IS IT THE GREAT EQUALIZER? A SOCIAL CLASS BASED LONGITUDINAL ANALYSIS OF TECHNOLOGY DIFFUSION

Research-in-Progress

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Abstract

Technology in general and the Internet in particular have often been seen as the "great equalizer" in that it provides a level playing field for all individuals in the society in terms of competing for social and economic opportunities. However, technology philosophers such as Andrew Feenberg have argued that technology diffusion mirrors the existing social order. Which of these worldviews actually holds is an open question, and in this research, we try to answer it using data on adoption of multiple technologies by individuals in the US over different time periods. Our results suggest that technology diffusion largely takes place along existing social class lines, and that the arrival of newer technologies ensures that the digital divide perpetuates.

Keywords: Information technology diffusion, social classes, critical theory of technology, technology diffusion lifecycle, digital divide

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Introduction

Modern society is characterized by the ubiquity of information and communication technology (ICT) in all spheres of activities. Everyday routine tasks such as banking and shopping, and important value laden activities such as paying taxes and renewing a driver's license are now increasingly handled with ICT. Scholars use the term digital divide as a measure of technology diffusion to refer to the separation between those who have access to ICT in the society and those who do not (Dewan and Riggins 2005). Technology diffusion has also been widely discussed by the news media, policy planners and academics. A recent article on Wall Street Journal (WSJ) titled *On the Street and On Facebook: The Homeless Stay Wired* features a 37 year old homeless San Franciscan managing his digital life from his residence under a bridge (WSJ 2009). The New York Times reported (NYTimes 2006) that *"African-Americans are steadily gaining access to and ease with the Internet, signaling a remarkable closing of the 'digital divide' that many experts had worried would be a crippling disadvantage in achieving succe*ss." Upgrading the public infrastructure from dial-up access to advanced connections, Federal Communications Commission (FCC) continues to spend great efforts in promoting universal broadband access with government policies (NYTimes 2010). And industry leaders such as Google's co-founder Sergey Brin and Netflix founder Reed Hastings agree that connecting to Internet will *"eventually"* be cheap and easy like electricity, but there is disagreement on when this will be realized. Prior research in academia suggests that demographic factors such as age, gender, education, and income are significant predictors of the digital divide (Akhter 2003; Dewan and Riggins 2005; Eamon 2004; Hargittai 2003; Hoffman and Novak 1998; Katz and Rice 2002; Kraut et al. 1999; Rice and Katz 2003; Selwyn et al. 2005). And factors such as peer influence (Agarwal et al. 2009) and user cognition and need for Internet (Cha et al. 2005) are also identified. While such studies have been instrumental in advancing our understanding of the digital divide, there has been little discussion on how technology diffusion mirrors the existing social order. Is technology the great leveler among different social classes, or are class barriers reinforced by technology?
Academic paradigms such as Feenberg's critical theory of technology (Feenberg 1991) suggest that IT adoption and use mirrors the social order and reproduces extant models of hierarchy, social organization and demarcation. Several industry leaders and policy makers agree, such as:

"... a troubling trend has emerged; the promise and power of information technology and the Internet is not being realized equally in our society. The lack of technology access and corresponding skills puts disadvantaged members of our society increasingly at risk of becoming disenfranchised spectators of a digital world that is passing them by."- Dr. Mark David Milliron, Suanne Davis Roueche Endowed Fellow, Senior Lecturer, & Director, National Institute for Staff and Organizational Development (NISOD), College of Education, University of Texas at Austin, in a letter to the FCC dated April 18, 2007

In this paper we study *how technology diffuses among social classes, and whether the diffusion rate reflects the order of social classes*. To answer these questions, we analyze data on how technologies such as personal computer (PC), Internet, and hi-speed Internet (e.g. Broadband) are diffusing among different social classes and to what extent this diffusion follows existing social class boundaries. Our main finding, contrary to the utopian ideal of IT, is that the *digital divide is more explained by social classes than individual predictors such as demographic variables*. We find that both the level and rate of technology diffusion is higher for higher social classes than classes which are lower in the social hierarchy. Overall, our findings provide support for Feenberg's critical theory of technology (1991), which suggests that the process of technological choice-making and design is often biased towards agendas such as reproduction of the status quo and propagation of hegemony.

The main contribution of this paper is three fold. First, we integrate two theoretical frameworks (critical theory of technology, and classical theory of diffusion) to propose and provide evidence that single dimensions of demographics may not be adequate to explain the digital divide and a multi-dimensional grouping scheme such as social classes is needed. Second, we propose a construct, based on classical theory of diffusion, for measuring the rate at which different social groups are bridging the digital divide over time. Finally, we analyze multiple technologies (PC ownership, Internet access, and high-speed Internet) over different time periods to understand how technology lifecycle impacts diffusion.

Literature Review

Technology Diffusion

According to Rogers (2003), the rate of adoption (of innovation/ technology) is defined as the relative speed with which members of a social system adopt an innovation. It is usually measured by the length of time required for a certain percentage of the members of a social system to adopt an innovation. He identified five groups of people who are in different stages of technology diffusion: innovators, early adopters, early majority, late majority and laggards (see Figure 1). These different groups of people are characterized by different age, social status, and traits.

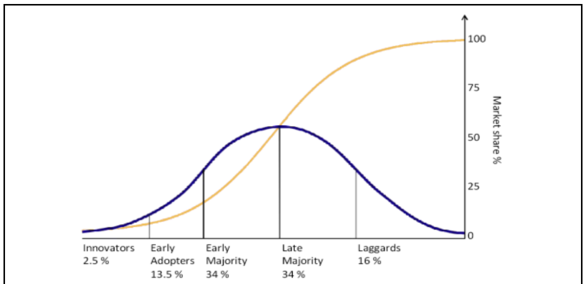

Figure 1. Innovation Adoption by Rogers (1962)

Bass (1969; 2004) presented the intuition and logical arguments of Rogers by formulating a mathematical model. Though the Bass model is initially developed for consumer durables (Bass 1969), it proves to be of good fit with other products and services, including "telecom services and equipments, component products such as semiconductor chips, medical products and many other technology-based products and services" (Bass 2004). Bass mathematically proved and empirically validated that the rate of adoption was determined by the number of non-adopters. While Bass did not measure the effects of individual characteristics on adoption rate, a lot of extensions have been made to complement the original model (Bass 2004; Bass et al. 1994; Robinson and Lakhani 1975). We argue that Bass model is related to the ICT context and can be used to model digital divide since digital divide concerns the adopter – non-adopter issue.

Digital Divide

Several studies have examined technology diffusion in society as an issue of digital divide, which normally refers to the gap between people with effective access to ICT, and those with very limited or no access to ICT. Dewan and Riggins (2005) formally defined digital divide as "the separation between those who have access to digital information and communications technology (ICT) and those who do not (p298)." Digital divide is perceived as both a social phenomenon and economic phenomenon. Factors giving rise to digital divide have been identified by IS scholars, such as physical access to technology and the resources and skills needed to effectively participate as a digital citizen. Research has shown that that income, location, race, age and education were significant factors in determining digital divide (Eamon 2004; NTIA 2004; Rice and Katz 2003). Besides the traditional view of digital divide predictors, recent work by Agarwal et al. (2009) showed that social influence via geographical proximity was a significant predictor of digital divide. And recent report by Pew Internet Research found that the role of traditional demographics such as race in predicting the digital divide is diminishing (PewInternet 2003).

Recent studies of digital divide has shifted from the focus of adoption of PC and Internet to high speed Internet such as broadband, and the use of digital technology (second order digital divide). Prieger and Hu (2008) studied broadband access between minority groups and white households, and find that the gaps in DSL demand for blacks and Hispanics do not disappear when income, education, and other demographic variables are accounted for. (Wei et al.) conceptualized three levels of digital divide, and utilized social cognitive theory and computer self-efficacy literature to develop a model to show how the digital access divide affects the digital capability divide and the digital outcome divide among students. Scholars also study how government efforts bridge digital divide. Kvasny and Keil (2006) examined efforts undertaken by two cities – Atlanta and LaGrange – to redress the digital divide issue, and they found that a persistent divide exists even when cities are giving away theoretically free goods and services, because the group of people who are at a disadvantage in technology diffusion are not willing to go further than simply taking the free lunch provided by the government. This study implies that digital divide did not actually go away – even for basic technology such as computer and Internet – and it is not likely they will go away as it is a social-economic problem embedded in the society.

Social Classes

The literature on digital divide analyzes technology diffusion in the context of individual demographic factors; however, it ignores the impact and role of social classes, i.e., the groups that individuals belong to. For example, showing that income is positively associated with technology access precludes the possibility that some high income individuals can be on the wrong side of the digital divide. Therefore, understanding technology diffusion calls for a richer classification of individual characteristics. One such classification is the concept of social classes – the different groups in society which reflect inequalities in wealth, prestige, and other socioeconomic positions. As Kreiger et al. (1997) suggest, social class is "*A social category referring to social groups forged by interdependent economic and legal relationships, premised upon people's structural location within the economy—as employers, employees, self-employed, and unemployed, and as owners, or not, of capital, land, or other forms of economic investments; possession of educational credentials and skill assets also contribute to social class position* (p345)." Many researchers in social science have produced works on the categorization of social classes. According to prior studies in sociology literature (Krieger et al. 1997), social classes can be defined in multiple ways: social classes based on wealth (upper class versus middle class), education (college educated versus high school dropouts), occupation (farmers versus office workers), location (downtown versus rural) and poverty (% individuals below the poverty line). Beeghley (2000), Gilbert (2002), and Thompson and Hickey (2002) provide a multidimensional defintion of social classes based on multiple demographics – income, education and occupation. In their definitions and categorizations of social classes, there is no clear cut line between upper, middle and lower class, however, they mostly agree upon our claim that social class is not determined only by income, but also education and occupation. A simple example will be, a university scientist may not earn more than a highly skilled car repairer, or a car dealer, but he could be of higher social status and thus belongs to higher social class. Besides, all of them agreed that *management, professional and related occupations such as politicians, professors* as higher class, and *blue collar worker, service occupation, clerical workers, farmers* as lower class. As far as education is concerned, all of them mentioned higher education versus only high school or less as attributes to distinguish upper from lower class. With these distinctions in social classes we are able to construct different social classes, which we elaborate in detail in the methodology section.

Theoretical Framework

We use the critical theory of technology (CTT) by Andrew Fernberg to frame our study. The CTT (Feenberg 1991; 1995; 1999) has evolved out of the contributions of a progression of theorists who have voiced criticism against the "fetishism of efficiency" (Feenberg 1999 , p96) pursued by scientific ideology and technical rationality, and have cautioned against uncritical acceptance of technology by drawing attention to the recurrent use of technology to impose and perpetuate hegemony and domination. Thus summarizing the ideas of the above, as per Fernberg's CTT, two principles hold (Feenberg 1999 , p76):

Conservation of hierarchy: social hierarchy can generally be preserved and reproduced as new technology is introduced. This principle explains the continuity of power in advanced capitalist societies over the last several generations, made possible by technocratic strategies of modernization despite enormous technical changes.

Democratic rationalization: new technology can also be used to undermine the existing social hierarchy or to force it to meet needs it has ignored. This principle explains the technical initiatives that often accompany the structural reforms pursued by union, environmental, and other social movements.

Feenberg provides arguments in support of both these principles. He proposes that "new technology can often be used to undermine or sidestep the existing social hierarchy" (1991, p92), and that "reason is inherently ambivalent and can either support a technological order or subvert it, depending on how it is deployed socially" (1991, p112). On the other hand, he also presents a stringent criticism of technology's potential to impose and perpetuate a hegemonic order (he defines hegemony as "domination so deeply rooted in social life that it seems natural to those it dominates" [1999, p 86]).

Overall, Feenberg opines that "the computer's structure bears an ominous resemblance to mechanistic rationalization (1991, p91)" and wonders if the computer is "predestined to strengthen the administrative grip of the powers that be?" (1991, p91). He further suggests that a technology imposes an order (technocracy) which has historically served class power. Technocracy eventually becomes "the use of technical delegations to conserve and legitimate an expanding system of hierarchical control" and as increasing aspects of life are mediated by technology, "the technical hierarchy merges with the social and political hierarchy" (1999, p75). In fact, classical theory of technology diffusion also argues that people belonging to different technology diffusion stage are characterized by different age, social status, and traits (Bass 2004; Rogers 2003). Though Rogers and Bass did not specifically link social class with technology diffusion, their theory is not contradictory to Fernberg's CTT. Thus based on this discussion and classical theory of technology diffusion, we propose our main hypotheses as follows:

H1: Higher social classes have a higher level of technology diffusion than lower social classes.
H2: Higher social classes have a higher rate of technology diffusion than lower social classes.

Methodology

We construct a measure of technology diffusion based on the classical diffusion model (Bass 1969). Consider a time period t and let x_t denote the proportion of individuals who have access to technology at time t. According to the Bass model (Bass 1969), the fraction of individuals who acquire a technology during time period $t+1$ depends on the fraction of individuals who have not acquired the technology till time t. Mathematically,
$x_{t+1} – x_t = c*(1-x_t)$, where c is a function of the technology characteristics.
We define the construct 'rate of technology diffusion' (*RTD*) as follows:

$$RTD = (x_{t+1} – x_t)/(1-x_t). \qquad (1)$$

RTD measures the speed at which uninitiated individuals in the society acquire the new technology during a particular time period. We also define another variable to measure the 'level of technology diffusion' (LTD) to capture the fraction of individuals who have acquired the technology at a given point in time. LTD follows directly from prior literature on digital divide:

$$LTD = x_t \qquad (2)$$

To test our hypotheses, we check that $LTD_{class1}> LTD_{class2}$ and $RTD_{class1}> RTD_{class2}$, if class 1 is a higher social class than class 2.

Data

We use raw data from the Census Bureau's Current Population Survey (CPS) for the years 2001, 2003, 2007 and 2009. The CPS is a monthly survey of about 50,000 households (about 143,300 people) intended to produce current estimates on a variety of topics including demographic trends and labor force characteristics. According to the Census Bureau: "*The CPS is the primary source of information on the labor force characteristics of the U.S. population. The sample is scientifically selected to represent the civilian non-institutional population… [and to provide] estimates for the nation as a whole… CPS data are used by government policymakers and legislators… [and also by] the press, students, academics, and the general public.*"
We collected four samples from the CPS database for the periods 2001, 2003, 2007 and 2009. We recoded the raw data in accordance with our conceptualization of social classes. Data points with missing values are deleted. Each year the sample has 50,000 - 60,000 data points. Definitions for the variables are presented in Table 1.

Table 1. Variable definitions

Variables	**Operationalization: recoded from CPS raw data**[1]
Technology Variables	
PC Ownership	Yes=1; No=0
Internet Access (anywhere)	Yes=1; No=0
Hi-speed Connection (home)	Advanced connection=1; No connection or dial-up=0
Social Class Variables	
(Annual family) Income[2]	<$35000=1; $35000-75000 = 2; >$75000 = 3; also coded as individual variable (For details please request appendix from the authors)
Education	High school or less=0; College or higher=1
Occupation	White collar=1; Blue collar=0 (recoded in accordance with Beeghley (2000), Gilbert (2002), and Thompson and Hickey (2002))
Other Digital Divide Variables	
Age	[15, 90]
Gender	Male=1; Female=0
Race	White=1; Non-white=0

We follow the classification of Beeghley (2000), Gilbert (2002), and Thompson and Hickey (2002) to segment our data into different social classes in the following table. For the following categorization of social classes, we can safely conclude that upper college white collar (UCW) is in a higher social class than other groups, however, it is not clear whether UHW is in a higher social class than UCB, as the weight in consideration for social class for education and occupation is not clear cut.

Table 2. Social classes

Social Class	**Income**	**Education**	**Occupation**
UCW	upper	attended college	white collar

[1] CPS raw data (survey items) are given in Appendix
[2] In the data analysis we also adjusted inflation for income and the results are qualitatively the same. http://www.bls.gov/data/inflation_calculator.htm

UHW	upper	high school or less	white collar
UCB	upper	attended college	blue collar
UHB	upper	high school or less	blue collar
MCW	middle	attended college	white collar
MHW	middle	high school or less	white collar
MCB	middle	attended college	blue collar
MHB	middle	high school or less	blue collar
LCW	lower	attended college	white collar
LHW	lower	high school or less	white collar
LCB	lower	attended college	blue collar
LHB	lower	high school or less	blue collar

We present the descriptive statistics in the following figures[3]. In Figure 2, X-axis represents PC Ownership and the Y-axis represents the demographic variables income, education, and occupation. For example, the graph suggests that among the people who do not have PCs at home *(PC Ownership = 0)*, 40% are white collar. However, of the people who have PCs at home *(PC Ownership = 1)*, around 75% are white collar workers. Similarly, Figure 3 and 4 have Internet Access and Broadband access as the X-axis respectively.

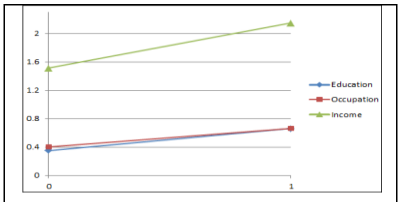

Figure 2. PC ownership and social class variables

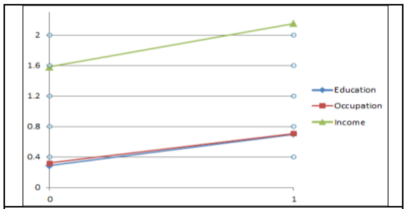

Figure3. Internet access and social class variables

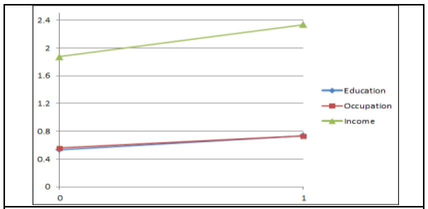

Figure 4. Broadband and social class variables

Figures 2, 3 and 4 reiterate prior studies on digital divide which suggest a monotonic relation between demographic variables and the digital divide. As our results in the following section show, the monotonicity does not always hold, and there are several instances on the contrary.

Rank Analysis

We present our results in Table 4, 5 and 6. For each table, the first column lists the social class. Columns 2 list the level of technology diffusion (*LTD*) for Internet access/ high speed Internet/ PC. Column 3 mentions the sample size. Columns 4 and 5 are similar to columns 2 and 3, but for the year 2007. Column 8 conducts a t-test to check whether the change in level of adoption between 2003 and 2007 is statistically significant. We show the *RTD* is column 9 and in column 10, we report the rank of *RTD* across the 12 social classes. We found that a single demographic is not adequate in explaining the level of technology diffusion. For example, while income has been shown to be a significant predictor of digital divide, we find that middle class, college educated, and white collar individuals (**MCW**) are more likely to have Internet access in 2003 (as shown by the *LTD 2003* column) than upper class individuals who did not have either college education or are blue collar workers (**UCB, UHW, UHB**). Similarly, upper class blue collar workers with only high school education (**UHB**) are more likely to have a high speed Internet connection than middle class, college educated and white collar workers (**MCW**). So our hypothesis is partially supported.

Internet Diffusion[4]

Table 4. Level and rate of Internet diffusion among different social classes

Class Code	*LTD 2003*	*2003 Sample Size*	*LTD 2007*	*2007 Sample Size*	*Sig.(t-test)* $LTD_{2007} - LTD_{2003}$	*RTD*	*Rank of RTD*
UCW	0.95	10134	0.98	11110	0.01	0.65	3
UHW	0.83	1927	0.95	1732	0.01	0.72	2
UCB	0.86	2065	0.96	1686	0.01	0.73	1

[3] detailed descriptive statistics for sample of years 2003 to 2009 can be obtained upon request from authors, we omit them in this paper for brevity.
[4] We also performed analysis for the data of 2009 for Internet diffusion and high speed Internet diffusion. We omit the results for brevity to save space, nevertheless, we will be able to present the results at the conference.

UHB	0.68	1925	0.89	1599	0.01	0.64	4
MCW	0.90	7247	0.95	8447	0.01	0.47	6
MHW	0.75	2592	0.86	3346	0.01	0.45	8
MCB	0.77	2829	0.89	3094	0.01	0.53	5
MHB	0.51	4366	0.74	4947	0.01	0.46	7
LCW	0.81	2923	0.88	3910	0.01	0.37	10
LHW	0.55	1980	0.65	2686	0.01	0.22	12
LCB	0.61	1870	0.77	2310	0.01	0.41	9
LHB	0.29	4742	0.50	6274	0.01	0.29	11

Overall, Columns 3 and 4 in Table 4 suggest that the proportion of individuals with Internet access is higher among the higher classes than the lower classes. For example LTD_{UCW} is the highest and LTD_{LHB} is the lowest for both 2003 and 2007 for Internet access as well as high-speed Internet connection. Ranking the twelve social classes is difficult considering that the relation between different dimensions may not be linear, e.g. it is not clear if *UCB* is a higher social class than *UHW*. However, some social classes are clearly higher than others – *UCB* is a higher class than *MCB* or *LCB*; *MCW* is a higher social class than *MCB.* Table 4 suggests that between any two such social classes where one is clearly higher, the *LTD* is always greater for the higher social class. Our results also broadly support the assertion that the rate of diffusion is higher in the higher social classes. For example, 65% of the individuals without Internet access in 2003 in the social class *UCW* bridged the digital divide by 2007. On the other hand, only 29% individuals without Internet access in 2003 in the class *LHB* bridged the digital divide in 2007. To complement the data analysis we did t-tests for LTD of 2003 and 2007, it is shown that LTDs (Internet diffusion) for all classes have significant change (p<0.01) over 2003 and 2007.

High-speed Internet Connection Diffusion

Table 5. Level and rate of high speed Internet diffusion among different social classes

Class Code	*LTD 2003*	*2003 Sample Size*	*LTD 2007*	*2007 Sample Size*	*Sig. (t-test)* $LTD_{2007} - LTD_{2003}$	*RTD*	*Rank of RTD*
UCW	0.48	10134	0.87	11110	0.01	0.76	1
UHW	0.37	1927	0.79	1732	0.01	0.66	3
UCB	0.39	2065	0.81	1686	0.01	0.68	2
UHB	0.32	1925	0.70	1599	0.01	0.56	5
MCW	0.29	7247	0.73	8447	0.01	0.62	4
MHW	0.24	2592	0.57	3346	0.01	0.44	8
MCB	0.26	2829	0.65	3094	0.01	0.51	9
MHB	0.17	4366	0.48	4947	0.01	0.37	10
LCW	0.23	2923	0.6	3910	0.01	0.47	7
LHW	0.1	1980	0.34	2686	0.01	0.27	11
LCB	0.15	1870	0.48	2310	0.01	0.38	9
LHB	0.07	4742	0.24	6274	0.01	0.19	12

Analogous to discussions on Table 4, Table 5 also suggests that the rate of technology diffusion (*RTD*) for high speed Internet is also higher for the higher classes: *RTD* for Internet access seems more driven by income in general, than by the other dimensions. For example, individuals in upper class (UCW, UCB, UHW, UHB) are ranked 1-4 in terms on RTD, but within this class, it is *UCB* that has the fastest rate of Internet diffusion. Similarly, individuals in the middle class are ranked (5-8) and those in the lower class are ranked (9-12) in *RTD* for Internet access. To complement the data analysis we did t-tests for LTD of 2003 and 2007, analogous to Internet diffusion, it is shown that LTDs (high speed Internet diffusion) for all classes have significant change over 2003 and 2007.

PC Diffusion

Table 6. Level and rate of PC diffusion among different social classes

Class Code	*LTD* 2001	2001 Sample Size	*LTD* 2003	*2003 Sample Size*	*Sig. (t-test)* $LTD_{2007} - LTD_{2003}$	*RTD*	Rank of *RTD*
UCW	0.93	7425	0.94	10134	0.01	0.16	4
UHW	0.90	3883	0.92	1684	0.01	0.15	5
UCB	0.87	737	0.89	1732	0.01	0.13	6
UHB	0.84	3789	0.85	1598	0.01	0.04	10
MCW	0.85	5848	0.87	8447	0.01	0.18	3

MHW	0.78	6110	0.82	3090	0.01	0.2	1
MCB	0.75	1154	0.79	3346	0.01	0.19	2
MHB	0.66	7420	0.7	4945	0.01	0.11	7
LCW	0.72	2026	0.74	3910	0.01	0.09	9
LHW	0.59	3977	0.63	2308	0.01	0.1	8
LCB	0.53	840	0.52	2686	0.01	-0.01	12
LHB	0.36	8228	0.39	6273	0.01	0.04	11

We repeat this analysis for PC ownership for years 2001 and 2003[5] (see Table 6), it is clear that the higher social classes are more likely to own a PC at home in both 2001 and 2003. However, the interesting result is that the rate of technology diffusion is higher for the middle class (as is evident in the Rank of *RTD* column). On the other hand, the speed of technology diffusion is slowest among the lower classes – in fact, fewer households in the *LCB* class owned a PC at home in 2003 than in 2001.

Regression Analysis

We utilized linear probability model (LPM) to test whether social classes will be more predictive than individual variables. We did same analysis for years 1994, 1997, 1998, 2000, 2001, 2003, 2007 and 2009, but for brevity purpose, we only report regression results for year 2009.

We run the regression with three models. In model 1, only the control variables such as age, gender and race are entered. In model 2, control variables and other demographic variables - income, education, and occupation are entered. Finally, in model 3, we replace the individual demographic variable income, education, and occupation with 11 dummy variables for social classes. As Table 7 attests, first, evidenced by variance explained (R-squared), either composite social class variables (UCW etc., herein referred to as social class variables) or the individual social class predictors (income, education, occupation, herein referred to as individual variables) has a much stronger impact on Internet diffusion than other digital divide variables (location, age, race and gender). Specifically, social class variables explain 15.4% more variance than the control variables, and individual variables explain at least 11.5% more variance, the increase of R-squared is statistically significant ($p<0.01$). And the Columns 2, 3 of Table 7 stand to provide evidence that social class variables are more predictive than individual variables ($p<0.01$). We used the formula $F=\frac{(RSS0-RSS1)/(P1-P0)}{RSS1/(N-P1-1)}$, RSS0 is sum of squares residuals for model with social variables, RSS1 is the RSS for model with individual variables, P1 is the number of variables for individual variables model, P0 is the number of variables for social class variable model, and N is number of observations.

Regression results for Broadband (Models Broadband 1, 2 and 3) provides similar results, social class variables explains at least 14.6% more variance than other digital divide variables, and the R-squared increase is statistically significant ($p<0.01$). And the Columns 2, 3 Table 8 stand to provide evidence that social class variables are more predictive than individual variables ($p<0.01$).

Table 7. Regression results for Internet and Broadband diffusion (Year 2009) N=56598

Models		Internet 1	Internet 2	Internet 3	Broadband 1	Broadband 2	Broadband 3
Social Class Variables	*UCW*			0.406***			0.580***
	UHW			0.377***			0.517***
	UCB			0.392***			0.537***
	UHB			0.341***			0.463***
	MCW			0.381***			0.485***
	MHW			0.314***			0.368***
	MCB			0.337***			0.426***
	MHB			0.245***			0.306***
	LCW			0.325***			0.367***
	LHW			0.146***			0.131***
	LCB			0.215***			0.247***
Individual Variables	*Income*		1.50e-06***			2.78e-06***	
	Education		0.105***			0.141***	
	Occupation		0.067***			0.074***	
Control	*Age*	-0.001***	-0.002***	-0.002***	-0.001***	-0.002***	-0.002***
	Gender	-0.022***	-0.004	-0.003	-0.013***	0.006*	0.008**

[5] Data for PC ownership for 2007 is not available in the CPS dataset.

	Race	0.048***	0.025***	0.019***	0.093***	0.054***	0.049***
	Constant	0.873***	0.745***	0.644***	0.643***	0.454***	0.371***
	R-squared	0.010	0.134	0.172	0.019	0.176	0.197

Robustness Checks

We conduct the following robustness checks. The presence of heteroskedasticity was tested using White's (White 1980) test, and no evidence of heteroskedasticity was found. The effect of multicollinearity was checked with the variation inflation factors (VIFs) for all the models; the VIFs across all models range from 1 to 2, suggesting that the estimates obtained are not biased because of multicollinearity (Hair Jr et al. 1995). We did not detect influential observations or outliers for the dataset across all models using Cook's distance (Cook 1977; Cook and Weisberg 1982) following the guidelines specified by Belsley et al.(Belsley et al. 1980).

Discussion and Conclusion

The results show that social classes largely determine technology adoption among individuals, as argued in Feenberg's *conservation of hierarchy* principle. The higher social classes are likely to adopt earlier, and the rate of diffusion is also greater among these higher classes. In general, technology diffusion takes place along the traditional social hierarchy - in other words, technology diffusion broadly reinforces the status quo in the society. None of the social classes in our model have a distinctly higher level of technology diffusion than a higher social class. The rate of technology diffusion, which is an indicator of "bridging the digital divide", is also more for the higher social classes, which implies that higher classes are moving much faster towards universal adoption than the lower classes; statistically, upper classes have more than 80% diffusion of PC ownership, Internet access, and high speed Internet.

We consider three different technologies at different points in their lifecycle, and shed light on the level and rate of technology diffusion. For example, PCs were a mature technology by 2003, whereas Internet was relatively newer. Moreover, in 2003, technologies such as social networks which fueled the widespread adoption of the Internet were not heavily in use. High speed Internet access at home was just starting to become popular in 2003. Some of the differences in the results between the three technologies can be attributed to their different lifecycle stages. For example, the rate of technology diffusion for PCs is higher for middle class than the upper classes. A potential reason for these anomalous results is that the diffusion for the higher classes has reached a saturation point, and that further diffusion is likely to be slower. This reasoning is further validated by the fact that adoption of high-speed Internet, which was a relatively newer technology in 2003, is predictable along the lines of social class – none of the lower social classes have a faster rate of adoption than the higher classes.

The question which merits discussions at this stage is whether the digital divide will disappear over time, and whether the lower social classes will ultimately catch up with the higher social classes. *Will Feenberg ultimately be proven wrong?* While we don't have evidence to answer this question conclusively, our data analysis provides interesting insights into this question. First, lower classes suffer from a double whammy of lowest technology adoption, as well as lowest rate of diffusion. Second, even though the lower classes are catching up with the higher classes on technology adoption, the changing technology landscape ensures that newer technologies get introduced, and the lower classes are less poised to adopt the newer technologies, so the digital divide will be increasing in the long run. For example, higher classes, who have PCs at home, are more likely to use PC applications such as the Internet; or social classes who adopt the Internet earlier are more likely to use it for a variety of purposes, and hence feel the need for high speed Internet.

Limitations

As with every research study, this paper is not without limitations. First, one may argue that the composition of social classes could be changing as a consequence of technology diffusion; for example, it is likely that individuals use technology to climb to a higher social class. Second, we are not able to investigate digital divide in terms of the use of different ICTs or how people find relevant information given the limitation of available data, nevertheless we are planning to acquire more data and analyze use of ICT among different social classes.

This study also opens avenues for future research by showing the importance of social classes in studying digital divide. Future research could expand our study to include data on diffusion of additional technologies such as PC applications (spreadsheet application, word processing, financial software, etc.), web 2.0 (blogs, forums, etc.). Moreover, future research could analyze how the critical theory of technology applies to specific sub-groups among the different social classes – for example, use of PC applications by government employees at work, or use of PCs at school by kids – and determine whether technology usage in these sub-groups varies based on broader social class to which an individual member belongs.

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