6.7%	11.4%

Table 3.2: Sample Demographic Characteristics (Percentages)

	Population	Unweighted Sample (N=1000)	Weighted Sample
<i>Gender</i>			
Male	48.2	47.6	49.3
Female	51.8	52.4	50.7
<i>Age</i>			
18-24	13.2	7.4	12.7
25-34	17.4	11.7	17.6
35-44	17.3	11.8	16.6
45-54	18.9	14.2	18.5
55-64	16.1	23.9	16.7
65+	17.1	31.0	17.9
<i>Education</i>			
HS Grad or less	42.3	29.6	41.0
Some College/Assoc Degree	31.3	28.8	31.4
College Graduate	26.4	41.6	27.6
<i>Race/Ethnicity</i>			
White/not Hispanic	66.8	75.8	68.3
Black/not Hispanic	11.6	10.4	11.7
Hispanic	14.6	8.4	13.1
Other/not Hispanic	7.0	5.4	6.9
<i>Region</i>			
Northeast	18.3	18.3	18.7
Midwest	21.7	24.8	22.2
South	37.3	37.3	37.5
West	22.7	19.6	21.6
<i>County Pop. Density</i>			
1 - Lowest	19.9	23.3	20.4
2	20.0	20.7	20.3
3	20.1	21.0	20.2
4	20.0	18.0	19.5
5 - Highest	20.0	17.0	19.6
<i>Household Phone Use</i>			
Landline Only	6.5	4.1	5.8
Dual	54.2	70.9	56.1
Cell Phone Only	39.3	25.0	38.1

Data files are publically available for download from Pew Research Center's website.

The respondents for this survey had a mean age of 53.1 years ($\sigma=17.9$) with participants ranging in age from 18 to 91. Females made up 52.4% of the sample. The majority of the sample lived in suburban areas (52.6%), followed by urban (28.7%), and rural residents comprising the remainder (18.7%). The vast majority of the sample was white (79%) with blacks making up 11.1% of the respondents. Just fewer than eight percent (7.7%) of the sample identified themselves as Asian or Pacific Islander, Mixed Race, Native American/American Indian, or

other. There was a fair amount of diversity in educational levels: 29.6% reported they had a high school diploma or less, 28.8% reported having some college education or a two year degree, and 41.6% holding a college diploma or higher.

Given the research question's focus on Internet uses it is beneficial to describe the subsample of Internet users separately from the larger sample. As stated above, of the 1000 participants sampled for this project, 835 said that they either at least occasionally used the Internet or email (including on a cell phone or mobile device). Among these Internet users the mean age was slightly lower than the total sample at 50.9 years old ($\sigma=17.4$). The breakdown by residence for Internet users was similar to that of the total sample with 53.3% living in in suburban areas (, 29.5% living in urban areas, and 17.2% of Internet users in rural areas. The racial composition was also relatively similar compared to the total sample. The largest portion of the sample identified as white (79.8%), followed by black (9.6%) and then Asian or Pacific Islander, Mixed Race, Native American/American Indian, or other (8.3%). The diversity in educational levels seen in the full sample is still seen, but skewed towards higher educational levels among Internet users: 2.8% with less than a high school diploma, 37.7% with a high school diploma, 12.7% with a two year degree, 26.5% with a four year degree, and 19.9% with a postgraduate or professional degree.

Dependent Variables

Internet Use

To measure whether a respondent used the Internet the interviews asked each respondent two questions. The first was "Do you use the Internet or email, at least occasionally?", and gave the respondent the option of answering yes or no. Respondents could also indicate that they did not know or refused to answer, however these two choices were not read out by the interviewer. From these responses a dichotomous variable for Internet use was created with 1 indicating that a responded did use the Internet or email at least occasionally and a 0 denoting a non-user. Responses of "Don't Know" or "Refused" were coded as missing data.

In the administration of the survey, Pew Research Center defined an Internet user in a slightly different way. In addition to those who answered affirmatively to the question of using the Internet or email at least occasionally, participants were also asked “Do you access the internet on a cell phone, tablet or other mobile handheld device, at least occasionally?” and given the same set of response choices as the first Internet use question. If a respondent answered yes to either of these two questions they were coded as an Internet user by the interviewer. This distinction is important because the survey items measuring the other dependent variables, posting and sharing of photos and videos, were only asked to those participants who had been identified as Internet users.

An analysis of the data found that all respondents who answered yes to at least occasionally using a mobile device, such as a cell phone or tablet to access the Internet, also answered yes to the broader question of if they used the Internet for email at least occasionally. This overlap allowed for the broader Internet use question to be used as a standalone measure of being an Internet user for the statistical analysis.

Posting Photos or Videos

To determine if a respondent had posted photos online a question about posting photos online was asked to all participants who were identified as Internet users (those who responded yes to occasionally using the Internet or email or who responded yes to accessing the Internet via a mobile device). These individuals were asked “Do you ever post photos that you, yourself, have taken to any kind of website?”. The interviewer then gave the respondent a choice between yes or no. Participants could also indicate that they did not know or they could refuse to answer, but these choices were not read by the interviewer. These responses were then recoded into a dichotomous variable with those who responded yes being coded as a one and those answering no coded with a zero. The “don’t know” responses and refusals to answer were treated as missing data. This variable will be referred to as ‘Posting Photos’.

A very similar question with a focus on video content was posed to the respondents classified as Internet users by Pew Research Center’s survey protocol. Like the item focused on posting photos, participants who responded in the affirmative to either occasionally using

Internet or email or accessing the Internet via a mobile device were asked “Do you ever post videos that you, yourself, have taken to any kind of website?”. Just as with the photo question, respondents were given the choice between answering yes or no, with the additional options of don’t know and refusal to answer left unread. Again, a dichotomous variable was created from the responses with yes being coded as one, no being coded as zero and responses of don’t know or refusals to answer coded as missing data. Throughout the analysis this variable will be called ‘Posting Videos’.

Sharing Photos and Videos

In addition to the items about posting photos and videos to any kind of website, the survey contained items asking participants about their photo and video sharing habits. The same skip pattern was followed for these questions as for the pair of questions about the posting of photos and videos. These questions were only asked of participants who had answered yes to either using the Internet or email at least occasionally or who accessed the Internet via a mobile device such as a cell phone or tablet. To determine if Internet users had shared photos online they were asked “Do you ever take images that you find online and share or repost them on sites designed for sharing images with many people?” and for videos they were asked “Do you ever take videos that you find online and share or repost them on sites designed for sharing videos with many people?”. Just as with the questions dealing with posting of content, the interviewer gave the participant a choice between answering yes or no. The interviewer did not list don’t know and refuse to answer as response choices, but they were included as possible answers.

The key difference between these variables and the posting photos and posting video variables is the source of the content. Where the posting content variable measured whether an individual has uploaded their own unique content to the Internet, these content sharing variables measured whether a user has taken content that was already uploaded by someone else and reposted or shared it online.

In the same fashion as the content posting variable the responses from this pair of questions were recoded into dichotomous variables using the same coding scheme. Responses of yes were coded as one, responses of no were coded as zero, and the “don’t know” and refusals

were treated as missing data. This process created two new variables, Sharing Photos and Sharing Videos, that indicated whether an Internet user had ever shared existing photos or videos they had found online on a website designed for content sharing.

Combined, this set of four dependent variables allows the research to focus on differences between who is more likely to post content they created (Sharing Own Photos and Sharing Own Videos) or share content that they themselves did not create (Sharing Photos and Sharing Videos).

Independent Variables

Residence

The Pew Internet Research Project classified residence at the Census Tract level into one of three types of places: urban, suburban, or rural. These classifications were made based on where the plurality of population in a Census Tract lived. If that plurality of the population in a particular tract lived within a Principal City, as defined by the Office of Management and Budget (OMB 2013), that tract was coded as Urban. If the plurality of a tract's population was in a Metropolitan Statistical Area (MSA), but not in a Principal City, that tract was coded as suburban. The OMB defines MSAs as a county with at least one urbanized area with a population of 50,000 or more, plus adjacent territory that has high social and economic ties to the urban area (OMB 2013) All Census Tracts with a plurality of the population that is not in a MSA were coded as rural. Dummy variables were created to represent each of the residence categories.

Sex

The sex of the respondent was recorded by the interviewer during the interview process. This data were then recoded into a dummy variable for sex with females being the reference category.

Race

Race was initially measured in the survey instrument by the question “What is your race? Are you white, black, Asian, or some other race?” The response categories for this item were as follows: White, Black or African American, Asian or Pacific Islander, Mixed Race, Native American/American Indian, or other. Based on the descriptive statistics, responses were recoded into three categories, White, Black or African American, and Other, with the other category consisting of those who responded with Asian or Pacific Islander, Mixed Race, Native American/American Indian, or other. Dummy variables were then created from these three categories to be included in the analysis using White as the reference group.

Hispanic

In the survey, participants were asked the following yes or no question “Are you, yourself, of Hispanic or Latino origin or descent, such as Mexican, Puerto Rican, Cuban, or some other Latin American background?” These yes or no responses were recoded into a dichotomous variable for Hispanic identity where one was assigned to Hispanics and zero was assigned to non-Hispanics.

Education

Participants in the survey were asked by the interviewers “What is the highest level of school you have completed or the highest degree you have received?” Responses were then coded by the interviewer into the categories shown in Table 3.1.

Table 3.3: Original Educational Level Response Categories

Category	Description (If Provided)	Percent of Respondents (Weighted)
Less than high school	Grades 1-8 or no formal schooling	1.4%
High school incomplete	Grades 9-11 or Grade 12 with NO diploma	6.1%
High school graduate	Grade 12 with diploma or GED certificate	33.5%
Some college, no degree	(includes community college)	19.4%
Two year associate degree from a college or university		12.0%
Four year college or university degree/Bachelor's degree	e.g., BS, BA, AB	15.3%
Some postgraduate or professional schooling, no postgraduate degree		1.1%
Postgraduate or professional schooling, including master's, doctorate, medical, or law degree	e.g., MA, MS, PhD, MD, JD	11.0%
Don't know		0.3%

These responses were recoded into categories of highest degree obtained. Those with less than a high school and high school incomplete were combined into one category, less than high school. High school graduates and those with some college, but no degree were combined into high school diploma. The category of two year associate degree from a college or university was used as initially coded. Participants who had a four year college or university degree and those who had some postgraduate or professional school were combined into the category four year degree. The final category of postgraduate or professional degree remained unchanged. This recoding is represented visually in Figure 3.1. Dummy variables were created to represent each of these categories with post graduate or professional degree as the reference group, following the method used for similar analysis by Hargittai and Walejko (2008). The results of this recoding can be seen in Table 3.2.

Figure 3.1: Recoding Scheme for the Variable Education

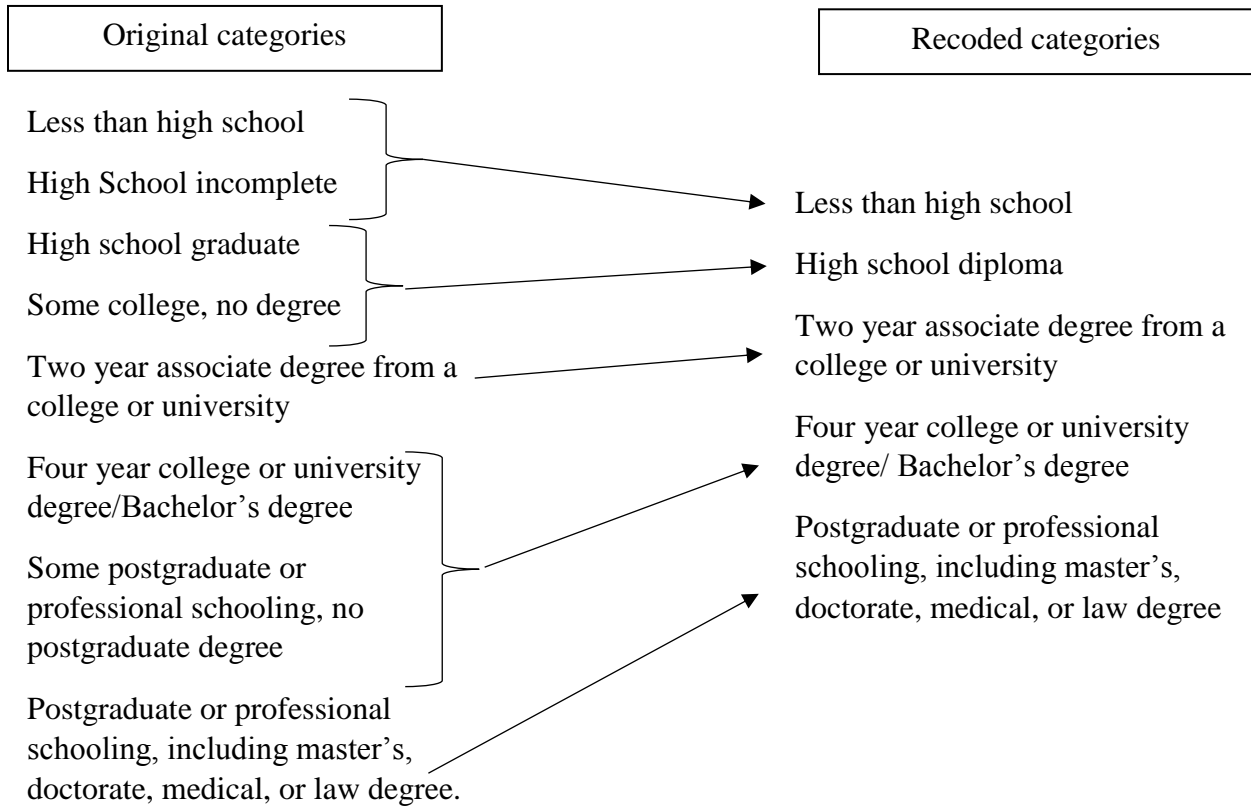


Table 3.4: Recoded Educational Level Response Categories

Category	Description	Percent of Respondents (Weighted)
Less than high school		7.5%
High school graduate	Grade 12 with diploma or GED certificate	52.9%
Two year associate degree from a college or university		12.0%
Four year college or university degree/Bachelor's degree	e.g., BS, BA, AB	16.4%
Postgraduate or professional schooling, including master's, doctorate, medical, or law degree	e.g., MA, MS, PhD, MD, JD	11.0%
Don't know		0.3%

Income

The interviewers asked participants “Last year – that is in 2012 – what was your total family income from all sources before taxes?” The interviewer then read the income categories listed in Figure 3.2 under Original Income Categories, asking the participant to stop them at the right category. The weighted percentage of respondents falling into each of these original income categories can be seen in Table 3.3. Using weighted percentages, 9.3% of participants either responded Don't Know or refused to answer the question of family income. Due to this high item non-response it was decided that these missing values would be replaced with the modal family income category, \$50,000 to Less Than \$75,000. To do this a new Income variable was created where all participants who had supplied income information retained their original values and the cases that had been either Don't Know responses or refusals were coded as having a 2012 family income of \$50,000 to \$75,000.

Following this substitution, a dummy variable (Imputed Income) was created to differentiate between cases that had original income data and those in which that data had been

imputed. Cases that had imputed data were coded with a value of one in this new variable and all other cases were coded with a zero.

These income categories were then recoded into a new variable to create fewer categories as shown in Figure 3.2 under ‘Recoded Income Categories’. These categories were then transformed into six dummy variables to be included in the analysis. The distribution of the weighted sample across these recoded categories can be seen in Table 3.4.

Figure 3.2 Recoding of Income Categories

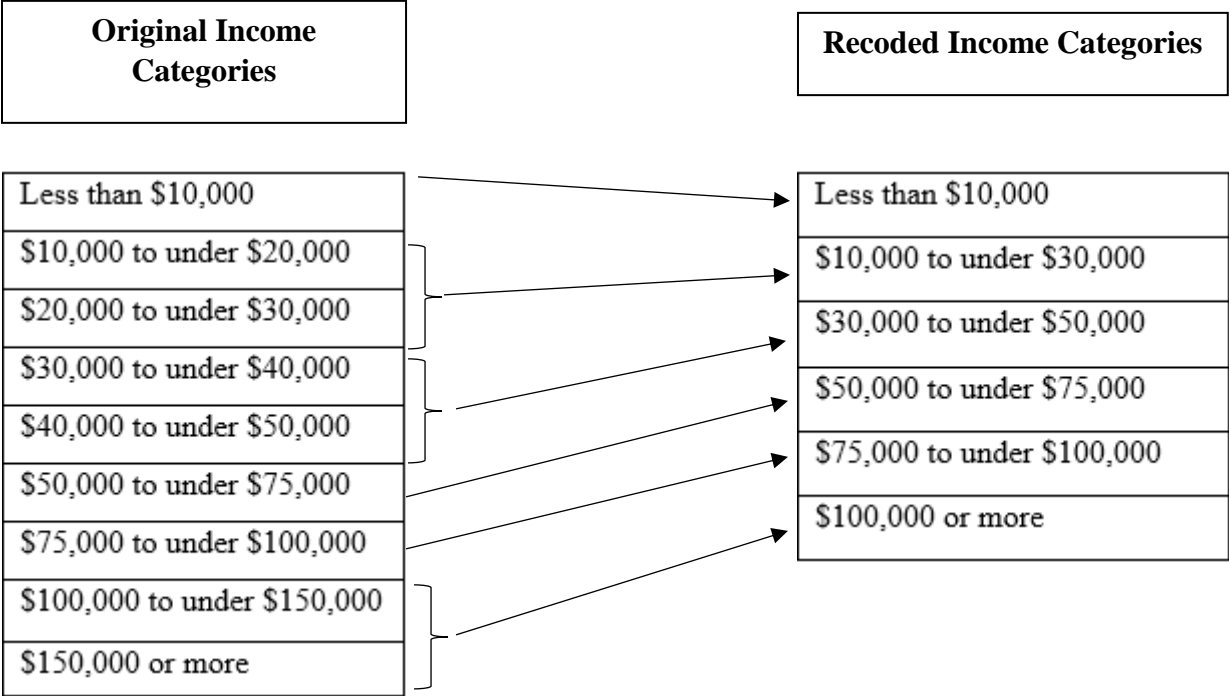


Table 3.5: Original Income Response Categories

Category	Percent of Respondents (Weighted)
Less than \$10,000	8.9%
\$10,000 to under \$20,000	11.5%
\$20,000 to under \$30,000	10.5%
\$30,000 to under \$40,000	10.5%
\$40,000 to under \$50,000	6.9%
\$50,000 to under \$75,000	14.9%
\$75,000 to under \$100,000	11.6%
\$100,000 to under \$150,000	8.0%
\$150,000 or more	8.0%
Don't know/Refused	9.3%

Table 3.6: Recoded Income Response Categories

Category	Percent of Respondents (Weighted)
Less than \$10,000	8.9%
\$10,000 to under \$30,000	22.0%
\$30,000 to under \$50,000	17.4%
\$50,000 to under \$75,000	24.2%
\$75,000 to under \$100,000	11.6%
\$100,000 or more	16.0%

Smartphone Ownership

The survey posed the following question to all cell phone owners, “Some cell phones are called ‘smartphones’ because of certain features they have. Is your cell phone a smartphone such as an iPhone, Android, Blackberry or Windows phone, or are you not sure?” A cell phone owner was determined by whether the respondent was in the cell phone sample or if they were in the landline sample and responded yes to the question “Do you have a cell phone?”. Those who

responded that they had a smartphone were coded as a one for Smartphone Ownership and those who responded that their phone was not a smartphone were coded as zero. Those who were not sure were coded as missing data.

Statistical Methods

The dependent variables of interest in this study are dichotomous measures of specific Internet uses (whether or not an individual had engaged in the following activities): any Internet use, posting photos online, sharing photos online, posting videos online, and sharing videos online. Given the binary nature of the outcomes measures, to determine the relationships between the independent variables described above and the Internet use measures logistic regression analyses were performed for each outcome (Pampel 2000).

The first set of logistic regression models estimated examined the relationships between the independent variables and the likelihood of an individual being an Internet user. In order to explore the complex set of variables that has been shown to influence Internet use four separate logistic regression models were estimated. The first model included only residence, as defined above, as a predictor of Internet use. A second model was then estimated using both residence and a block of demographic variables (sex, race, Hispanic ethnicity, and age). The third and fourth models included the measures for education and income, respectively.

A similar approach was used for the analysis of the other four outcome variables (posting photos online, sharing photos online, posting videos online, and sharing videos online) with two modifications. First, the sample was restricted to only those participants who were Internet users (n=835). This was done because these outcome variables are only applicable to Internet users, it is assumed that someone who does not use the Internet will not be sharing or posting any content online. The second modification was the inclusion of a fifth logistic regression model that added a dummy variable for smartphone ownership as a predictor in addition to the residence, demographic, education, and income variables.

The use of logistic regression does pose some challenges for the interpretation of the results from the models to follow. As Mood (2010) highlights, the comparison of beta

coefficients across models with different predictors poses challenges within logistic regression. The fact that the beta coefficients produced by logistic regression are dependent on both the effect size as well as magnitude of unobserved heterogeneity complicates the type of cross model comparisons that are generally used in linear regressions. Given these limitations, discussion of the results on implications will focus primarily on the most complete model predicting each outcome variable. Statistical analysis for the project was performed using IBM SPSS Version 22 (2013).

Results

The results from five logistic regression analyses aimed at answering the research question of whether digital divides based on residence continue to exist are presented in this chapter. The first analysis tested for a more traditionally conceptualized digital divide by using Internet Use as the dependent variable. The other four regressions then go on to test for more nuanced conceptualizations of use-specific, place-based digital divides. These analyses each examined a specific use of the Internet (posting photos online, posting videos online, sharing pictures online, and sharing videos online) and were limited to only those participants in the sample who were identified as Internet Users.

Internet Use

A binary logistic regression was performed to assess whether residence (rural, suburban, or urban) is significantly associated with the likelihood of an individual being an Internet User. Internet Use was determined based on participants' responses to two questions: "Do you use the Internet or email, at least occasionally?" and "Do you access the Internet on a cell phone, tablet or other mobile handheld device?" Using these two variables, an Internet Use dummy variable was constructed with a positive response to either question causing the participant to be coded as a 1, or an Internet User, and a 0 if not a user.

This model represents the simplest conceptualization of a place-based digital divide in the United States, with the only independent variables included being dummy or indicator variables for both suburban residential status and urban residential status (reference category = rural). This model was statistically significant at the 0.05 level ($\chi^2(2, N=956) = 31.37, p < 0.001$). Even though this model was statistically significant it was only able to account for between 0.8% (Cox & Snell R square) and 1.3% (Nagelkerke R square) of the variation in Internet User status (Table 4.1). In this model being either a suburban or urban resident were statistically significant predictors of higher odds of being an Internet user. The model shows that suburban residents were 1.77 and urban residents 1.87 times more likely to use the Internet than rural residents.

Table 4.1: Logistic Regression of Residence on Likelihood of being an Internet User (N=956)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.57	0.11	27.53	1	0.000***	1.77	1.43	2.19
Urban	0.62	0.12	26.85	1	0.000***	1.87	1.47	2.36
Constant	1.13	0.09	153.06	1	0.000***	3.08		

*Significant at 0.05

Cox & Snell R Square=0.008, Nagelkerke R Square = 0.013

The logistic regression model in Table 4.2 also examines the relationship between residence and likelihood of being an Internet User. This model adds controls for key demographic characteristics that have been shown in previous research to be related to Internet Use. Specifically a dummy variable for sex was included (Male), dummy variables representing race (White, Black, or Other), a binary variable for Hispanic Ethnicity, and Age. With the addition of these control variables the model remained statistically significant at the 0.001 level (χ^2 (df=7, N=956) = 706.33, $p < 0.001$). This model that included residence as well as demographic variables explains between 16.0% (Cox & Snell R square) and 26.9% (Nagelkerke R square) variation in whether respondents were Internet users.

Controlling for Sex, Race, Hispanic Ethnicity, and Age the statistically significant differences in the odds of being an Internet user between rural and suburban and rural and urban areas observed in the Residence only model remains statistically significant. Individuals living in suburban or urban areas are significantly more likely to use the Internet. Compared to those who reside in a rural place, individuals in the suburbs remain 1.87 times as likely to be an Internet user and individuals in urban areas are 1.66 times more likely, even after basic demographic variables are included in the model.

Table 4.2: Logistic Regression of Residence and Demographic Traits on Likelihood of being an Internet User (N=956)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.62	0.12	26.12	1	0.000***	1.87	1.47	2.38
Urban	0.51	0.14	14.17	1	0.000***	1.66	1.28	2.17
Male	0.04	0.10	0.15	1	0.702	1.04	0.86	1.25
<i>Race (ref=White)</i>								
Black	-1.22	0.13	86.75	1	0.000***	0.30	0.23	0.38
Other	-0.22	0.18	1.49	1	0.222	0.80	0.56	1.14
Hispanic Ethnicity	-1.12	0.14	60.15	1	0.000***	0.33	0.25	0.43
Age	-0.07	0.00	471.07	1	0.000***	0.93	0.93	0.94
Constant	5.06	0.22	521.99	1	0.000***	157.85		

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.160, Nagelkerke R Square = 0.269

Of the control variables added, older individuals, participants who identified as Black, and those with Hispanic Ethnicity had statistically significant negative relationships—they were less likely to be an Internet User than the respective reference group. Individuals identifying as Black were just under one-third as likely to be an Internet User compared to those who self-identified as White. There was no statistically significant difference between white respondents and those in the other race category (non-white non-blacks). Supplementary analysis that altered the reference category for race from white to other confirmed that the difference in odds ratios shown here between blacks and individuals identifying with another non-white, non-black race were statistically significant at the 0.01 level ($p=0.01$). Hispanics also were one-third as likely to use the Internet as non-Hispanics. Older age was associated with lower odds of Internet use. Interestingly, there were no gender differences in Internet use.

The next step in the analysis was to add a set of dummy variables representing each participant's highest level of education obtained into the model. The model continued to be

statistically significant at the 0.001 level (χ^2 (df=11, N=956) = 1048.01, $p < 0.001$). The addition of educational variables also increased the amount of variance in Internet Use that was accounted for by the independent variables in the model as indicated by the increases in both the Cox & Snell R Square (0.228) and Nagelkerke R Square (0.383).

With the addition of educational control variables, being Black, Hispanic Ethnicity and Age continued to be statistically significant predictors of Internet Use and all maintain their negative relationship that was previously observed. Compared to Whites, those participants who identified as Black had about 66% lower odds of being an Internet User and those who identified as Hispanic had 10% lower odds of being an Internet User as non-Hispanics. As participants' age increased their likelihood of being an Internet User decreased. Participants identifying as non-black racial minorities still were not statistically significantly different from the white participants. Sex continued to not be a statistically significant predictor of use.

In comparison to the reference group of participants whose highest level of education was a post-graduate degree, individuals with all other educational levels were statistically significantly less likely to be Internet Users. Supplemental analyses showed that the differences between each educational level were statistically significant except for between those with Two Year and Four Year Degrees. The general pattern observed was that as educational levels increase, the likelihood of being an Internet User also increases, but the use by those with graduate degrees was almost double that of individuals with the next highest level of use—those with two or four-year degrees.

Controlling for the education variables and the demographic controls in the second model caused the Residence dummy variable for Urban to become nonsignificant. This means there is no statically significant difference in Internet Use between urban and rural residents. This change indicates that the lower rates of Internet Use seen in rural areas compared to urban areas may be driven by the lower educational levels observed in rural places rather than Residence itself. The suburban residence variable continued to have a positive relationship that was statistically significant at the 0.01 level. Controlling for demographic characteristics and educational attainment those who live in suburban areas are almost one and a half times more likely to be Internet Users than their rural counterparts.

Table 4.3: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of being an Internet User (N=956)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.37	0.13	7.76	1	0.005**	1.44	1.12	1.87
Urban	0.13	0.14	0.82	1	0.364	1.14	0.86	1.52
Male	0.06	0.10	0.31	1	0.557	1.06	0.87	1.29
<i>Race (ref=White)</i>								
Black	-1.08	0.14	56.70	1	0.000***	0.34	0.26	0.45
Other	-0.11	0.20	0.30	1	0.583	0.90	0.61	1.32
Hispanic Ethnicity	-1.14	0.16	51.90	1	0.000***	0.32	0.23	0.44
Age	-0.07	0.00	428.13	1	0.000***	0.94	0.93	0.94
<i>Education (ref=Post-Graduate Degree)</i>								
< High School	-3.56	0.30	136.75	1	0.000***	0.03	0.02	0.05
High School	-2.34	0.27	73.14	1	0.000***	0.10	0.06	0.16
<i>College degrees</i>								
Two-year Degree	-0.71	0.34	4.53	1	0.033*	0.49	0.25	0.94
Four-year Degree	-0.96	0.32	8.92	1	0.003**	0.38	0.20	0.72
Constant	7.23	0.36	395.64	1	0.000***	1384.88		

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.228, Nagelkerke R Square = 0.383

In the final model of this analysis, shown in Table 4.4, dummy variables for income were included as predictors for Internet Use. With the addition of income the overall model remained statistically significant at the 0.001 level, χ^2 (df=17, N=866) = 1231.62, $p < 0.001$. The model explained between 26.2% (Cox & Snell R square) and 44.0% (Nagelkerke R square) of the variation in Internet User status. Hispanic ethnicity, identifying as black, and age remained statistically significant predictors of internet use. Although it should be noted that the Dummy variable for sex approached statistical significance at the 0.05 level ($p=0.051$) indicating that

males were slightly more likely to be Internet Users than females when income was added to the model.

This analysis shows that generally, as both educational level and income level increase, individuals are more likely to be Internet users, controlling for residence, race, Hispanic ethnicity, and age. Those with the lowest educational levels continue to be less likely to use the Internet even when income is included, as do those with four-year degrees. This relationship is not linear, there was no statistically significant relationship between having a two-year college degree and being an Internet User. Individuals with less than a high school degree were 6% as likely to be Internet users as those who have a postgraduate degree. Those with a high school diploma were 18% as likely to be Internet Users. Individuals with a four-year degree were nearly half as likely to be Internet users as those with post-graduate degrees, even when income was added to the model.

A similar decrease in odds of using the Internet can be observed across the income categories, beginning with those who earned \$50,000 to \$75,000. Individuals with a family income between \$50,000 and \$75,000 were 37% as likely to be Internet users compared to those earning more than \$100,000. Individuals in the next highest family income bracket (\$30,000 to \$50,000) were 27% as likely to use the Internet. With each lower income category the likelihood of being an Internet user falls by about 10 points. Those with incomes greater than \$75,000 are similar to those with the highest incomes in terms of Internet usage.

Statistically significant negative relationships continued to be observed between age, Black race, and Hispanic ethnicity and the likelihood of being an Internet user. Individuals who identified as Hispanic were one third as likely to be users than non-Hispanics and Blacks were about half as likely to be Internet Users as Whites.

The estimated coefficients for dummy variables for residence were not statistically significant in the model when demographic characteristics, education and income were included in the model.

Table 4.4: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of being an Internet User (N=956)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.09	0.14	0.39	1	0.532	1.09	0.83	1.43
Urban	0.08	0.15	0.29	1	0.590	1.08	0.81	1.46
Male	0.21	0.11	3.80	1	0.051+	1.23	1.00	1.52
<i>Race (ref=White)</i>								
Black	-0.64	0.15	18.12	1	0.000***	0.53	0.39	0.71
Other	0.24	0.21	1.28	1	0.257	1.27	0.84	1.91
Hispanic Ethnicity	-1.13	0.17	45.56	1	0.000***	0.32	0.23	0.45
Age	-0.07	0.00	400.85	1	0.000***	0.93	0.93	0.94
<i>Education (ref=Post-Graduate Degree)</i>								
Less Than High School	-2.78	0.32	76.12	1	0.000***	0.06	0.03	0.12
High School	-1.70	0.27	35.44	1	0.000***	0.18	0.10	0.32
Two-year Degree	-0.27	0.35	0.61	1	0.434	0.76	0.39	1.50
Four-year Degree	-0.73	0.33	4.86	1	0.027*	0.48	0.25	0.92
<i>Income (ref=\$100K+)</i>								
<\$10K	-2.76	0.28	99.90	1	0.000***	0.06	0.04	0.11
\$10K-LT\$30K	-1.81	0.25	51.25	1	0.000***	0.16	0.10	0.27
\$30K-LT\$50K	-1.32	0.26	26.05	1	0.000***	0.27	0.16	0.44
\$50K-LT\$75K	-1.00	0.27	13.75	1	0.000***	0.37	0.22	0.62
\$75K-LT\$100K	0.02	0.36	0.00	1	0.965	1.02	0.50	2.07
Non-Imputed Income	-0.10	0.22	0.22	1	0.640	0.90	0.58	1.39
Constant	7.95	0.48	272.36	1	0.000***	2831.05		

+ Significant at 0.10; *Significant at 0.05; **Significant at 0.01; ***Significant at 0.001; Cox & Snell R Square=0.262, Nagelkerke R Square = 0.440

In summary, there is a difference in Internet usage by rural, urban and suburban residence, but these differences are explained primarily by the individual's education level, income, ethnicity, and age. This analysis indicates that in regards to Internet use, the digital divide that had been observed along the dimension of place seems to have been replaced by variations in Internet use associated with educational attainment and income. Let us now turn our attention towards only those individuals in the sample who are Internet users and assess whether place is a predictor for specific uses of the Internet.

Who Is More Likely to Engage in Specific Uses of the Internet?

The next question examined is whether residence is associated with how individuals use the Internet. The models in this section examine four specific uses of the Internet: posting own photos online, posting own videos online, sharing photos online, and sharing videos online. The next four sets of logistic regression models used the same procedure and independent variables as the models that predicted Internet Use. One change is the addition of a dummy variable for Smartphone Ownership to the models predicting whether an individual would engage in a particular use of the internet. Since the outcome variable in these analyses is a specific use of the Internet, the analyses were limited to only those individuals who were Internet Users. Four different uses of the Internet are examined: Posting own photos, posting own videos, sharing other's photos, and sharing other's videos.

Posting Own Photos

The first of these behaviors examined was whether or not the individual posted photos online. This dependent variable was measured using responses to the question "Do you ever post photos that you, yourself, have taken to any kind of website?"

Model 1, presented in Table 4.5, only used the dummy variables for residence as predictor variables for whether an Internet User has Posted Photos online. Using only these variables the model was statistically significant at the 0.01 level, $\chi^2(2, N=796) = 70.31$, $p < 0.001$. This significant model only accounts for somewhere between 2.1% (Cox & Snell R

Squared) and 2.8% (Nagelkerke R Squared) of the variation in Posting Photos. This limited model states that compared to those Internet Users in Rural places, Suburban residents are 1.37 times more likely to Post Photos online and Urban residents are 1.85 times more likely to do so. Once this baseline was established, control variables were added to the model in the same fashion as the models predicting Internet Use above.

Table 4.5: Logistic Regression of Residence on Likelihood of Posting Photos Online among Internet Users (N=796)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.32	0.10	9.46	1	0.002**	1.37	1.12	1.68
Urban	0.83	0.11	56.28	1	0.000***	2.30	1.85	2.86
Constant	-0.31	0.09	11.51	1	0.001***	0.73		

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.021, Nagelkerke R Square = 0.028

The next model estimated incorporated demographic variables (Sex, dummy variables for Race, Hispanic Ethnicity, and Age) as predictors of Posting Photos online. The addition of these variables increase the amount of variation in Posting Photos that was explained to between 17.2% (Cox & Snell R Squared) and 22.9% (Nagelkerke R Squared). The model remained statistically significant at the 0.001 level $\chi^2(7, 796) = 714.13, p < 0.001$.

In this model, Sex, Age, and identifying as black were statistically significant at the 0.001 level. Male Internet Users were 1.66 times more likely to have Posted Photos Online than the reference group of females $p < 0.001$). Age was shown to have a statistically significant negative relationship with the probability of an Internet User Posting Photos Online ($p < 0.001$). Each year of age reduced the odds of posting photos by six percent. Compared to Whites, Blacks were about one third less likely to post photos online.

When controlling for Sex, Race, Hispanic Ethnicity, and Age the relationships between Residence and Posting Photos Online remained statistically significant. Compared to those Internet Users in Rural places users from the Suburbs were 1.33 times more likely to Post Photos Online and those who lived in Urban areas were 1.95 times more likely than rural people to post photos taken themselves to a website. The residential difference in posting photos was moderately reduced but not eliminated with the addition to the model of the basic demographic characteristics of the individuals in the study.

Table 4.6: Logistic Regression Residence and Demographic Traits on Likelihood of being Posting Photos Online among Internet Users (N=796)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.29	0.12	6.14	1	0.013*	1.33	1.06	1.67
Urban	0.67	0.12	28.46	1	0.000***	1.95	1.53	2.50
Male	0.51	0.08	42.25	1	0.000***	1.66	1.43	1.94
<i>Race (ref=White)</i>								
Black	-0.47	0.12	14.80	1	0.000***	0.62	0.49	0.79
Other	-0.19	0.13	2.08	1	0.149	0.83	0.64	1.07
Hispanic Ethnicity	-0.13	0.12	1.21	1	0.272	0.88	0.69	1.11
Age	-0.06	0.00	486.65	1	0.000***	0.94	0.94	0.95
Constant	2.19	0.16	175.49	1	0.000***	8.93		

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.191, Nagelkerke R Square =0.255

The next step of this analysis was to add the Education variables into the model to determine if variations in educational attainment across residence affect Internet usage behaviors. These additions did little for the model's ability to explain the variation in Posting Photos Online among Internet Users. The Cox & Snell R Squared and Nagelkerke R Square only increased by 0.002. The overall model remained statistically significant at the 0.001 level $\chi^2(11, N=796) = 722.51, p < 0.001$. None of the dummy variables representing education were statistically significant predictors of Posting Photos Online at the 0.05 level. Both those participants with a two-year degree and less than a high school degree were shown to be statistically significantly less likely to post photos online at the less restrictive 0.10 level. When Education was included, the relationships of Sex, Age, and identifying as Black to Posting Photos Online remained very similar. Male Internet Users were still about 1.7 times more likely to Post Photos Online than female Internet Users. Age retained its statistically significant negative relationship with the likelihood of Posting Photos Online. Compared to White users, Black users were about one third less likely to post photos online.

When Demographic Traits and Education were controlled Residence remained a statistically significant predictor of Posting Photos Online, although the strength of the

relationship was very slightly diminished. Compared to the reference group of Rural Internet Users, users from the suburbs were 1.31 times more likely to Post Photos Online and users from Urban areas were 1.85 times more likely to do so.

Table 4.7: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of Posting Photos Online (N=796)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.27	0.12	5.22	1	0.022*	1.31	1.04	1.64
Urban	0.62	0.13	23.36	1	0.000***	1.85	1.44	2.38
Male	0.51	0.08	42.18	1	0.000***	1.67	1.43	1.94
<i>Race (ref=White)</i>								
Black	-0.47	0.12	14.30	1	0.000***	0.63	0.49	0.80
Other	-0.18	0.13	1.86	1	0.173	0.84	0.65	1.08
Hispanic Ethnicity	-0.14	0.12	1.26	1	0.262	0.87	0.69	1.11
Age	-0.06	0.00	476.10	1	0.000***	0.94	0.94	0.95
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	-0.38	0.22	2.87	1	0.090+	0.68	0.44	1.06
High School	-0.12	0.12	0.91	1	0.341	0.89	0.70	1.13
Two-year Degree	-0.27	0.15	3.28	1	0.070+	0.76	0.57	1.02
Four-year Degree	0.05	0.14	0.15	1	0.700	1.06	0.80	1.39
Constant	2.33	0.21	125.15	1	0.000***	10.30		

+ Significant at 0.10

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.193, Nagelkerke R Square =0.257

The next logistic regression model estimated to predict the likelihood of Posting Photos Online added dummy variables for Family Income categories. Similar to the step that added Education variables, the addition of Income only slightly improved the overall model's ability to

explain the variation in Posting Photos Online among Internet Users to between 21.3% (Cox & Snell R Squared) and 28.4% (Nagelkerke R Squared) of variation explained. The model continued to be significant at the 0.001 level, $\chi^2 (17, N=796) = 808.34, p<0.001$.

Of the added dummy variables for income, only the Less Than \$10K category's dummy variable was statistically significant ($p<0.001$) indicating that compared to the reference group of Internet Users with a family Income of \$100K+, those Internet Users in families making Less Than \$10K were three-fourths as likely to Post Photos Online. Additional analysis showed that this lowest income category was statistically significantly different than all other categories in regards to Posting Photos Online at the 0.05 level. The relationships between Age, Sex, and identifying as Black with Posting Photos Online remained significant with similar strength as in the previous model that did not include Income.

The inclusion of Income in the model caused the dummy variable for Suburban Residence to become insignificant. This means that when Demographic Traits, Education, and Income are controlled, Internet Users in Suburban areas do not differ significantly from Rural Internet Users in their Posting of Photos Online. Compared to Rural Internet users, those users in Urban areas do still differ significantly ($p<0.001$). With this set of variables in the model, Urban Internet Users are 1.84 times more likely to Post Photos Online than Rural Users.

Table 4.8: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of Posting Photos Online (N=796)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.16	0.12	1.79	1	0.181	1.17	0.93	1.48
Urban	0.61	0.13	21.84	1	0.000***	1.84	1.43	2.38
Male	0.58	0.08	50.43	1	0.000***	1.78	1.52	2.08
<i>Race (ref=White)</i>								
Black	-0.35	0.13	7.63	1	0.006**	0.70	0.55	0.90
Other	0.15	0.13	1.30	1	0.254	0.86	0.66	1.12
Hispanic Ethnicity	-0.14	0.12	1.22	1	0.269	0.87	0.68	1.11
Age	-0.06	0.00	496.67	1	0.000***	0.94	0.93	0.94
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	-0.24	0.23	1.11	1	0.292	0.78	0.50	1.23
High School	0.01	0.13	0.01	1	0.923	1.01	0.79	1.30
Two-year Degree	-0.22	0.15	2.00	1	0.158	0.80	0.60	1.09
Four-year Degree	0.09	0.14	0.38	1	0.536	1.09	0.82	1.45
<i>Income (ref=\$100K+)</i>								
LT\$10K	-1.44	0.19	59.01	1	0.000***	0.24	0.16	0.34
\$10K-LT\$30K	-0.01	0.17	0.00	1	0.956	0.99	0.76	1.30
\$30K-LT\$50K	-0.19	0.13	1.96	1	0.162	0.83	0.64	1.08
\$50K-LT\$75K	-0.18	0.14	1.85	1	0.174	0.83	0.64	1.08
\$75K-LT\$100K	0.08	0.14	0.33	1	0.564	1.08	0.83	1.42
Non-Imputed Income	-0.34	0.17	4.10	1	0.043*	0.71	0.51	0.99
Constant	2.62	0.22	139.45	1	0.000***	13.69		

*Significant at 0.05; **Significant at 0.01; ***Significant at 0.001; Cox & Snell R Square=0.213, Nagelkerke R Square =0.284

The final logistic regression model in this analysis added a dummy variable for Smartphone Ownership to the model. The inclusion of this variable generated a model that remained statistically significant at the 0.001 level (χ^2 (18, N=796) = 1871.62, $p < 0.001$) and increased the amount of variation in Posting Photos Online explained to somewhere between 22.8% (Cox & Snell R Square) and 30.4% (Nagelkerke R Squared). Smartphone Ownership was a statistically significant predictor of Posting Photos Online ($p < 0.001$). Among Internet Users, those who owned a smartphone were 2.15 times as likely to Post Photos Online.

Adding Smartphone Ownership did not drastically alter the other statistically significant relationships seen in previous models. Male Internet Users were 1.76 times more likely to Post Photos Online ($p < 0.001$), Age continues to be negatively related to Posting Photos Online ($p < 0.001$), and compared to Internet Users with a Family Income of \$100K+, those with Incomes Less than \$10K were 67% less likely to Post Photos Online.

Controlling for Demographic Traits, Education, Income, and Smartphone Ownership a digital divide along the dimension of Residence can be observed in regards to the specific activity of Posting Photos Online. Compared to Rural Internet Users, users in Urban places are 1.68 times more likely to Post a Photo Online. No statistically significant difference was observed between Rural Internet Users and those users in the Suburbs.

Table 4.9: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Posting Own Photos Online (N=796)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.06	0.12	0.23	1	0.634	1.06	0.83	1.35
Urban	0.52	0.14	14.93	1	0.000***	1.68	1.29	2.17
Male	0.57	0.08	47.71	1	0.000***	1.76	1.50	2.07
<i>Race (ref=White)</i>								
Black	-0.41	0.13	10.10	1	0.001**	0.66	0.51	0.85
Other	-0.10	0.14	0.60	1	0.440	0.90	0.69	1.17
Hispanic Ethnicity	-0.20	0.13	2.57	1	0.109	0.82	0.64	1.05
Age	-0.06	0.00	335.69	1	0.000***	0.95	0.94	0.95
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	0.03	0.23	0.02	1	0.896	1.03	0.65	1.63
High School	0.14	0.13	1.08	1	0.298	1.15	0.89	1.48
Two-year Degree	-0.16	0.15	1.13	1	0.288	0.85	0.63	1.15
Four-year Degree	0.09	0.14	0.40	1	0.527	1.10	0.82	1.46
<i>Income (ref=\$100K+)</i>								
LT\$10K	-1.11	0.19	32.50	1	0.000***	0.33	0.23	0.48
\$10K-LT\$30K	0.15	0.14	1.12	1	0.290	1.16	0.88	1.54
\$30K-LT\$50K	-0.10	0.14	0.50	1	0.478	0.91	0.70	1.19
\$50K-LT\$75K	-0.04	0.14	0.07	1	0.797	0.96	0.74	1.26
\$75K-LT\$100K	0.14	0.14	1.04	1	0.309	1.15	0.88	1.51
Imputed Income	-0.44	0.17	6.51	1	0.011*	0.65	0.46	0.90
Smartphone Ownership	0.77	0.01	63.07	1	0.000***	2.15	1.78	2.60
Constant	1.63	0.25	41.81	1	0.000***	5.12		

*Significant at 0.05; **Significant at 0.01; ***Significant at 0.001; Cox & Snell R Square=0.228, Nagelkerke R Square =0.304

Posting Own Videos

Next, a similar logistic regression analysis was performed for the same independent variables but with participant’s response to “Have you ever posted videos that you, yourself, have taken to any kind of website?” as the outcome variable. Five models for this logistic regression were estimated, adding to the model in order: Residence, Demographic Traits, Education, Income, and Smartphone Ownership. The results of this analysis are presented below.

The first model examined the predictive power of Residence alone on the likelihood of Posting Videos online (Table 4.10). This regression generated a statistically significant model at the 0.05 level (χ^2 (2, N=797) = 77.48, $p < 0.001$), but Residence only could only account for somewhere between 2.3% (Cox & Snell R Squared) and 3.3% (Nagelkerke R Squared) of the variation in Posting Videos Online. Only the dummy variable for Urban residents was statistically significant ($p < 0.001$). Compared to Rural residents, Urban residents were 1.76 times as likely to post their own videos online. There was no statistically significant difference between Rural and Suburban residents’ likelihood of Posting Videos Online.

Table 4.10: Logistic Regression of Residence on Likelihood of Posting Own Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	-0.18	0.12	2.28	1	0.131	0.84	0.66	1.06
Urban	0.56	0.12	21.30	1	0.000***	1.76	1.38	2.24
Constant	-1.13	0.10	115.50	1	0.000***	0.32		

**Significant at 0.05*

Cox & Snell R Square=0.023, Nagelkerke R Square = 0.033

The next model added a set of variables for the following key Demographic Traits: Sex, Race, Hispanic Ethnicity, and Age (Table 4.11). With the addition of these variables the model remained significant (χ^2 (7, N=797) = 560.11, $p < 0.001$) and jumped to accounting for somewhere between 15.3% (Cox & Snell R Squared) and 22.3% (Nagelkerke R Squared) of the variance. Age has a negative relationship with the likelihood of Posting Videos online, meaning that as individuals get older they are less likely to be uploading videos they have personally

taken to websites. Compared to White participants, Blacks were 28% less likely to Post Videos online. Males were found to be 1.41 times more likely than females to post a video online.

Including these demographic control variables in the model altered the relationship between Residence and Posting Videos Online so that the dummy variable for both Suburban and Urban Residence were statistically significant predictors at the 0.05 level. Compared to the reference group of rural respondents, those who resided in Urban areas were 1.35 times as likely to post a video online and those who resided in a suburban area were 27% less likely than rural Internet users to engage in the same activity.

Table 4.11: Logistic Regression Residence and Demographic Traits on Likelihood Posting Own Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	-0.31	0.13	5.50	1	0.019*	0.73	0.57	0.95
Urban	0.30	0.14	4.84	1	0.028*	1.35	1.03	1.77
Male	0.34	0.09	15.92	1	0.000***	1.41	1.19	1.67
<i>Race (ref=White)</i>								
Black	-0.33	0.14	6.03	1	0.014*	0.72	0.55	0.94
Other	-0.12	0.13	0.94	1	0.332	0.88	0.69	1.14
Hispanic Ethnicity	0.22	0.12	3.49	1	0.062+	1.25	0.99	1.58
Age	-0.06	0.00	348.48	1	0.000***	0.94	0.94	0.95
Constant	1.26	0.18	49.20	1	0.000***	3.52		

+ Significant at 0.10

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.153, Nagelkerke R Square =0.223

The next set of variables to be added was the dummy variables for Education. As would be expected the model remained significant (χ^2 (11, N=797) = 605.41, $p < 0.001$). This block of variables only marginally increased the explanatory power of the model as evidenced by the small increases in both the Cox & Snell R Squared (+0.011) and Nagelkerke R Squared (+0.016). The independent variables to have a statistically significant, at the 0.05 level,

relationship with Posting Videos Online were Age, Sex, Hispanic Ethnicity when controlling for Education. Age continued negatively related to the likelihood of Posting Videos Online ($p < 0.001$). Males were found to be 1.39 times as likely as females to Post Videos Online ($P < 0.001$). Compared to non-Hispanics, Hispanics were 1.34 times more likely to Post Videos Online. Among the educational categories, statistically significant differences were only observed between the reference group, those with post-graduate degrees, and individuals who had a four-year degree. Those who had a four-year degree were 1.82 times more likely to have posted a video online to a website.

When controlling for demographic traits and education the previously observed difference between rural and urban residents become nonsignificant. A statistically significant difference did remain between those in rural places and suburban places, those in the suburban areas were about one-third less likely to have posted videos online.

Table 4.12: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of Posting Own Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	-0.38	0.13	8.18	1	0.005**	0.68	0.52	0.89
Urban	0.14	0.14	1.03	1	0.310	1.15	0.88	1.52
Male	0.33	0.09	14.29	1	0.000***	1.39	1.17	1.65
<i>Race (ref=White)</i>								
Black	-0.26	0.14	3.59	1	0.058+	0.77	0.59	1.01
Other	-0.08	0.13	0.41	1	0.523	0.92	0.72	1.19
Hispanic Ethnicity	0.29	0.12	5.79	1	0.016*	1.34	1.06	1.70
Age	-0.06	0.00	333.17	1	0.000***	0.94	0.93	0.95
<i>Education (ref=Post Grad Degree)</i>								
Less than High School	-0.31	0.25	1.56	1	0.212	0.73	0.45	1.19
High School	-0.09	0.15	0.39	1	0.534	0.91	0.68	1.22
Two-year Degree	-0.18	0.18	0.91	1	0.341	0.84	0.58	1.20
Four-year Degree	0.60	0.16	13.98	1	0.000***	1.82	1.33	2.50
Constant	1.35	0.24	30.90	1	0.000***	3.84		

+Significant at 0.10

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.164, Nagelkerke R Square =0.239

The next group of variables added to the model was the dummy variables for Income (Table 4.13). Similar to the results observed when the block of Education variables was added, the inclusion of Income saw the model remain statistically significant ($\chi^2 (17, N=797) = 629.96$, $p < 0.001$), but with only marginal increases in both Cox & Snell R Squared (+0.006) and Nagelkerke R Squared (+0.009). Age remained a statistically significant predictor ($p < 0.001$) with Posting of Videos Online decreasing as Age increases. The relationships between Hispanic Ethnicity as well as Education remained very similar to what had been observed in earlier models. Of the freshly added Income variables, only two categories differed significantly from the reference group of those earning \$100,000+ a year. Participants with families that earned

either \$10,000 to \$30,000 or \$30,000 to \$50,000 a year were about one-third less likely to have Posted Videos Online compared to those with incomes over \$100,000.

In comparison to rural residents, there continued to be no statistically significant relationship between urban residence and Posting Own Videos Online. Suburban residence continued to have a negative relationship with Posting Videos Online. Compared to those in the rural parts of the county, those in the suburbs were about one-third less likely to have posted videos online.

Table 4.13: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of Posting Own Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	-0.45	0.14	10.98	1	0.001***	0.64	0.49	0.83
Urban	0.06	0.14	0.16	1	0.689	1.06	0.80	1.40
Male	0.35	0.09	15.46	1	0.000	1.42	1.19	1.69
<i>Race (ref=White)</i>								
Black	-0.22	0.14	2.41	1	0.121	0.80	0.61	1.06
Other	-0.01	0.13	0.01	1	0.917	0.99	0.76	1.27
Hispanic Ethnicity	0.31	0.12	6.16	1	0.013*	1.36	1.07	1.73
Age	-0.06	0.00	334.51	1	0.000***	0.94	0.93	0.94
<i>Education (ref=Post Grad Degree)</i>								
Less than High School	-0.22	0.26	0.70	1	0.4.03	0.81	0.49	1.34
High School	0.06	0.15	0.14	1	0.706	1.06	0.78	1.43
Two-year Degree	-0.05	0.19	0.08	1	0.775	0.95	0.66	1.67
Four-year Degree	0.66	0.16	16.54	1	0.000***	1.94	1.41	2.67
<i>Income (ref=\$100K+)</i>								
LT\$10K	-0.30	0.20	2.44	1	0.119	0.74	0.50	1.08
\$10K-LT\$30K	-0.47	0.15	9.40	1	0.002**	0.63	0.46	0.84
\$30K-LT\$50K	-0.46	0.15	8.66	1	0.003**	0.64	0.47	0.86
\$50K-LT\$75K	0.14	0.15	0.89	1	0.346	1.15	0.86	1.53
\$75K-LT\$100K	-0.23	0.16	2.11	1	0.147	0.80	0.59	1.08
Non-Imputed Income	0.34	0.18	3.49	1	0.062+	1.41	0.98	2.02
Constant	1.22	0.31	15.94	1	0.000***	3.38		

+ Significant at 0.10; *Significant at 0.05; **Significant at 0.01; ***Significant at 0.001
Cox & Snell R Square=0.170, Nagelkerke R Square = 0.248

The final model in this analysis included a dummy variable for Smartphone Ownership as a predictor. The model containing Residence, Demographic Traits, Education, Income, and Smartphone Ownership was statistically significant ($\chi^2 (17, N=721) = 136.542, p < 0.001$). As was observed in all previous iterations of the model where it was included, Age continued to be negatively associated with Posting Videos Online—older individuals were less likely to do this. . The newly added dummy variable for Smartphone Ownership had a statistically significant ($p = 0.013$) relationship with Posting Videos Online. Controlling for Residence, Demographic Traits, Education, and Income an individual who owns a smartphone is twice as likely to Post a Video Online as someone who does not own a smartphone.

In this final model, including all controls, The dummy variable for Urban residence was not a statistically significant predictor of Posting Videos Online, along with many of the other variables traditionally associated with digital divides. This model however does offer evidence that a place-based digital divide exists relative to the specific behavior of Posting Own Videos Online. Compared to Rural users, those in Suburban areas were about half as likely to post their own videos online.

Table 4.14: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Posting Own Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	-0.54	0.14	14.70	1	0.000***	0.58	0.44	0.77
Urban	-0.02	0.15	0.02	1	0.882	0.98	0.73	1.30
Male	0.31	0.09	12.07	1	0.001***	1.36	1.14	1.63
<i>Race (ref=White)</i>								
Black	-0.28	0.14	4.04	1	0.044*	0.75	0.57	0.99
Other	0.00	0.13	0.00	1	0.998	1.00	0.77	1.30
Hispanic Ethnicity	0.25	0.12	4.11	1	0.043*	1.27	1.01	1.64
Age	-0.06	0.00	233.08	1	0.000***	0.95	0.94	0.95
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	0.07	0.26	0.08	1	0.778	1.08	0.64	1.80
High School	0.17	0.16	1.22	1	0.270	1.19	0.88	1.61
Two-year Degree	0.01	0.19	0.00	1	0.943	1.01	0.70	1.47
Four-year Degree	0.67	0.16	16.59	1	0.000***	1.95	1.41	2.68
<i>Income (ref=\$100K+)</i>								
LT\$10K	0.06	0.20	0.07	1	0.785	1.06	0.71	1.58
\$10K-LT\$30K	-0.37	0.16	5.72	1	0.017*	0.69	0.51	0.94
\$30K-LT\$50K	-0.37	0.16	5.78	1	0.016*	0.69	0.51	0.93
\$50K-LT\$75K	0.28	0.15	3.49	1	0.062+	1.32	0.99	1.76
\$75K-LT\$100K	-0.16	0.16	1.09	1	0.296	0.85	0.62	1.16
Non-Imputed Income	-0.41	0.18	4.85	1	0.028*	1.50	1.05	2.16
Smartphone Ownership	0.85	0.12	45.98	1	0.000***	2.34	1.83	2.99
Constant	0.53	0.30	3.18	1	0.075+	1.70		

+Significant at 0.10; *Significant at 0.05; **Significant at 0.01; ***Significant at 0.001

Cox & Snell R Square=0.182, Nagelkerke R Square =0.266

Sharing Photos Online

The final two analyses conducted shifted the focus from content generation to content sharing on the Internet. The previous two regression analyses dealt with the posting of photos and videos created by the person posting them to websites. The regression analyses in this section model the sharing of photos and the sharing of videos as the outcome variable. First, a logistic regression predicting the likelihood that an individual would “take images that you find online and share or repost them on sites designed for sharing images with many people”. For each logistic regression a series of five models was estimated, as done above. All independent variables remain the same as in the logistic regressions for the posting of one’s own photos and videos.

The first of these logistic regression models (Table 4.15) that contained only the Residence variables was statistically significant ($\chi^2 (2, N=795) = 18.67, p < 0.001$). Compared to rural residents, those who lived in urban areas were 1.45 times more likely to have shared photos online. No statistically significant relationships were observed between suburban and rural residents.

Table 4.15: Logistic Regression of Residence on Likelihood of Sharing Photos Online (N=795)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.07	0.10	0.43	1	0.512	1.07	0.87	1.31
Urban	0.37	0.11	11.23	1	0.001***	1.45	1.16	1.80
Constant	-0.43	0.09	21.49	1	0.000***	0.65		

**Significant at 0.05*

Cox & Snell R Square=0.006, Nagelkerke R Square = 0.007

Using Residence and Demographic Traits as predictors accounted for between 15.5% (Cox & Snell R Squared) and 20.8% (Nagelkerke R Squared) of the variance in Sharing Photos Online to be explained ($\chi^2 (7, N=795) = 566.74, p < 0.001$). The results of this logistic regression are presented in Table 4.16 below.

The only independent variables included in this model that were statistically significant predictors for Sharing Photos Online were Sex ($p < 0.001$), Age ($p < 0.001$), and Race. Compared to females, males were over two times as likely to Share Photos Online. Age had a negative relationship with Sharing Photos with the likelihood of Sharing a Photo Online decreasing as Age increases. Compared to Whites, Blacks were almost half as likely to share photos online. Residence was no longer a statistically significant predictor of Sharing Photos Online.

Table 4.16: Logistic Regression Residence and Demographic Traits on Likelihood Sharing Photos Online (N=795)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.06	0.12	0.29	1	0.591	1.06	0.85	1.33
Urban	0.18	0.12	2.03	1	0.154	1.19	0.94	1.52
Male	0.76	0.08	94.62	1	0.000***	2.13	1.83	2.48
<i>Race (ref=White)</i>								
Black	-0.62	0.12	25.90	1	0.000***	0.54	0.42	0.68
Other	-0.15	0.12	1.43	1	0.231	0.86	0.68	1.10
Hispanic Ethnicity	-0.19	0.12	2.80	1	0.094+	0.82	0.66	1.03
Age	-0.05	0.00	385.86	1	0.000***	0.95	0.94	0.95
Constant	1.57	0.16	95.06	1	0.000***	4.81		

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.155, Nagelkerke R Square =0.208

The next model included the dummy variables for Education. This inclusion only provided minimal increases in the amount of variation in Sharing Photos that was accounted for in the model. This is observed in both the Cox & Snell R Squared and Nagelkerke R Squared increasing by only 0.002 and 0.003 respectively. That being said, the overall model remained statistically significant at the 0.001 level ($\chi^2 (11, N=795) = 575.89, p < 0.001$). Given the lack of explanatory power added by the Educational controls it is not surprising that only one category was found to be a statistically significant predictor of Sharing Photos Online. Compared to those

with a post-graduate degree, individuals with a high school diploma were 1.3 times more likely to have shared photos online.

As in the previous model, Sex, Age, and Race were found to be statistically significant predictors for the likelihood of Sharing Photos Online ($p < 0.001$ for both). Controlling for Residence, Demographic Traits, and Education, Males continued to be slightly more than twice as likely as females to Share Photos Online. The negative relationship between Age and Sharing Photos Online described earlier also persisted as well as the difference in likelihood of sharing photos between Whites and Blacks, with Blacks less likely to do so. Controlling for Demographic Traits and Education, Residence continues to not be a statistically significant predictor of Sharing Photos Online at the 0.05 level. If the significance criterion is relaxed to the 0.10 level, Urban users are more likely to Share Photos Online than those in rural places.

Table 4.17: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of Sharing Photos Online (N=795)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.08	0.12	0.51	1	0.474	1.09	0.86	1.36
Urban	0.21	0.13	2.79	1	0.095+	1.23	0.96	1.58
Male	0.77	0.08	96.71	1	0.000***	2.15	1.85	2.51
<i>Race (ref=White)</i>								
Black	-0.66	0.12	28.17	1	0.000***	0.52	0.41	0.66
Other	-0.13	0.12	1.12	1	0.291	0.88	0.69	1.12
Hispanic Ethnicity	-0.21	0.12	3.27	1	0.070+	0.81	0.64	1.02
Age	-0.05	0.00	363.20	1	0.000***	0.95	0.94	0.96
<i>Education (ref= Post-Graduate Degree)</i>								
Less than High School	-0.08	0.22	0.14	1	0.714	0.92	0.60	1.42
High School	0.27	0.12	4.70	1	0.030*	1.31	1.03	1.66
Two-year Degree	0.12	0.15	0.58	1	0.448	1.12	0.83	1.51
Four-year Degree	0.06	0.14	0.19	1	0.663	1.06	0.80	1.41
Constant	1.36	0.21	43.27	1	0.000***	3.89		

+ Significant at 0.10

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.157, Nagelkerke R Square =0.211

Similar to the outcome of adding Education as a control to the model, the addition of Income offered only slight improvements to the model's predictive power (Table 4.18). The overall model continued to be statistically significant (χ^2 (17, N=795) =640.65, $p<0.001$), but this significance continued to be driven by the relationships between Sex, Age, and Race to Sharing Photos previously described ($p<0.001$ for both). The valence and strength of both of these relationships was nearly the same as in the previous models that did not take Income into consideration. With the addition of Income the relationship between Hispanic Ethnicity and Sharing Photos Online was now significant at the 0.05 level. Compared to non-Hispanics, Hispanics were 24% less likely to have Shared Photos Online. Compared to those participants who had a Family Income of \$100,000K+, the only income categories to differ significantly (at

the 0.05 level) in their likelihood of sharing photos online were those earning between \$30,000 and \$50,000 and those earning less than \$10,000. Both groups were about half as likely to have shared photos online. Controlling for Demographic Traits, Education, and Income, Residence continues to not be a statistically significant predictor of Sharing Photos Online (Income seems to wipe out the marginally significant relationship of urban and posting photos online.).

Table 4.18: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of Sharing Photos Online (N=795)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.07	0.12	0.37	1	0.541	1.08	0.85	1.36
Urban	0.19	0.13	2.09	1	0.148	1.20	0.94	1.55
Male	0.76	0.08	91.73	1	0.000***	2.14	1.83	2.51
<i>Race (ref=White)</i>								
Black	-0.67	0.13	27.44	1	0.000***	0.51	0.40	0.66
Other	-0.10	0.12	0.61	1	0.434	0.91	0.71	1.16
Hispanic Ethnicity	-0.28	0.12	5.46	1	0.019*	0.76	0.60	0.96
Age	-0.05	0.00	362.96	1	0.000***	0.95	0.94	0.95
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	-0.07	0.22	0.11	1	0.744	0.93	0.60	1.44
High School	0.32	0.13	5.84	1	0.016*	1.37	1.06	1.77
Two-year Degree	0.16	0.16	1.02	1	0.312	1.17	0.86	1.59
Four-year Degree	0.07	0.14	0.22	1	0.638	1.07	0.81	1.42
<i>Income (ref=\$100K+)</i>								
LT\$10K	-0.44	0.18	5.72	1	0.017*	0.65	0.45	0.92
\$10K-LT\$30K	0.19	0.13	2.11	1	0.146	1.21	0.94	1.58
\$30K-LT\$50K	-0.68	0.14	25.04	1	0.000***	0.51	0.39	0.66
\$50K-LT\$75K	0.06	0.13	0.22	1	0.638	1.06	0.82	1.38
\$75K-LT\$100K	-0.26	0.14	3.48	1	0.062+	0.77	0.59	1.01
Non-Imputed Income	0.14	0.16	0.68	1	0.409	1.14	0.83	1.58
Constant	1.53	0.22	48.99	1	0.000***	4.61		

+ Significant at 0.10

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.173, Nagelkerke R Square =0.232

The final logistic regression model of Residence on Sharing Photos Online adds Smartphone Ownership to Demographic Traits, Education, and Income as a control variable. This additional control generated a model that remained statistically significant (χ^2 (18, N=795) =662.24, $p < 0.001$) that accounted for somewhere between 17.8% (Cox & Snell R Squared) and 23.9% (Nagelkerke R Squared) of the variation in Sharing Photos Online.

In this model, Sex, Age, Race, Hispanic Ethnicity, and having only a high school diploma compared to a post-graduate degree remained statistically significant predictors. The newly introduced Smartphone Ownership variable was shown to have a positive relationship with sharing photos online ($p = 0.042$). Smartphone owners were 1.5 times more likely to have shared a photo online than those who did not own a smartphone. The relationships of Sex, Age, Race, and Hispanic Ethnicity to Sharing Photos Online remain very similar to those seen in the previous models. Controlling for all other variables included in the model, men were slightly more than two times as likely to Share Photos Online compared to women. Age had a negative relationship with Sharing Photos online, as age increased the likelihood of Sharing Photos Online decreased. Blacks were half as likely to share photos as Whites. Hispanics were 27% less likely to share photos online than non-Hispanics.

The addition of Smartphone Ownership as a control altered some of the relationships between Income and likelihood of sharing photos online. Compared to those with a family income of \$100,000+, individuals whose families earned between \$30,000 and \$50,000 were half as likely to share photos and those earning between \$10,000 and \$30,000 were 1.3 times more likely to engage in the same behavior. There were no other statistically significant differences among the other income categories.

Controlling for Demographic Traits, Education, Income, and Smartphone Ownership, Residence continue to not be a statistically significant predictor of Sharing Photos Online. This provides evidence that there does not appear to be a use specific, place-based digital divide in the Sharing of Photos Online.

Table 4.19: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Sharing Photos Online (N=795)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.01	0.12	0.01	1	0.922	1.01	0.80	1.28
Urban	0.12	0.13	0.91	1	0.341	1.13	0.88	1.46
Male	0.75	0.08	88.27	1	0.000***	2.12	1.81	2.48
<i>Race (ref=White)</i>								
Black	-0.71	0.13	30.08	1	0.000***	0.49	0.38	0.64
Other	-0.07	0.12	0.32	1	0.512	0.93	0.73	1.19
Hispanic Ethnicity	-0.32	0.12	6.91	1	0.009**	0.73	0.58	0.92
Age	-0.05	0.00	259.85	1	0.000***	0.95	0.95	0.96
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	0.09	0.23	0.16	1	0.690	1.10	0.70	1.71
High School	0.39	0.13	8.64	1	0.003**	1.47	1.14	1.91
Two-year Degree	0.19	0.16	1.508	1	0.219	1.21	0.89	1.65
Four-year Degree	0.07	0.14	0.22	1	0.641	1.07	0.81	1.42
<i>Income (ref=\$100K+)</i>								
LT\$10K	-0.23	0.19	1.47	1	0.225	0.80	0.55	1.15
\$10K-LT\$30K	0.28	0.14	4.19	1	0.041*	1.32	1.01	1.72
\$30K-LT\$50K	-0.63	0.14	21.52	1	0.000***	0.53	0.41	0.69
\$50K-LT\$75K	0.14	0.13	1.16	1	0.282	1.15	0.89	1.50
\$75K-LT\$100K	-0.22	0.14	2.55	1	0.110	0.80	0.61	1.05
Non-Imputed Income	0.09	0.16	0.30	1	0.586	1.09	0.79	1.51
Smartphone Ownership	0.46	0.10	21.46	1	0.000***	1.58	1.30	1.91
Constant	0.95	0.25	14.22	1	0.001***	2.82		

*Significant at 0.05; **Significant at 0.01; ***Significant at 0.001

Cox & Snell R Square=0.178, Nagelkerke R Square =0.239

Sharing Videos Online

The final logistic regression analysis that was performed used the same set of independent variables to predict the likelihood that an individual would “take videos that you find online and share or repost them on sites designed for sharing images with many people”, Sharing Videos Online. The first model (Table 4.20) that only included Residence variables was statistically significant at the 0.05 level (χ^2 (2, N=797) =24.95, $p<0.001$). Compared to rural residents, those who lived in urban areas were 1.57 times more likely to share videos online ($p<0.001$).

Table 4.20: Logistic Regression of Residence on Likelihood of Sharing Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.09	0.11	0.75	1	0.387	1.10	0.89	1.36
Urban	0.45	0.12	15.27	1	0.000***	1.57	1.25	1.96
Constant	-0.77	0.10	63.16	1	0.000***	0.46		

***Significant at 0.001

Cox & Snell R Square=0.007, Nagelkerke R Square = 0.010

The second model, presented in Table 4.21, added Demographic Traits as control variables. These additions caused the model to reach statistical significance at the 0.001 level (χ^2 (7, N=797) =689.62, $p<0.001$). With these controls Urban Residence remains a statistically significant predictor of Sharing Videos Online at the 0.05 level. The regression did show that some Demographic Traits were statistically significant predictors of this online behavior. Compared to females, males were 1.41 times more likely to Share Videos Online ($p<0.001$). Race also had a significant relationship with individuals who identified as Black being 73% less likely to Share Videos Online than those who identified as White, but compared to Whites those in the Other race category were 1.41 times more likely to share videos online. Age was the other Demographic Trait to have a statistically significant relationship with Sharing Videos Online ($p<0.001$). This relationship was negative with older participants being less likely to Share Videos Online.

Table 4.21: Logistic Regression Residence and Demographic Traits on Likelihood Sharing Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.02	0.12	0.03	1	0.869	1.02	0.80	1.30
Urban	0.33	0.13	6.34	1	0.012*	1.39	1.08	1.80
Male	0.34	0.08	17.97	1	0.000***	1.41	1.20	1.65
<i>Race (ref=White)</i>								
Black	-0.72	0.13	87.63	1	0.000***	0.27	0.20	0.35
Other	-0.72	0.13	32.46	1	0.000***	1.41	1.20	1.65
Hispanic Ethnicity	0.06	0.12	0.23	1	0.630	1.06	0.84	1.33
Age	-0.06	0.00	472.61	1	0.000***	0.94	0.93	0.94
Constant	2.00	0.17	134.53	1	0.000***	7.36		

+Significant at 0.10

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.185, Nagelkerke R Square =0.253

Following the template of the previous analyses, the Education dummy variables were added to the model next (Table 4.21). With this addition, the statistical significance of the model remained intact (χ^2 (11, N=797) =708.41, $p<0.001$). Only two of the educational categories differed significantly from the reference category, post-graduate degree. Participants who had less than a high school degree were 40% less likely and four-year degree holders were 27% less likely to share videos online than their post-graduate degree contemporaries. Their inclusion did not alter the relationships observed in the previous iteration of the model. Men remained about 1.4 times more likely to Share Videos Online than women ($P<0.001$), Blacks were 74% less likely to Share Videos Online as Whites ($p<0.001$), those in the Other race category were about half as likely to share as Whites ($p<0.001$), and as age increased the likelihood of Sharing Videos Online decreased ($p<0.001$).

Controlling for Demographic Traits and Education, Residence continued to have a statistically significant relationship with the likelihood of Sharing Videos Online. Compared to rural residents, urban residents were 1.41 times more likely to have shared videos online.

Table 4.22: Logistic Regression of Residence, Demographic Traits, and Education on Likelihood of Sharing Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	0.00	0.12	0.00	1	0.993	1.00	0.78	1.28
Urban	0.34	0.13	6.59	1	0.010*	1.41	1.08	1.84
Male	0.35	0.08	18.60	1	0.000***	1.42	1.21	1.66
<i>Race (ref=White)</i>								
Black	-1.36	0.14	92.31	1	0.000***	0.26	0.19	0.34
Other	-0.74	0.13	33.77	1	0.000***	0.48	0.37	0.61
Hispanic Ethnicity	0.05	0.12	0.16	1	0.692	1.05	0.83	1.32
Age	-0.07	0.00	469.37	1	0.000***	0.94	0.93	0.94
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	-0.52	0.23	5.08	1	0.024*	0.60	0.38	0.94
High School	-0.17	0.13	1.66	1	0.198	0.85	0.66	1.09
Two-year Degree	0.21	0.16	1.78	1	0.182	1.23	0.91	1.68
Four-year Degree	-0.31	0.15	4.38	1	0.036*	0.73	0.54	0.98
Constant	2.24	0.22	100.57	1	0.000***	9.37		

+Significant at 0.10

*Significant at 0.05

**Significant at 0.01

***Significant at 0.001

Cox & Snell R Square=0.189, Nagelkerke R Square =0.259

The next step was to add the dummy variables for Income into the model as shown in Table 4.23. With these additional controls the model remained significant (χ^2 (17, N=797) =764.94, $p < 0.001$). From the block of Income dummy variables the only category that did not differ significantly from the reference group (Family Incomes over \$100,000) was those individuals with Family Incomes between \$30,000 and \$50,000. All other income categories were statistically significantly less likely to Share Videos Online than those earning more than \$100,000. Compared to the highest Income category, those at the bottom were nearly 70% less likely to Share Videos Online.

In addition to the relationship with Income described above, Sex, Race, and Age remained statistically significant contributors to the model. Controlling for income did not alter the direction or strength of these relationships from the previous version of the regression model. Men remained about one and a half times more likely to Share Videos Online than women ($P < 0.001$), Blacks were only about 70% less likely to Share Videos Online as Whites ($p < 0.001$), Other races were about half as likely to Share Videos Online as Whites ($p < 0.001$), and as age increased the likelihood of Sharing Videos Online decreased ($p < 0.001$).

Controlling for Demographic Traits, Education, and Income, Residence no longer had a statistically significant relationship with the likelihood of Sharing Videos Online at the 0.005 level. However, at the 0.10 level the previously observed differences between rural and urban residents can still be observed. Urban residents were 1.29 times more likely to Share Videos Online than Urban Residents ($p = 0.66$).

Table 4.23: Logistic Regression of Residence, Demographic Traits, Education, and Income on Likelihood of Sharing Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	-0.10	0.13	0.59	1	0.441	0.91	0.71	1.16
Urban	0.25	0.14	3.38	1	0.066+	1.29	0.98	1.68
Male	0.39	0.08	22.41	1	0.000***	1.48	1.26	1.75
<i>Race (ref=White)</i>								
Black	-1.25	0.14	75.03	1	0.000***	0.29	0.22	0.38
Other	-0.64	0.13	24.54	1	0.000***	0.53	0.41	0.68
Hispanic Ethnicity	0.04	0.12	0.13	1	0.723	1.04	0.82	1.33
Age	-0.07	0.00	480.23	1	0.000***	0.93	0.93	0.94
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	-0.32	0.24	1.80	1	0.179	0.72	0.45	1.16
High School	0.06	0.14	0.23	1	0.635	1.07	0.82	1.40
Two-year Degree	0.37	0.16	5.13	1	0.024*	1.44	1.05	1.98
Four-year Degree	-0.24	0.15	2.60	1	0.107	0.78	0.58	1.06
<i>Income (ref=\$100K+)</i>								
LT\$10K	-1.07	0.19	30.62	1	0.000***	0.34	0.23	0.50
\$10K-LT\$30K	-0.60	0.14	18.05	1	0.000***	0.55	0.41	0.72
\$30K-LT\$50K	-0.68	0.14	23.49	1	0.000***	0.51	0.38	0.67
\$50K-LT\$75K	-0.02	0.14	0.02	1	0.877	0.98	0.75	1.28
\$75K-LT\$100K	-0.45	0.14	9.61	1	0.002**	0.64	0.48	0.85
Imputed Income	-0.43	0.18	5.93	1	0.015*	0.65	0.46	0.92
Constant	2.66	0.24	123.80	1	0.000***	14.23		

+Significant at 0.10; *Significant at 0.05; **Significant at 0.01; ***Significant at 0.001

Cox & Snell R Square=0.203, Nagelkerke R Square =0.278

The final model of this analysis added Smartphone Ownership as a control to the model that already included Residence, Demographic Traits, Education, and Income. This final model was statistically significant ($\chi^2 (18, N=797) = 786.67, p < 0.001$) and can be seen in Table 4.24. The model accounted for between 20.8% (Cox & Snell R Squared) and 28.5% (Nagelkerke R Squared) of the variation in Sharing Videos Online. This model shows that Sex, Race, Age, and Income continue to be statistically significant independent variables for predicting the likelihood of Sharing Videos online.

When it comes to Sharing Videos Online, Men are one and half times more like than Women to engage in this online behavior. Similarly compared to Blacks, Whites are about one and one-half times more likely to Share Videos Online. Age also has a statistically significant negative relationship with Sharing Videos Online ($p < 0.001$). The relationship between Income and Sharing Videos Online was also still present. Smartphone Ownership was a statistically significant predictor ($p < 0.001$) of Sharing Videos Online with those who owned a smartphone being 1.64 times as likely to engage in this behavior.

Controlling for Demographic Traits, Education, Income, and Smartphone Ownership, Residence was not a statistically significant predictor of Sharing Videos Online. This provides evidence that there does not appear to be a use-specific, place-based digital divide in regards to the Sharing of Videos Online.

Table 4.24: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Sharing Videos Online (N=797)

	B	S.E.	Wald	df	p	Odds Ratio	95% C.I.	
							Lower	Upper
<i>Residence (ref=Rural)</i>								
Suburban	-0.15	0.13	1.37	1	0.242	0.86	0.67	1.11
Urban	0.19	0.14	1.95	1	0.162	1.21	0.92	1.59
Male	0.37	0.08	19.86	1	0.000***	1.45	1.23	1.71
<i>Race (ref=White)</i>								
Black	-1.29	1.45	80.02	1	0.000***	0.27	0.21	0.36
Other	-0.62	0.13	23.13	1	0.000***	0.54	0.42	6.91
Hispanic Ethnicity	0.00	0.12	0.00	1	0.972	1.00	0.79	1.28
Age	-0.06	0.00	374.58	1	0.000***	0.94	0.93	0.94
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	-0.16	0.24	0.41	1	0.522	0.86	0.53	1.38
High School	0.14	0.14	0.98	1	0.323	1.15	0.87	1.50
Two-year Degree	4.06	0.16	6.23	1	0.013*	1.50	1.09	2.06
Four-year Degree	-0.24	0.15	2.52	1	0.113	0.78	0.58	1.06
<i>Income (ref=\$100K+)</i>								
LT\$10K	-0.85	0.20	18.16	1	0.000***	0.43	0.29	0.63
\$10K-LT\$30K	-0.53	0.14	13.52	1	0.000***	0.59	0.44	0.78
\$30K-LT\$50K	-0.63	0.14	19.85	1	0.000***	0.53	0.40	0.70
\$50K-LT\$75K	0.07	0.14	0.25	1	0.620	1.07	0.82	1.40
\$75K-LT\$100K	-0.41	0.14	8.03	1	0.005**	0.66	0.50	0.88
Imputed Income	-0.48	0.18	7.41	1	0.006**	0.62	0.44	0.88
Smartphone Ownership	0.49	0.11	21.46	1	0.000***	1.64	1.33	2.02
Constant	2.04	0.27	56.25	1	0.000***	7.70		

+ Significant at 0.10; *Significant at 0.05; **Significant at 0.01; ***Significant at 0.001
Cox & Snell R Square=0.208, Nagelkerke R Square =0.285

Summary

The analysis presented above shows that residential differences in being an Internet user are no longer observed once other factors are considered. The distribution of Internet users across society is still far from even (See Table 4.26 for Summary of Logistic Regression Models). Persistent inequalities in the likelihood of being an Internet user were observed along racial, ethnic, educational levels, and income levels. This analysis found that compared to whites, blacks were about half as likely to be Internet users. It was also found that those who identified as Hispanic were two-thirds less likely to be an Internet user than non-Hispanics. Between educational levels there was a pattern of increasing likelihood of being an Internet User with higher educational levels. Compared to those with a post graduate degree, individuals who did not graduate high school were 94% less likely to be users, high school graduate were 88% less likely, and four year degree holders were 52% less likely. A similar pattern was observed across income categories with all income brackets except the second highest (\$75,000 to \$100,000) being statistically significantly less likely to be users than the reference group of those earning more than \$100,000. Expanding the significance level to a 90% confidence interval also shows that males were 1.23 times more likely to be users than females.

These findings indicate that individuals who are living in rural areas are less likely to be Internet users than those in urban or suburban areas, but these differences are due to the demographic and socioeconomic factors in rural areas rather than rurality itself. The findings about the relationships between age, educational levels, and income on the likelihood of being an Internet user are most likely driving the differences that were observed in the bivariate model. It has been well documented that those living in rural areas are more likely to be older (Brown 2014), poorer (Sherman 2014), and less educated (Schafft and Biddle 2014) than their urban or suburban contemporaries. These previously established differences are also present within the sample used in this study (Table 4.25).

**Table 4.25: Demographic Difference across Residence Types,
(Percentages of each residence subgroup sample reported for
Education and Income; Weighted)**

	Rural (n=680)	Suburban (n=2208)	Urban (n=1289)
Mean Age	50.1	47.2	43.1
<i>Education</i>			
Less Than High School	12.4	7.7	4.5
High School	61.7	51.1	51.3
Two-year Degree	10.2	14.2	9.2
Four-year Degree	8.0	15.4	22.7
Post Graduate	7.6	11.3	12.2
Don't Know/Refused	0.1	0.4	0.1
<i>Income</i>			
<\$10K	14.7	4.7	12.8
\$10K-LT\$30K	27.5	20.1	22.2
\$30K-LT\$50K	18.2	19.5	13.3
\$50K-LT\$75K	10.2	14.7	17.7
\$75K-LT\$100K	8.2	14.3	8.6
\$100K+	11.0	17.9	15.4
Don't Know/Refused	10.2	8.8	9.9

This project generally supports the finding of previous researchers in regards to content production (represented here by posting photos online or posting videos online). Females and racial and ethnic minorities were less likely to post their own photos and videos than males and whites. This analysis found an interesting divergence from the previous literature with lower income levels being associated with a lower likelihood of sharing content. This surprising finding may be due the fact that this analysis included smartphone ownership as a variable in the model. Prior research has indicated that those with lower income rely more heavily on mobile technologies as their sole source of Internet access (Horrigan 2009b).

Similar relationships were found when the sharing of photos and videos were investigated. For both sharing uses, age was negatively associated with the likelihood of sharing photos and videos. For both sharing uses males were more likely to participate than females and blacks less likely than whites (for sharing videos only those of Hispanic ethnicity were less likely to share than non-Hispanics). Similar to the results from posting content, individuals in lower income levels were less likely to share videos than those who earned more. The same was not true in regards to the likelihood of sharing photos, where the lowest income level was marginally more likely to share than those earning more than \$100K a year, but the second lowest income level was less than half as likely to share than those same high earners.

No residential differences were observed in the likelihood of sharing either photos or videos online, although interesting relationships emerged in the analysis of posting photos or videos. Among Internet Users, controlling for age, race/ethnicity, sex, education, income, and smartphone ownership, it was found that urban users were significantly more likely to post photos they have taken online. Compared to their rural peers these urbanites were 1.68 times more likely to post their photos online. No statistically significant differences were observed between rural users and suburban users. When posting of videos online was analyzed, again controlling for demographic characteristics, education, income, and smartphone ownership, suburban users were actually less likely to post than those in rural places.

Table 4.26: Logistic Regression of Residence, Demographic Traits, Education, Income, and Smartphone Ownership on Likelihood of Posting Photos, Posting Videos, Sharing Photos, and Sharing Videos Online

	Posting Own Photos Online (N=796)		Posting Own Videos Online (N=797)		Sharing Photos Online (N=795)		Sharing Videos Online (N=797)	
	B	S.E.	B	S.E.	B	S.E.	B	S.E.
<i>Residence (ref=Rural)</i>								
Suburban	0.06	0.12	-0.54***	0.14	0.01	0.12	-0.15	0.13
Urban	0.52***	0.14	-0.02	0.15	0.12	0.13	0.19	0.14
Male	0.57***	0.08	0.31***	0.09	0.75***	0.08	0.37***	0.08
<i>Race (ref=White)</i>								
Black	-0.41***	0.13	-0.28*	0.14	-0.71***	0.13	-1.29***	1.45
Other	-0.10	0.14	0.00	0.13	-0.07	0.12	-0.62***	0.13
Hispanic Ethnicity	-0.20	0.13	0.25*	0.12	-0.32**	0.12	0.00	0.12
Age	-0.06***	0.00	-0.06***	0.00	-0.05***	0.00	-0.06***	0.00
<i>Education (ref=Post-Graduate Degree)</i>								
Less than High School	0.03	0.23	0.07	0.26	0.09	0.23	-0.16	0.24
High School	0.14	0.13	0.17	0.16	0.39**	0.13	0.14	0.14
Two-year Degree	-0.16	0.15	0.01	0.19	0.19	0.16	4.06*	0.16
Four-year Degree	0.09	0.14	0.67***	0.16	0.07	0.14	-0.24	0.15
<i>Income (ref=\$100K+)</i>								
LT\$10K	-1.11***	0.19	0.06	0.20	-0.23	0.19	-0.85***	0.20
\$10K-LT\$30K	0.15	0.14	-0.37*	0.16	0.28*	0.14	-0.53***	0.14
\$30K-LT\$50K	-0.10	0.14	-0.37*	0.16	-0.63***	0.14	-0.63***	0.14
\$50K-LT\$75K	-0.04	0.14	0.28+	0.15	0.14	0.13	0.07	0.14
\$75K-LT\$100K	0.14	0.14	-0.16	0.16	-0.22	0.14	-0.41**	0.14
Imputed Income	-0.44*	0.17	-0.41*	0.18	0.09	0.16	-0.48**	0.18
Smartphone Ownership	0.77***	0.01	0.85***	0.12	0.46***	0.10	0.49***	0.11
Constant	1.63***	0.25	0.53+	0.30	0.95***	0.25	2.04***	0.27

+Significant at 0.10; *Significant at 0.05; **Significant at 0.01; ***Significant at 0.001

Discussion and Conclusions

The discussion presented here will highlight key findings from the statistical analyses described in the previous chapter that examine who is more likely to be an Internet user, as well as who is more or less likely to post their own photos online, post their own videos online, share photos online, or share videos online. While a full explanation of results can be found in the previous chapter, the focus here will begin with striking findings and overall patterns across models. The striking role of smartphone ownership in regards to the likelihood of engaging in the posting (posting one's own photos or videos) or sharing (sharing other's photos or videos) of content online will then be considered and this chapter will end with a discussion of residential differences in the likelihood of being an Internet user, and of engaging in one of the four specific uses in order to determine if place-based digital divides still are prevalent as had been found in previous research.

Are We Still Digitally Divided in Terms of Our Internet Use?

Research on the digital divides originally began with an interest in the unequal diffusion of information communication technologies across the country. As was discussed in the review of literature, these early forays into digital divides research primarily focused on whether individuals had access to the Internet or, later, if they were using the Internet. These studies showed that cutting edge communication technologies were not being distributed equally across the United States, both geographically and socially.

Given these previous findings it was important to begin the analyses with an exploration into whether these digital divides, defined in terms of use/non-use, still persist. Specifically, whether inequalities in adoption persist based on residence (rural/urban/suburban). To test this, a logistic regression of residence on the likelihood of being an Internet user (Table 4.1) was used. This bivariate model showed that, indeed residence was a statistically significant predictor of the likelihood of being an Internet user. However, once demographic traits, education, and income were added to the model as alternative explanations for the residential difference in use, this

relationship was no longer statistically significant (See Table 4.26). It would appear that the imbalance between rural, urban, and suburban areas in terms of Internet use has become an imbalance that may be more attributable to demographic and economic differences between individuals that live in these residence types and the opportunities available to them.

One possible explanation for the continued lower likelihood of the groups described above to use the Internet has been proposed by Warren (2007) and is referred to as the vicious digital cycle. The vicious cycle that Warren described was a relationship between the social exclusion of groups of people in a society and the digital exclusion of those same groups.

Warren also argues that this cycle of exclusion may be of special concern to rural areas because in these geographically distributed rural communities the price of exclusion is higher than in urban or suburban areas. This increased price of exclusion comes from the higher costs of transmitting information in more traditional ways in rural areas compared to more populated communities. While the analysis at hand did not show any statistically significant differences in the likelihood of being an Internet User between residence types, the possibility remains that digital divides in terms of quality of connection or technological literacy may exist.

The results obtained from the analysis do not support a residence-based digital divide. However, the relationships of other variables to the likelihood of being an Internet user support the broader concept of a link between social exclusion and digital exclusion. Logistic regression models that included variables to represent these often socially excluded groups (racial and ethnic minorities, those with lower education, the poor, and females) showed that these groups are still less likely to be Internet users.

One striking example of this cycle can be observed in the differences in likelihood of being an Internet user between individuals of Hispanic ethnicity and those of non-Hispanic ethnicity. The analysis presented here shows that when controlling for residence, age, sex, race, education, and income those of Hispanic origin were two-thirds less likely to be an Internet user than their non-Hispanic peers. It has been argued that this lower level of use among Hispanics could be due to less readily available Spanish language content on the Internet. A recent report by an advertising agency (360i 2012) suggests that a lack of Spanish language content may be partially responsible for lower levels of use among Hispanics compared to non-Hispanics. Through the introduction of Spanish language content to websites, this advertising agency was

able to demonstrate increases in the number of Hispanics searching for and visiting those sites. Here the social exclusions due to lack of content in a preferred language contributes to the digital exclusions of Hispanics.

Do Digital Divides Exist in *How* People Use the Internet?

These usage-based divides are only one part of the larger picture of information age inequalities in the present day. As other researchers have noted, efforts to understand the digital divide need to go beyond measurements of access and use to explore the potentially unequal ways that ICTs are being understood, used, and incorporated into individual's lives. Following in this spirit, the majority of the analyses in this project were designed to answer whether inequalities in how people used the Internet existed among Internet users. What follows is a discussion of these use-specific digital divides: posting own photos online, posting own videos online, sharing photos online, and sharing videos online.

This study focused its second set of analyses on four specific Internet behaviors among Internet users. These behaviors were posting their own photos online, posting their own videos online, sharing photos online, and sharing videos online. Summarized results from the final logistic regression models of residence, demographic characteristics, education, income, and smartphone ownership on the likelihood of each of these behaviors can be seen in Table 4.26. The section also provides a summary of the factors that were associated with the likelihood of engaging in each behavior.

The general trends among content production can be summed up as follows, content on the Internet, especially entertainment and social, is created by those who are young and low income but technologically skilled. It is important to note though that different uses of the Internet should be considered separately, using the Internet for entertainment is vastly different from using it for political purposes. This idea is supported by Block's (2013) research into typologies of Internet uses that found that the relationships between individual traits and uses varied by the type of use (skilled use, social and entertainment uses, and political uses).

The Importance of Smartphones

From the results discussed above it is clear the smartphone ownership plays a significant role in the likelihood of an Internet user engaging in any of the four behaviors (posting photos, posting videos, sharing photos, and sharing videos). In all four analyses owning a smartphone was associated with a higher likelihood of the behavior controlling for residence, demographic traits, education, and income. Compared to non-smartphone owners, those with smartphones were more likely to post photos online, more likely to post videos online, more likely to share photos online, and more likely to share videos online (See Table 4.26). It is clear that smartphone technology is greatly influencing the way that Internet users are interacting with the World Wide Web.

The role of mobile devices, particularly smartphones, in accessing the Internet has exploded in the past decade. Over the past four years the number of adults in the United States who own a smartphone rose sharply from 35% in 2011 to 64% in 2014 (Smith and Page 2015: 13). Given the rise in importance of smartphones in individuals' Internet landscapes, it is not surprising that the measure of smartphone ownership was a statistically significant predictor of all four Internet activities that were analyzed (posting photos, posting videos, sharing photos, and sharing videos). In all four analyses owning a smartphone was associated with a higher likelihood of the behavior controlling for residence, demographics, education, and income. Compared to non-smartphone owners.

These positive relationships are likely driven in part by the conveniences afforded by the smartphone technology. Each smartphone is essentially a mini computer that serves as a variety of tools, including a camera for both photographs and videos. Having a recording device in your pocket makes it much more likely that smartphone owners will be using their devices to capture pictures and videos. This functionality combined with smartphones' many applications for running social media and photo video sharing make it incredibly easy for smartphone users to capture, store, and share photos and video on the Internet. This affordance created by the features of smartphones may be responsible for the stronger relationships observed between smartphone ownership and the two content creation uses that were measure (posting photos online and posting videos online).

Another important factor in contributing to smartphones' role in the posting and sharing of photos and videos is the rise of various smartphone applications designed to facilitate these behaviors. Social networking applications and communication apps have been designed to make it incredibly easy for a user to take advantage of the photo and video recording capabilities of smartphones. With a few quick motions users can capture photos or videos and post them to a variety of platforms, including but not limited to Facebook, Instagram, Twitter, Vine, Snapchat, Myspace, or Yik Yak. These applications also facilitate users browsing the Internet and social networks-related platforms more frequently leading to more opportunities to share photos and videos that they had found online, again with only a few simple motions.

This positive relationship between smartphone ownership and engaging in specific uses of the Internet may indicate a potential avenue for bridging some of the digital divides that have been observed in this analysis as well as previous research. The potential role of smartphones in narrowing these divides is increasingly apparent when the characteristics of those most likely to be dependent on smartphones for Internet access are considered. In the winter of 2014, Pew Research Center (Smith and Page, 2015) completed a nationally representative telephone survey using a random digit dial sample of both landlines and cell phones. This survey was designed to measure the role that smartphones play in how individuals access, share, and create information.

Using this Pew Research Center data on smartphone ownership and use, Smith and Page (2015) found that for the subset of smartphone owners who are dependent on the smartphone for Internet access this mobile connection was very unstable, both financially and technically. Among those users who were dependent on their smartphone for Internet access, 48% of them had to cancel or shut off their cellular service because the cost of the service was a financial hardship. The smartphone-dependent users also reported issues with cellular service data caps. Thirty percent claimed that they frequently reached their data limits and another 51% reported this happening occasionally. Smartphones users also reported being plagued by poor quality or dropped signals and information not displaying properly on their phones.

The distribution of who is a smartphone-dependent Internet user, and subject to the financial and technical burdens of the dependency, follows the general patterns observed in this study and previous research about who is on the wrong side of the digital divides. Smith and

Page found that lower income households, less educated individuals, and non-whites were all more likely to be considered dependent on their smartphones for Internet access.

The positive relationships found in this study between smartphone ownership and all four specific Internet uses (posting photos online, posting videos online, sharing photos online, and sharing videos online), controlling for residence, demographic traits, education, and income, show that mobile Internet connections can help people engage with the Internet. Unfortunately, those who rely on these mobile connections as their primary Internet connection are likely to be the ones who have the most difficulty maintaining them.

Residence-Based Digital Divides

The aim of this study was to determine if the previously established residential information age inequalities persist in the first half of the 2010s. In regard to Internet use, defined as using the Internet or email at least occasionally, the analyses conducted showed that there were statistically significant differences in the likelihood of being an Internet user between rural, suburban, and urban places. However, the addition of controls representing other potential fault lines for the digital divides (demographic traits, educational level, and income) caused this residential relationship to be explained by other factors. The differences in likelihood in being an Internet user by residence were driven by demographic differences, especially in income and educational level, that exist between Rural, Urban, and Suburban areas. So while there is no evidence for a purely residence based divide this study found that the inequalities based on other individual characteristics still exist and impact those in rural places more than other residential types because of the socioeconomic conditions/characteristics of the populations in those places.

Measures of use are not the only way to define potential digital divides and in an effort to paint a more complete picture of these information age inequalities this study also examined variations in specific uses across place. The answer to whether a place-based digital divide exists in relation to these four specific uses varies based on the use being analyzed.

In regard to the likelihood of sharing photos or videos that were found online there was no evidence of a residential digital divide once controls were included in the model. As discussed

in the section on those who post and those who share, this does not mean that these specific uses are being undertaken by everyone equally. Digital divides in who is sharing content online exist based on sex, race, ethnicity, age, and income. As was the case with the examination of Internet use, residence itself was not a significant predictor, but some of these predictors such as income and age may be not equally distributed by residence type (See Table 4.25).

Conclusions

It is clear that the Internet as a technology is drastically changing how society communicates and functions, often much faster than anticipated. It is precisely because of this transformative power of the Internet that research into the inequalities of the information age needs to be undertaken. In a society that is increasingly online, those who are on the wrong side of these digital divides face growing challenges. Given the evidence for a the vicious cycle of exclusion faced by those social groups who are on the wrong side of the digital divides, meaning they have lower rates of access or use of ICTs, understanding these inequalities of the information age, both in terms of access and use, is an important first step to bringing those that have been excluded into the digital age more fully.

This study sought to explore digital divides based on access and those based on use (known as first order and second order divides respectively) through an analysis of secondary survey data. Using a dataset from Pew Internet Project about individual's online pictorial activities, logistic regression analyses were performed predicting the likelihood that an individual would be an Internet user, post photos they have taken online, post videos they have made online, share pictures already online, or share videos already online. For each outcome, nested models were estimated, with the first model only included residence as a predictor variable, and then successive models added each of the following sets of variables that had been previously shown to be associated with online activities in turn: demographic traits (age, sex, race, and ethnicity), educational attainment, and income. For each of the specific Internet uses (posting photos, posting videos, sharing photos, and sharing videos) an additional predictor variable, smartphone use, was added to the regression models as a final step. The use of multivariate logistic regression models to analyze the survey data collected by the Pew Internet Project was

the key empirical contribution of this work. The Pew Internet project has released some publications using this particular dataset, but all of their statistics were limited to bivariate analyses that failed to capture the more complete understanding of the landscapes of digital divides presented here.

Based on these data there is evidence that in the 2010s the use of the Internet is still not equally distributed among all segments of the United States population. Consistent with the findings of various previous digital divides scholars, women, the elderly, Blacks, those of Hispanic ethnicity, the less educated, and those with lower incomes were all less likely to be even occasional Internet users. These inequities were most striking along educational and income categories. Controlling for the full set of variables, compared to the most educated (post-graduate degree) those who did not have a high school diploma were 94% less likely to be an Internet user and those individuals in the lowest income category were 96% less likely to be users. While statistically significant residential differences in the likelihood of Internet use were observed in the bivariate model, the inclusion of the full set of predictor variables caused this relationship to become insignificant. This pattern seemed to be driven primarily by the inclusion of income and education variables.

Similar patterns of inequality were observed in the logistical regressions predicting the likelihood of engaging in the four specific Internet uses analyzed. The general findings for each of the four uses are summarized in Table 5.1 below. Again the same divides that had been observed by previous scholars appear in the specific uses, although with some minor variations. One such interesting variation is in the sharing of videos where the individuals with the highest income levels were actually less likely to do this. While this finding seems at odds with the digital divides literature, it makes sense when considering that the richest segments of society have been shown to engage less with some forms of popular media such as television.

Table 5.1: Who is Less Likely to Engage in Each Specific Internet Use

Specific Use	Who is Less Likely to Use
Posting Photos	Females, Blacks, elderly, poor, rural (compared to urban)
Posting Videos	Females, Blacks, Hispanics, elderly, poor
Sharing Photos	Females, Blacks, Hispanics, elderly, poor
Sharing Videos	Females, Blacks, Hispanics, elderly, incomes <\$100K

For all four uses being a smartphone owner had a statistically significant and strong positive relationship with the likelihood of engaging in the behavior. Those who owned a smartphone were over two times as likely to post either photos or videos they had taken themselves online than their non-smartphone owning peers. When it came to sharing pictures and videos, those with a smartphone were 1.6 and 1.3 times more likely to share than those without one. This intriguing pattern could be attributed to the affordances that the technological innovation known as smartphones offer to their owners. The combination of a mobile Internet connection, high quality photo and video taking capabilities, and the multitude of applications available for posting and sharing photos and video combine to make these behaviors extraordinarily accessible to those that have access to the technology.

These relationships between smartphone ownership and specific uses must be considered within the larger context of mobile Internet connections in the United States. While these devices afford amazing opportunities for connectivity and creating and sharing content online, they can also be unreliable links to the online world, especially for those who depend on them most. Both technological issues and financial barriers make it difficult for those who rely solely on mobile devices, like smartphones, to have a reliable connection to the World Wide Web.

It appears that the United States is not divided digitally along residential lines, but rather along demographic, educational, and income lines. The characteristics of rural areas are such that these inequalities impact those living in rural areas more heavily than individuals in urban or suburban ones. The persistent trends of rural populations to be more elderly, less educated, and have lower incomes as manifests itself in absolute differences in the rates of Internet use as well specific uses of the Internet. In order to fully understand the complete picture of the relatively

recently emerged inequalities of the Internet age a wide variety of factors must be considered simultaneously. By including such a multivariate analysis, this project showed that the digital divides of greatest significance to the United States are not place-based, but rather divisions along demographic and socio-economic lines. Exceptions to this were found in regard to creating content online, where rural residents were less likely to post photos than those in urban places and, surprisingly, suburban residents were less likely to post videos compared to rural residents.

Limitations

The first major limitation of this study is that only a very narrow set of interrelated uses of the Internet was examined. The focus on sharing and posting of photos and videos among Internet users only captures a small fraction of social or entertainment uses. Given that previous studies on these second-level digital divides have found that the relationships between individual traits and uses vary based on the type of use, it would be unwise to attempt to generalize these findings to uses broadly, or even to any non-entertainment or social uses.

Another limitation faced by this study was the lack of a measure for Internet skills, Internet literacy, or a similar concept. Again, this limitation is a result of utilizing secondary data sources. Ideally future surveys and studies will include such a measure. Having some measure of Internet skills would have improved this study in two different but important ways. Had such a measure been collected it could have served as another operationalization of the digital divide and a sixth dependent variable. This would have expanded the study to include potential inequities in Internet skills and knowledge.

In addition to serving as another outcome variable, a measure for Internet skills would have been promising as a means to improve the logistic regression models for predicting the likelihood of the specific uses. The role of Internet skills has been established by previous research as a key control variable for understanding the relationships between individual traits, such as gender and education, and online content production (Hargittai and Walejko 2008; Block 2013). With the addition of Internet skills as a control previous research found that gender and education differences in use were no longer significant.

This supports the argument of Internet skills being a crucial mediator of the relationships between demographic and socioeconomic traits and specific uses. Had this research been able to test this idea and found that indeed Internet skills are a mediating variable, the policy implications would be centered more on increasing individual's Internet skills among those who are currently less skilled. These increases in skill levels would help to encourage some of the groups on the wrong side of these digital divides to use the Internet in a wider variety of ways and perhaps with a greater impact. This concept of Internet skills would have been useful for inclusion as another conceptualization of a digital divide, as well as a control variable for the analysis of specific Internet uses. Previous studies on content creation have found contradictory results on the exact relationship between Internet skills content creation and content sharing behaviors.

Implications

The Internet has been discussed as both a non-essential luxury and a panacea to society's ills. While neither of these characterizations accurately reflects the technology, the variation is illustrative of the fact that this technology is still relatively new. Even more novel is the idea of a ubiquitous Internet, or an always connected society. The young age of the Internet poses unique opportunities for creating an infrastructure, both technologically and socially, which can help all people take advantage of the benefits afforded by it.

Those benefits of the Internet are numerous. In the early days of Internet dissemination, researchers questioned whether the new technology would actually benefit society and communities. Often the images of individuals locked in front of a screen with no face-to-face interaction were employed to show the pitfalls to come. More recent research has shown that those who use the Internet experience positive outcomes in a multitude of areas. Being an Internet user has been shown to be related to increased community participation, both online and off (Hampton and Wellman 2003; Stern and Dillman 2006). Increased online activity is also positively related to engagement with participatory politics (Slyvester and McGlynn 2010) and conventional politics (FCC 2013).

One of the strongest stories to have emerged from this research is the importance of smartphone ownership in engaging with posting or sharing photos and videos. For all four uses analyzed, owning a smartphone meant an individual was more likely to engage in that use. For posting photos and video, the smartphone owners were more than twice as likely to post as non-smartphones owners.

This strong relationship points to one possible avenue for encouraging use among those populations that are on the losing sides of digital divides. This potential for policy solutions to the digital divides based on increasing mobile access should be undertaken with an eye towards the tenuous cell phone coverage that many of the less advantaged face. Those who are most dependent on a smartphone for their Internet connection are also those who are most likely to face technological or financial burdens in maintaining that link. If the challenge of overcoming digital divides is to be tackled through mobile connections, policies should be put in place that makes those mobile connections both affordable and technologically reliable. The technological reliability is of increasing importance in the rural parts of the United States that are often left with slower mobile networks or expensive satellite service when service is available at all.

Policymakers should also avoid advocating for a purely mobile solution for closing digital divides in regards to quality of Internet connections between rural and urban areas. In addition to the concerns about price and coverage discussed above, Noam (2011) raises a compelling argument that these mobile or wireless Internet solutions have and will always lag behind wired Internet solutions. Noam argues that the very nature of cell phone technology and the limited frequencies it can operate on will result in an infrastructure that will have slower data transfer than a wired infrastructure and be more costly to upgrade in the future. The upgradability of mobile networks compared to wired infrastructure may mean that mobile Internet connections can only serve as a temporary bandage to ensure access. Mobile network frequencies are already beginning to become overburdened and the costs of freeing up new airwaves for these services is estimated to be very high, especially when compared to the cost of a wired infrastructure (Noam 2011). In the very near future though, as higher quality access is needed to meet the needs of users for high quality video streaming and the receiving and sending of increasingly large files, these mobile connections will be at a disadvantage to those places that are hardwired. This disadvantage, if left unchecked, will become another chapter in the digital divides story, further

illustrating the vicious cycle of exclusion. For those who gain access through a mobile network in some of the more remote areas of the United States this upgrade will initially be a welcome reprieve. However, as time goes on and these mobile users recognize that their quality of service is in some cases 1/100th the speed of metropolitan areas with the most up to date infrastructure the call for better Internet infrastructure will be renewed.

So while mobile internet connections and the spread of smartphone technology may seem like a promising avenue for closing some digital divides, any efforts should be framed as a temporary access solution until high quality wired access can be provided for these underserved areas and populations. Noam (2011) and Strover (2001) offer the model of rural electrification and the expansion of telephone services as models by which the Internet can begin to be more equitably spread to all corners of the country. This model shows promise, but considering recent political fights in the United States over how the Internet should be regulated and whether it is a public utility this sort of approach seems highly unlikely.

Another key area for policy to help reduce the digital inequalities of the current age is to focus on the segment of the population that remains non-users. As the analysis of Internet use shows, here defined as only at least using the Internet or email occasionally, there still exists a sizable number of individuals who either cannot access the Internet or choose not to do so. This study showed that those who are Black or Hispanic, older, less educated, and in lower income categories were less likely to be using the Internet. All of these groups of people could also be said to be socially excluded. As the Internet becomes more ingrained in our society it is vital to create a society that enables these populations to escape the cycle of social and technological exclusion.

Again though, when developing policies to foster Internet use among non-users it is crucial to not view the Internet as a panacea. To echo Selwyn's (2004) point again, access is not the same as use and use is not the same as meaningful use. There is a sizeable portion (34%) of non-users that claim they do not use because they don't think the Internet is relevant to their lives and almost the same proportion (32%) who cite the difficulty of use as a barrier (Zickuhr 2013). Simply increasing the physical infrastructure will not be enough to help these non-users become users. Instead a more comprehensive approach that focuses on building technological literacy

and Internet skills is needed as well as ensuring that easily accessible, and meaningful, content is available for these would-be Internet users to access.

Final Thoughts

In closing, while the absolute rates of Internet access may be lower in rural areas compared to suburban or urban places, this analysis of secondary survey data found that once controls for demographic traits like sex, race, ethnicity, and age, education, and income are included these differences are not statistically significant. This should not be used to downplay the differences in ICT landscapes between rural and non-rural places, but highlights the role some of the other disadvantages faced by rural places, such as higher rates of poverty and lower educational attainment, play in creating what has been called the rural-urban digital divide.

Controlling for these important variables, as well as smartphone ownership, it was found that among Internet users, some residential differences in the likelihood of posting photos and posting videos online. In regards to the likelihood of posting own photos, rural users were less likely to post compared to those living in urban places. Looking at the likelihood of posting videos online yielded an unexpected result that rural residents were more likely to post than those in the suburbs. Further analysis of these patterns as well as qualitative research into the content of these postings and their purpose should be pursued.

One of the key findings from this work is the influence that smartphone ownership has on the likelihood of engaging in the content posting and sharing behaviors. This finding may seem to suggest that mobile Internet connections such as smartphones may be one avenue for encouraging use among underserved populations. This suggestion must come with a caveat that the mobile connections have lagged behind wired connections in terms of reliability and quality. However, in the absence of plans for universal wired high speed access it may be the best option available.

Moving forward, policy makers and those interested in rural development should continue to advocate for increased Internet access and the spread of the many positive outcomes that are associated with it. If programs can be implemented that work to illustrate to those individuals who do not see the Internet as relevant to their lives in useful ways that ICTs can

indeed be useful to them alongside increased efforts to improve the United States ICT infrastructure perhaps the optimism expressed by the USDA (2013) as well as others about the Internet as a savior of rural economies and communities can become a reality accessible to all and used by all.

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