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THE INCOME DIGITAL DIVIDE: AN INTERNATIONAL PERSPECTIVE

STEVEN P. MARTIN
JOHN P. ROBINSON

ABSTRACT

This article replicates previous findings that the diffusion of the Internet is becoming more polarized by family income in the United States. Using multiple logistic regression and other odds-based analyses to assess Internet access in the United States from 1998 to 2001, the recent analysis confirms that the odds of access increased most rapidly for individuals at highest family income levels, and most slowly for individuals with the lowest income levels. The unique divide in the U.S. is further evidenced by the lack of such static and dynamic income differences in the U.S. compared with income differences in data from 15 European nations.

Moreover, such application of odds-based measures of Internet diffusion is supported by the relative lack of differences in comparisons by education, age and other demographic variables (besides income) for the U.S. Issues about the assumptions underlying use of odds-based measures are discussed.

Steven P. Martin is an Assistant Professor in the Department of Sociology at the University of Maryland. smartin@socy.umd.edu

John P. Robinson is a Professor of Sociology at the University of Maryland, where he directs the Internet Scholars Program and the Americans' Use of Time Project.

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As the Internet becomes an increasingly important part of people's lives, those who remain offline face increasing economic, social and political disadvantages, and the persistence of the "digital divide" becomes a matter of increasing public concern. If the gap in Internet use between the "haves" and the "have-nots" is pronounced and long-lasting, then differential access to the Internet may reinforce already high levels of income inequality. Conversely, if the digital divide is temporary and/or is already shrinking, the Internet has the potential to alleviate other dimensions of inequality. Given the social implications of these possible futures, there is a growing urgency for social researchers to reach a consensus on the basic question of whether the digital divide is growing or shrinking.

Researchers and policy makers agree that there currently are pronounced differences in Internet use across incomes, educational levels, and ages in the United States and most other Western countries. The disagreements about the digital divide pertain to how long these differences will persist -- in other words, to questions about the shape of trends in the digital divide. Unfortunately, the statistical methodology in this field is not fully settled, and different methods applied to an analysis of trends can produce opposite results. For example, the Department of Commerce report, *A Nation Online* (U.S. Department of Commerce 2002), compared trends using a measure of the rate of growth of Internet use, and found remarkable levels of "catching up" among individuals with low family incomes. However, when the same data are assessed using odds ratios -- instead of simple growth rates or Gini indices -- the opposite patterns appear, with low-income individuals appearing to fall increasingly behind in Internet access, at least in relative terms (Martin 2003). It follows logically that at least one of these approaches (odds ratios, simple growth rates, Gini indices) is misleading.

This article reassesses trends in Internet access to test whether odds ratios are an appropriate way to compare trends in inequality of Internet use. The primary concern is that odds ratios assume a distinct tempo of diffusion – slow in the initial stages, fairly rapid around 50 percent diffusion, and slow again near saturation. Such an assumption can strongly affect the interpretation of diffusion rates among different income groups, potentially confounding *levels* of Internet use with *trends* in Internet use. If such confounding is occurring, it should appear not only for income, but also for all other demographic predictors of Internet access in the United States, such as education, race, sex, nativity/citizenship, and age. However, of the many social dimensions of inequality in Internet use in the United States, only income and nativity/citizenship show pronounced increases in inequality across a short time span in an analysis based on odds ratios. This result suggests that low-income individuals are indeed falling increasingly behind, and trends in odds ratios are *not* a mere statistical artifact.

A main focus, however, lies in comparing trends in Internet use across income levels for the United States with parallel trends by income in 15 European nations. Divergence in the odds of Internet use by income level is found not only to be universal, but to occur only in the United States and a few other nations. This finding reinforces both the credibility of the statistical use of odds ratios for comparing diffusion patterns, and the substantive importance of the distinctive trends in Internet use by income levels in the United States.

INTRODUCTION: PATTERNS OF TECHNOLOGICAL DIFFUSION

Debates about inequality in technological diffusion have made two general observations about the diffusion curves of advantaged and disadvantaged groups. The first observation is that the advantaged groups have a head start in the diffusion process, so that the diffusion curves have a several-year lag for disadvantaged groups (the poor, racial minorities, women, and/or the less educated). This observed pattern is almost universal across technologies. The second observation is that the diffusion curves for the disadvantaged groups *may but do not necessarily* "max out" at a point well below 100% saturation. Indeed the central debate about the digital divide is not whether socially disadvantaged groups were late in starting to take up the Internet (as they were), but whether or when they will catch up with more advantaged groups.

In her *Digital Divide,* Norris (2001) outlined two possible models of technological diffusion. The optimistic Normalization model assumes that Internet penetration will saturate all groups in society as the Internet becomes easier and less expensive to use, and its benefits become more widely recognized. A sample of a Normalized diffusion process is shown in Figure 1. By comparison, the more pessimistic Stratification model in Figure 2 assumes that socially disadvantaged groups will encounter cost and other obstacles that halt Internet penetration well before they reach 100 percent saturation.

Both the Normalization and Stratification models assume that the adoption of innovations follows an S-shaped pattern. The use of S-shaped or sigmoid curves follows classic diffusion theory, which predicts a slow rate of initial adoption, a surge in adoption in the middle of the diffusion process, and slowing adoption near a saturation point. Researchers can use numerous mathematical functions to describe S-shaped diffusion curves, of which the most common are based on the *odds* $P / (1- P)$. The *logistic regression* model makes the odds an outcome a function of one or more explanatory variables x_i and of time t:

$$P/(1-P) = \exp(b_0 + b_1 x_1 + ... + b_k x_k + ct) \qquad (1)$$

FIGURE 1: PATTERNS OF DIFFUSION CONSISTENT WITH A NORMALIZATION MODEL.

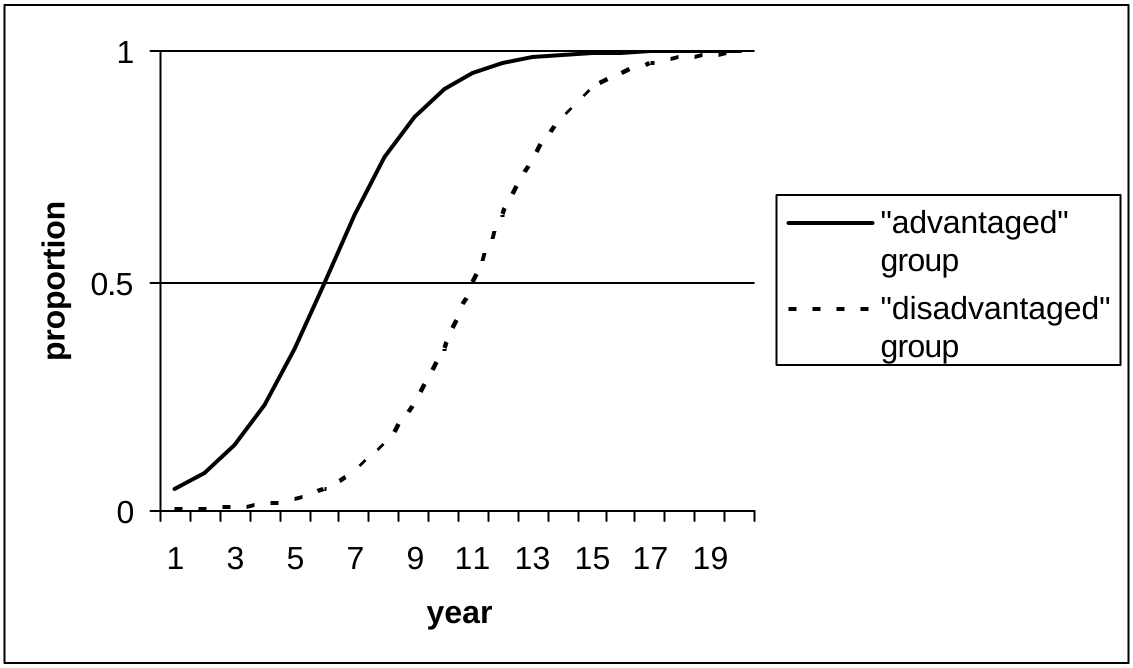
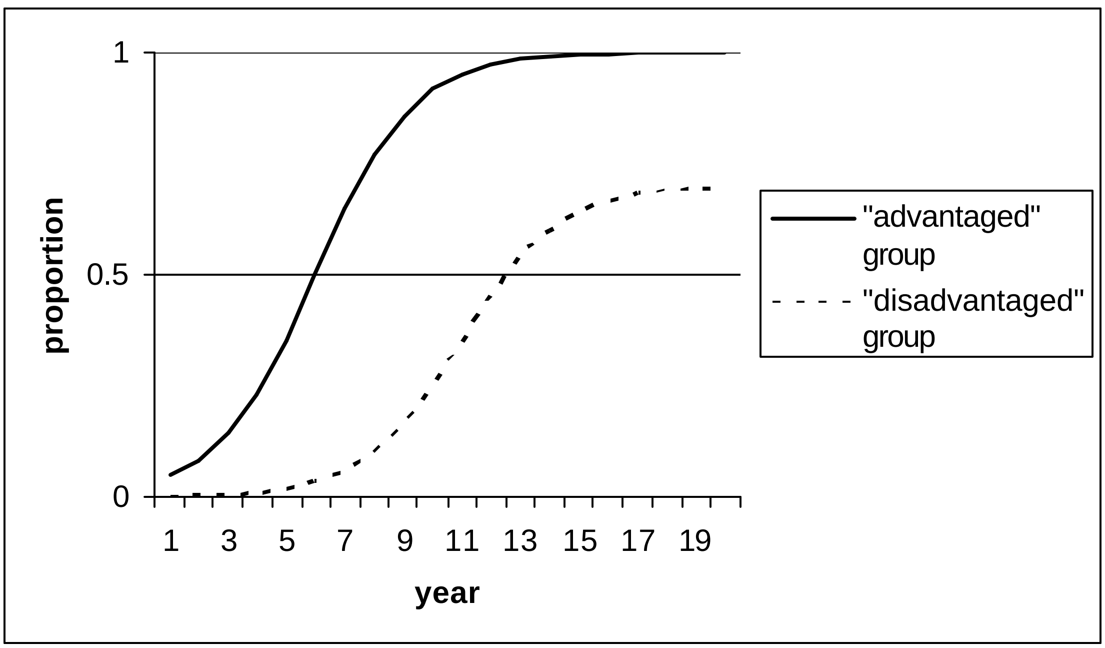


FIGURE 2: PATTERNS OF DIFFUSION CONSISTENT WITH A STRATIFICATION MODEL



Equation (1) is essentially a formula for the Normalization model, with x_1 a dichotomous variable for some indicator of inequality (such as low income), b_1 (if it is a negative number) reflecting the lag in log odds of Internet use at a given time t, and c serving as an indicator of the overall speed of Internet diffusion for all groups.

To estimate a Stratification model, one must add additional coefficients L_0 and L_1 to the equation to reflect that the saturation proportion is not 1, but is some smaller proportion $L_0 + L_1x_1$.:

$$P/(L_0 + L_1x_1 - P) = \exp(b_0 + b_1x_1 + ... + b_kx_k + ct) \qquad (2)$$

where $0 = L_0 = 1$ and $0 = L_0 + L_1x_1 = 1$, and L_1 represents the difference between the saturation levels of the two groups for which $x_1 = 0$ and $x_1 = 1$; a negative value for L_1 would indicate that some portion of the group for which $x_1 = 1$ is not taking up Internet use at all.

Unfortunately, equation (2) has some problems. First of all, L_0 and L_1 are properties of the *end* of the diffusion process, so these terms are difficult to estimate with any certainty using data from the *beginning and middle* of a diffusion process. The second problem is that equation (2) leaves out another possibility – that all groups will eventually achieve saturation, but some groups will achieve it later than others. Such a scenario would be described mathematically as follows:

$$P/(1-P) = \exp(b_0 + b_1x_1 + ... + b_kx_k + c_0t + c_1x_1t + ... + c_kx_kt) \qquad (3)$$

where c_1 represents the difference in the speed of the diffusion process of the two groups for which $x_1 = 0$ and $x_1 = 1$; a negative value for c_1 would indicate that the group for which $x_1 = 1$ is increasing the uptake of Internet use, but that group is taking up Internet use more slowly than the rest of the sample.

Ideally, one would like to estimate three differences between the two groups for which $x_1 = 1$ and $x_1 = 0$, that is the difference in times for the start of diffusion (reflected in b_1), the difference in speed of diffusion (reflected in c_1), and the difference in saturation level (reflected in L_1). Such a model would look like equation (4)

$$P/(L_0 + L_1x_1 - P) = \exp(b_0 + b_1x_1 + ... + b_kx_k + c_0t + c_1x_1t + ... + c_kx_kt) \qquad (4)$$

Unfortunately, equation (4) is almost impossible to identify until the diffusion process has run its course; it is not much good in the middle of a diffusion process, as is the case for Internet use in the last few years.

To cope with the identification problem, some form of equation (3) is involved, leaving open the possible implications of c_1. A negative value for c_1

could indicate, say, that 1) diffusion for the disadvantaged group is proceeding 30% more slowly than for the rest of the sample, or 2) diffusion for most of the disadvantaged group is proceeding at the same rate as for the rest of the sample, while 30% of the disadvantaged group is not taking up the Internet at all, or 3) some combination of the two.

Note that all the above equations are from the same family of models, based on form of $P / (1 - P)$. As such, they all assume a precise shape for an S-shaped diffusion curve. As the diffusion of Internet use is occurring in the real world -- affected by real social, economic, and technological changes -- there is no assurance that the spread of the Internet is following the precise functional form described by the logistic curve. Furthermore, at any given time, different groups will be experiencing diffusion at a different stage of the diffusion process. Hence, even a slight deviation between the shape of the observed diffusion curve and the shape suggested by the logistic function can create a false impression that socially disadvantaged groups are experiencing diffusion at a different pace than advantaged groups (when instead, all groups might be experiencing diffusion at an identical pace along an S-shaped curve that is not logistic in form).

To address this problem, one needs to estimate interactions between social variables and time (*c* coefficients) for various social variables such as sex, age, education, and race, in addition to income in a multivariate analysis. If one finds negative interaction coefficients for only a few variables, it is likely that some groups are taking up the Internet more slowly than others. If, however, one finds negative interaction coefficients for every variable, it is likely that those coefficients are merely a statistical artifact, a side effect of fitting a non-logistic diffusion curve into a logistic form. One still will not have predicted the eventual group differences in Internet use, nor will one have identified any negative consequences of such differences, but one will be one step further along in understanding the nature of current trends.

DATA AND METHODS

Data on Internet access in the United States come from Internet use supplements in the Current Population Surveys (CPS) for December 1998, August 2000, and September 2001. The sample is restricted to individuals aged 18 to 90 in the survey. With this age restriction, and excluding cases missing Internet data, the sample sizes are 89,545 for 1998, 89,580 for 2000, and 105,387 for 2001. The U.S. Department of Labor (2001) has published a full description of the procedures used in collecting the CPS data.

The following variables are examined in the analysis. Internet access, the outcome, is a dichotomous variable reflecting whether the individual used the Internet anywhere. Income was measured as total family income in the last twelve months, with dichotomous categories for \$0-14,999, \$15,000-29,999,

$30,000-49,999, $50,000-74,999, and $75,000 or more. Age is grouped into dichotomous categories for age 18-24, 25-44, 45-64, and 65-90. Dichotomous categories for education include no high school diploma, high school diploma or equivalent, some college, four-year college degree, and master's or other post-graduate degree. Gender, race/ethnicity (non-Hispanic white, non-Hispanic black, other non-Hispanic, and Hispanic), and nativity/citizenship variables were also included. Descriptive statistics for the outcome and explanatory variables are shown in Table A in the Appendix.

The main analytic procedure is a multivariate logistic regression analysis, with the outcome variable being the log odds of Internet access, predicted as a function of these various demographic variables. Separate surveys from December 1998, August 2000, and September 2001 are combined, or at time intervals of 0 years, 1.67 years, and 2.75 years after the first survey. A supplementary analysis updates the U.S. results using the April 2000 and February 2004 surveys by the Pew Internet and American Life Project. These surveys have much smaller samples than the CPS, but cover a more recent time period.

The analyses of these data sets is put into broader perspective by using the 1998 to 2001 Eurobarometer Surveys to compare Internet use across income quartiles for the United States with those in 15 European nations (including separate data for West and East Germany).

RESULTS

Table 1 shows observed patterns of Internet use for persons with various demographic characteristics for December 1998, August 2000, and September 2001. The fourth column in Table 1 shows the increase in proportions for each group from 1998 to 2001. As would be expected for S-shaped diffusion curves, the largest differences in proportions are for groups near the 50 percent mark in the diffusion process. For example, Internet use among persons with "some college" education increased from 43 percent to 66 percent, a difference of 23 percentage points. Conversely, the smallest differences in proportions are for groups farthest from the 50 percent level of Internet use, such as persons with low family income, no high school diploma, or age 65 and older. These patterns indicate that a group's change in Internet use expressed as a difference in proportions is largely a function of its stage in the diffusion process.

The final column in Table 1 shows the relative change in the odds of Internet use from 1998 to 2001. The odds ratio is much more pronounced for the highest income households (2.8) than for the lowest income households (1.9), and also appears to vary systematically by nativity and citizenship status. In contrast, education and age have no clear correlation with changes in the odds of Internet use, even though both education and age are strong predictors of the

TABLE 1: OBSERVED PROPORTIONS AND ODDS OF INTERNET USE, BY SURVEY YEAR AND DEMOGRAPHIC CHARACTERISTICS

	Percent using the Internet			Difference in proportions	Odds Ratio
	1998	2000	2001	2001 – 1998	2001/1998
Family income (yearly)					
$75,000+	61.9	74.5	82.1	20.2	2.8
$50,000-74,999	48.1	61.3	69.2	21.1	2.4
$30,000-49,999	33.6	46.2	54.5	20.9	2.4
$15,000-29,999	19.8	28.5	35.0	15.2	2.2
<$15,000	13.4	19.0	23.1	9.7	1.9
Education					
Master's or Prof. degree	66.4	78.4	83.8	20.7	2.6
4-year college degree	59.4	73.3	81.6	20.7	3.0
Some College	42.5	57.6	65.8	23.3	2.6
High school diploma	20.9	33.1	42.2	21.3	2.8
No high school diploma	7.3	11.6	16.6	9.3	2.5
Age					
18-24	44.3	56.8	65.1	20.8	2.3
25-44	41.0	55.7	64.4	23.4	2.6
45-64	33.1	45.8	54.8	21.7	2.5
65 or older	7.2	14.3	18.6	11.4	2.9
Sex					
Male	35.5	46.7	54.3	18.8	2.2
Female	31.9	45.7	54.1	22.2	2.5
Race/ethnicity					
NonHispanic white	37.7	51.4	59.7	22.0	2.4
NonHispanic Black	20.6	31.1	39.2	18.6	2.5
Hispanic	17.3	24.6	31.1	13.8	2.2
Other	36.5	50.1	58.6	22.1	2.5
Nativity/Citizenship					
US-Born Citizen	35.0	48.3	56.6	21.6	2.4
Naturalized US Citizen	26.0	36.7	44.0	18.0	2.2
Foreign Born, Non-Citizen	21.6	28.4	34.6	13.0	1.9

Source: Weighted Responses from Current Population Surveys for December 1998, August 2000, and September 2001.

overall level of Internet use. Hence, a group's change in Internet use expressed as an odds ratio appears to be largely independent of its stage in the diffusion process, *except* for comparisons across income groups. The distinctiveness of the income pattern constitutes supporting evidence for the appropriateness of the use of odds ratios to study diffusion patterns.

Logistic regression results: Table 2 shows coefficients from the logistic regression analysis. In the first column of numbers, negative coefficients for the "main effects" show how far behind (or ahead) of the comparison group the listed group was in December 1998, in terms of the log of the odds ratios. For example, as of December 1998, the log odds of Internet use for an individual with a family income below $15,000 were a factor of (exp{-1.1}), or 35% as high as for an individual with a family income of $75,000 or more. Note that the largest differences in odds of Internet use were across extremes of the education distribution (exp{-2.7}) for no high school diploma (compared to a master's or professional degree), and across extremes of the age distribution (exp{-2.6}) for age 65 and older, compared to age 18 to 24.

The second column of figures shows the coefficients of primary interest to this analysis, that is, the trends over time in the various coefficients. A negative log-odds ratio indicates a progressive "falling behind", or a yearly increase in difference in the odds of Internet use between the given category and the comparison category. For example, a log ratio of -.2 for individuals with a family income of less than $15,000 suggests that the income group is "losing ground" in relative terms to the top income category, from a log odds -1.3 lower in December1998 to a log odds - 1.8 lower (= -1.29 - .17*2.75) at a time 2.75 years later in September 2001. Note that the overall yearly change in the log odds of Internet use was +.4 across this time interval, a value greater than any of the negative coefficients. This means that the odds of using the Internet rose for all groups from 1998 to 2001, but that they rose more quickly for high income individuals than for low income individuals. In fact, the log odds of uptake for the lowest income group increased only (.41 - .17) / (.41) = .60 as quickly as for the highest income group, indicating either a slower rate of diffusion for the lowest income group as a whole, or a large fraction of the lowest income group not experiencing diffusion at all.

In Table 2, categories of family income and nativity/citizenship have consistently negative log ratios, indicating that the trailing groups were not only behind the more advantaged groups in 1998, but lagged further behind the leading groups from 1998 to 2001. In contrast, the comparison of log ratios shows little or no evidence of increasing inequality in Internet use across other social dimensions. Log ratios comparing minority groups to non-Hispanic whites suggest small lags for non-Hispanic blacks and Hispanics, while log ratios comparing education and age groups show no evidence of negative log ratios. Groups with extremely low levels of Internet use, such as high school

TABLE 2: MULTIPLE LOGISTIC REGRESSION COEFFICIENTS FOR INTERNET USE ON INCOME AND OTHER CHARACTERISTICS.

	Main effect (December 1998)		Effect*Year interaction	
Family income (yearly)				
$75,000 or more	---	---	---	---
$50,000 – 74,999	-.29	(.03)	**-.04**	**(.02)***
$30,000 – 49,999	-.67	(.03)	**-.04**	**(.02)***
$15,000 – 29,999	-1.07	(.03)	**-.09**	**(.02)***
Less than $15,000	-1.29	(.04)	**-.17**	**(.02)***
Educational attainment				
Master's or Professional Degree	---	---	---	---
4-year College Degree	-.40	(.04)	+.03	(.02)
Some College	-1.02	(.03)	-.01	(.02)
High school degree	-1.91	(.03)	+.01	(.02)
No high school degree	-2.72	(.05)	-.00	(.02)
Age				
18 – 24	---	---	---	---
25 – 44	-.61	(.03)	+.05	(.01)*
45 – 64	-1.11	(.03)	-.00	(.00)
65 or older	-2.56	(.04)	+.02	(.02)
Sex				
Male	---	---	---	---
Female	-.07	(.02)	.09	(.01)*
Race/Ethnicity				
Non-Hispanic white	---	---	---	---
Non-Hispanic black	-.70	(.03)	-.03	(.02)
Other non-Hispanic	-.14	(.04)	-.05	(.02)
Hispanic	-.62	(.04)	+.02	(.02)
Nativity/Citizenship				
US-Born Citizen	---	---	---	---
Naturalized US Citizen	-.30	(.05)	-.02	(.02)
Foreign Born, Non-Citizen	-.31	(.04)	-.12	(.02)*
Constant	2.34	(.04)	0.41	(.02)*
N	284,512			
Log pseudo-likelihood	-141846.0			

Source: Current Population Surveys for December 1998, August 2000, and September 2001. Robust logistic regression estimates are based on weighted scores. See text for details.

dropouts and persons 65 or older, appear to have had no shift in their levels of relative disadvantage from 1998 to 2001 -- but their odds of Internet use remain so far behind that uptake of Internet use remains a social concern for the least educated and oldest persons in society. The log ratios for females indicates that net of other characteristics, women have caught up and even passed men in their use of the Internet.

Appendix Figures A1 through A6 illustrate the trends in the coefficients from Table 2, translated from log odds to odds to make interpretation more convenient. By expressing comparisons in relative odds, these figures factor out the overall increase in Internet use and focus on how groups are doing relative to each other. Again, by these measures, increasing inequality is not automatically linked to groups with low levels of Internet use, but is a distinctive feature of low income groups and foreign-born non-citizens. In other words, while age and education remain the strongest independent predictors of Internet use, differences in income are becoming more pronounced over time.

Projected trends: Figure 3 translates the income coefficients from Table 2 into predicted levels of Internet use, then projects those trends forward to 2010. The S-shaped diffusion curves in Figure 3 are assumed by the model; the increasing lag across incomes follows from the model coefficients. This lag can be interpreted by measuring the time differences at different levels of Internet use. According to the model parameters, the top income category reaches the 20% level of Internet use *three* years ahead of the bottom income category (1996 versus 1999), but the top income category reaches the 80% level of Internet use *six* years ahead of the bottom income category (2002 versus 2008). Of course, this long-term extrapolation from three years of data is largely speculative, particularly for the lowest income categories that have not yet reached 40% Internet use. It is certainly possible that low income groups might accelerate their uptake of Internet use, or conversely, that diffusion of Internet use might stall completely for the lowest income groups.

More recent Pew Project data: Table 2 shows the most current data available from the Current Population Surveys last conducted in 2001. However, there is a source of data on more recent trends in Internet use from the Pew Internet and American Life Project. Table 3 shows trends in Internet use through February 2004 from the Pew Surveys. The descriptive results in Table 3 support those from Tables 1 and 2 -- but with some exceptions. The odds of Internet use from 2000 to 2004 changed most slowly for the lowest income groups, as in the CPS data for 1998 to 2001. However, odds of Internet use also appear to have slowed down for the highest income category (increasing by a factor of 2.3 from 2000 to 2004), perhaps indicating that the highest income households are approaching saturation at a level of Internet use a bit below 1.00. In addition, the Pew data suggest that the odds of Internet use have also

FIGURE 3: PROJECTED DIFFUSION OF INTERNET USE, BY FAMILY INCOME LEVEL

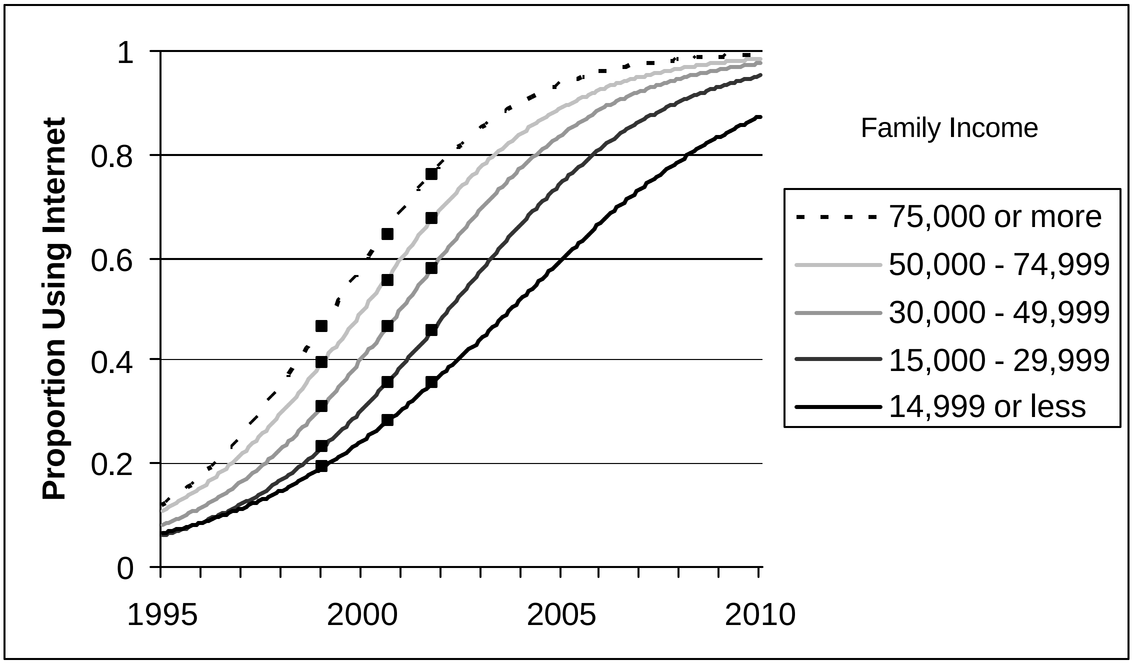


TABLE 3: TRENDS IN INTERNET USE FROM THE PEW INTERNET AND AMERICAN LIFE SURVEY 2000 - 2004. OBSERVED PROPORTIONS AND ODDS OF INTERNET USE, BY DEMOGRAPHIC CHARACTERISTICS.

	Percent Using the Internet		Difference in proportions	Odds Ratio
	Pew 2000	Pew 2004	2004 – 2000	2004 / 2000
Family Income				
$75,000 +	78	89	11	2.3
$50,000 to 74,999	67	86	19	3.0
$30,000 to 49,999	52	69	17	2.1
Less than $30,000	31	41	10	1.5
Education				
College +	75	85	10	1.9
Some College	63	78	15	2.1
High School	34	54	19	2.3
Less than High School	17	24	7	1.5
Age				
18-29	69	77	8	1.5
30-49	60	74	14	1.9
50-64	45	58	13	1.7
65 +	14	23	9	1.8
Sex				
Male	51	65	14	1.8
Female	46	61	15	1.8
Race/Ethnicity				
Nonhispanic White	50	64	14	1.8
Nonhispanic Black	34	46	12	1.7
Hispanic	43	63	20	2.3

Source: Pew Internet and American Life Project.
Surveys for April 2000 (N = 2503) and February 2004 (N=2204).

slowed down even more for the lowest income group – high school dropouts (increasing only by a factor of 1.5 from 2000 to 2004). In addition to covering a more recent time period, the Pew Surveys have a much smaller sample size and different sampling methodologies than the CPS, so it is impossible to tell if the differences in results reflect a true period shift or a sampling artifact.

International comparisons: Finally, in an international perspective comparison, Table 4 compares levels and trends in the log odds of Internet use with odds in various European countries, based on the Eurobarometer surveys about the Information Society for 1998 and 2001 (Eurobarometer 1998, Eurobarometer 2001). In all 16 nations in the sample, from East Germany through the United States, the odds of Internet use in 1998 were *highest* for the *top* income quartile, as shown by the Xs in column 1. Furthermore, in 11 of the countries (plus West Germany, but not East Germany), the odds of Internet use in 1998 were *lowest* for the *bottom* income quartile. These patterns are consistent with the "main effect" of income in the first column of Table 2 for the U.S. In four other countries, France and three (Denmark, Finland, and Netherlands) Northern European "welfare states", one does not find the odds ratio being lowest for the bottom income quartile, indicating a less pronounced divide in these countries

The third and fourth columns of Table 4 bring in the dynamics or *trends* in Internet use from 1998 to 2001. For seven of the European nations (including both East and West Germany), the odds of Internet use show no widening of the digital divide at all, neither rising most rapidly for the top quartile nor most slowly for the bottom quartile. This group includes both Northern countries like the U.K., Germany and Northern Ireland with higher Internet access and Southern countries like Italy and Portugal with notably lower access, so the patterns do not seem a simple function of levels of Internet diffusion.

That conclusion applies as well to the five countries (including Sweden and Greece) in Table 4 which increased most rapidly for the top income quartile, but not most slowly for the bottom quartile. For only four countries, (Denmark, Finland, France, and Netherlands), did the odds of Internet use increase most slowly for the bottom income quartile, and only for Denmark and Finland among them does one find corresponding increases in the top quartile.

Given that one might expect any column in Table 4 to have 4 to 5 "X" marks by chance alone, these results provide little evidence for any systematic pattern of increasing inequality in Internet use in Europe. Moreover, two of these four countries (Netherlands and Germany) had already reported remarkably high Internet use in the lowest income quartile by 1998. Significantly, then, only the United States tests positive for all four markers of high and rising income inequality in Internet use.

TABLE 4: INCOME QUARTILES AND INTERNET USE PATTERNS FOR EUROPE AND THE UNITED STATES

	Odds of Internet use			
	Level in 1998		Trend, 1998-2001	
	Highest for Top Income Quartile?	Lowest for Bottom Income Quartile?	Rising Most Rapidly for Top Income Quartile?	Rising Most Slowly for Bottom Income Quartile?
Germany, East	X			
Germany, West	X	X		
Austria	X	X		
Northern Ireland	X	X		
United Kingdom	X	X		
Italy	X	X		
Portugal	X	X		
Luxembourg	X	X	X	
Belgium	X	X	X	
Sweden	X	X	X	
Ireland	X	X	X	
Greece	X	X	X	
France	X			X
Netherlands	X			X
Denmark	X		X	X
Finland	X		X	X
United States	**X**	**X**	**X**	**X**

DISCUSSION

After comparing the effects of income with the effects of other demographic variables in the United States, one can tentatively conclude that there is something distinctive about income with respect to U.S. Internet access. Many social or demographic variables, such as education and age, show *continuing* inequality in the log odds of Internet use, and if the overall diffusion of Internet use slows down or stops in the coming years, these groups may not achieve full Internet penetration. In comparison, while income does not emerge as the strongest predictor of Internet access in a multivariate analysis (Robinson, DiMaggio and Hargittai 2003), income still remains a significant predictor or determinant, being relatively distinctive as a source of *increasing* inequality in the odds of Internet use – particularly for broadband access. This increasing inequality might simply result in a longer time period for lowest income groups to complete the diffusion of Internet use; but it could also be an early indication of a coming stall in Internet diffusion, well below full penetration for individuals in low income households.

This conclusion is reinforced by the international comparison of Internet use by income quartiles in the United States with Internet use by income quartiles in other countries. One can see that the increasing inequality of Internet use by income in Table 4 is not a universal phenomenon, but is relatively distinctive to the United States and a few other countries. To some extent, cross-national differences in the relationship between income and Internet use might be a measure of cross-national differences in income inequality – there may simply be much larger income differences between the top and bottom income quartiles in the United States. However, there are many possible mechanisms by which income might mediate Internet use in different ways in different countries, and these largely descriptive results justify continued study and possibly policy actions to overcome these economic obstacles to Internet use.

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APPENDIX:

Table A: Descriptive Statistics for the U.S. Samples

	Percent of Sample		
	1998	2000	2001
Any Internet Use	33.6	46.1	54.2
Family income (yearly)			
75,000+	16.3	19.8	21.0
50,000-74,999	16.5	16.3	16.6
30,000-49,999	21.0	19.2	18.7
15,000-29,999	18.2	16.4	15.5
<15,000	14.4	12.1	11.8
Missing data	13.6	16.2	16.6
Education			
Master's or Prof. degree	7.4	7.7	8.0
4-year college degree	15.5	16.1	16.0
Some College	26.7	26.9	27.1
High school diploma	33.0	32.9	32.9
No high school diploma	17.4	16.4	15.9
Age			
18-24	12.9	13.1	13.3
25-44	41.8	40.6	39.8
45-64	29.0	30.1	30.8
65-90	16.3	16.2	16.1
Sex			
Male	48.0	47.9	48.0
Female	52.0	52.1	52.0
Race/ethnicity			
Nonhispanic white	73.9	73.3	72.7
Nonhispanic Black	11.4	11.6	11.7
Hispanic	10.3	10.6	10.9
Other	4.4	4.6	4.7
Nativity/Citizenship			
US-Born Citizen	87.9	87.1	86.9
Naturalized US Citizen	4.8	5.2	5.3
Foreign Born, Non-Citizen	7.3	7.7	7.8

Figures A1-A6: Relative odds of Internet use, based on coefficients from the multivariate logistic regressions in Table 2.

Figure A1: Trends in Relative Odds of Internet Use Across Income Categories.

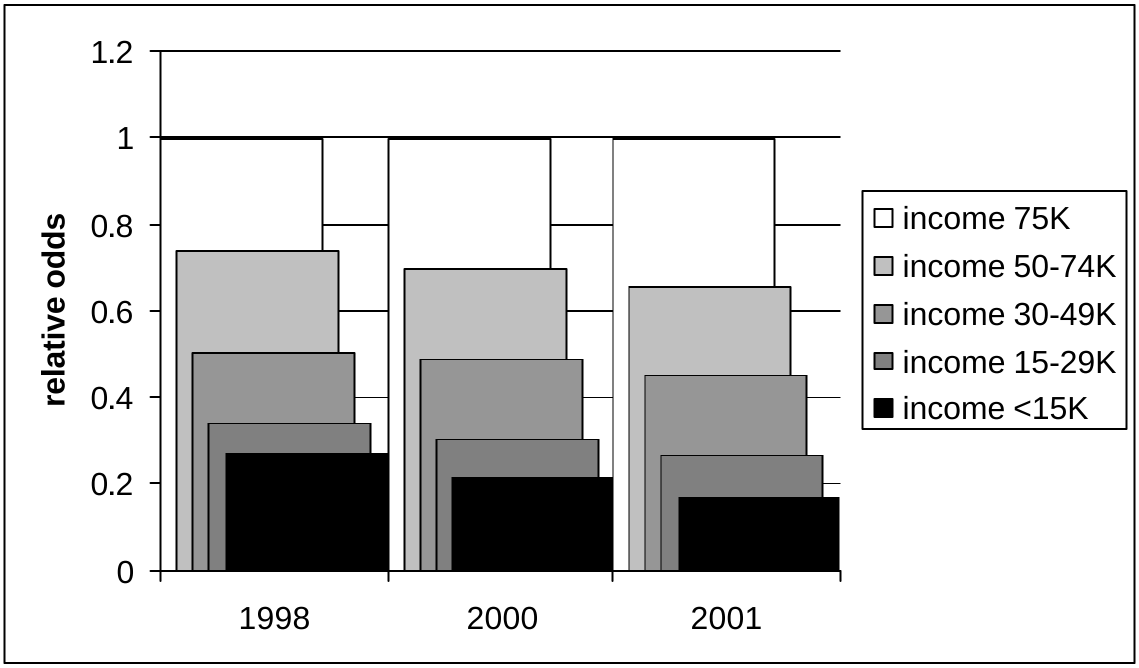


Figure A2: Trends in Relative Odds of Internet Use Across Education Levels

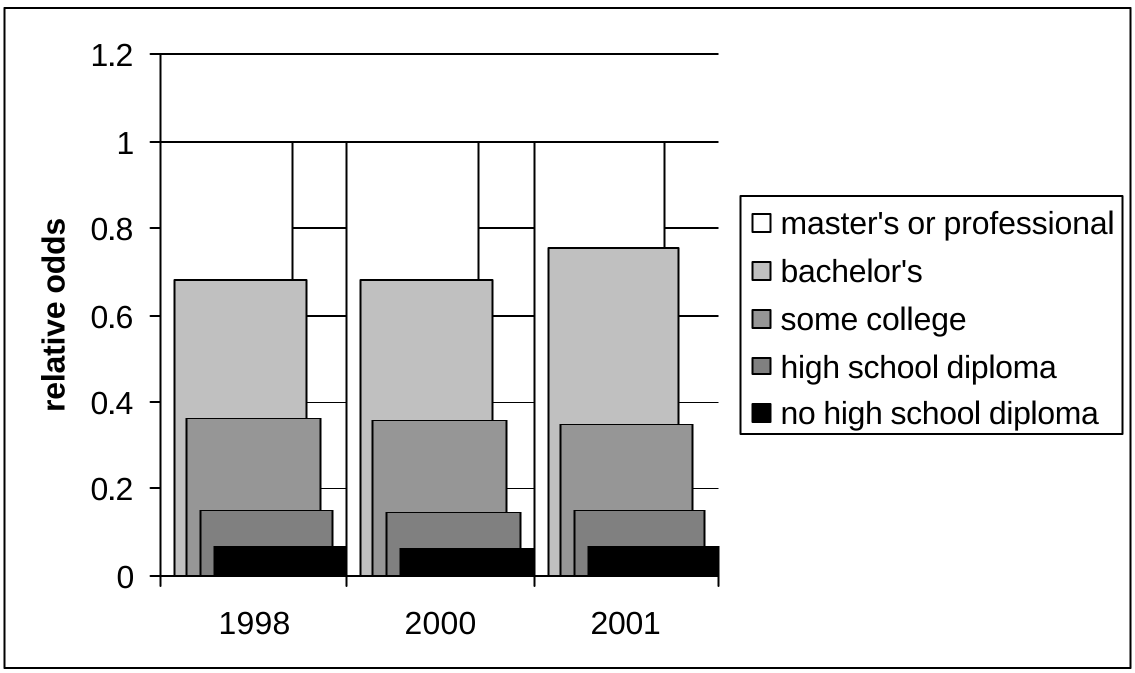


Figure A3: Trends in Relative Odds of Internet Use Across Race and Ethnic Groups.

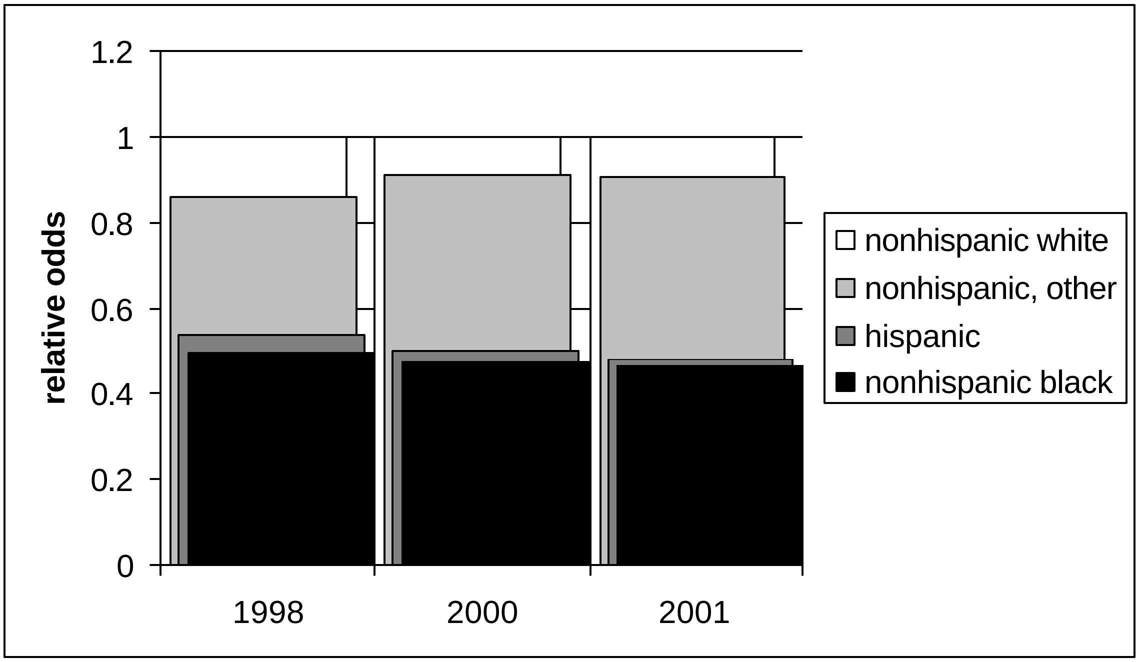


Figure A4: Trends in Relative Odds of Internet Use, By Nativity and Citizenship Status.

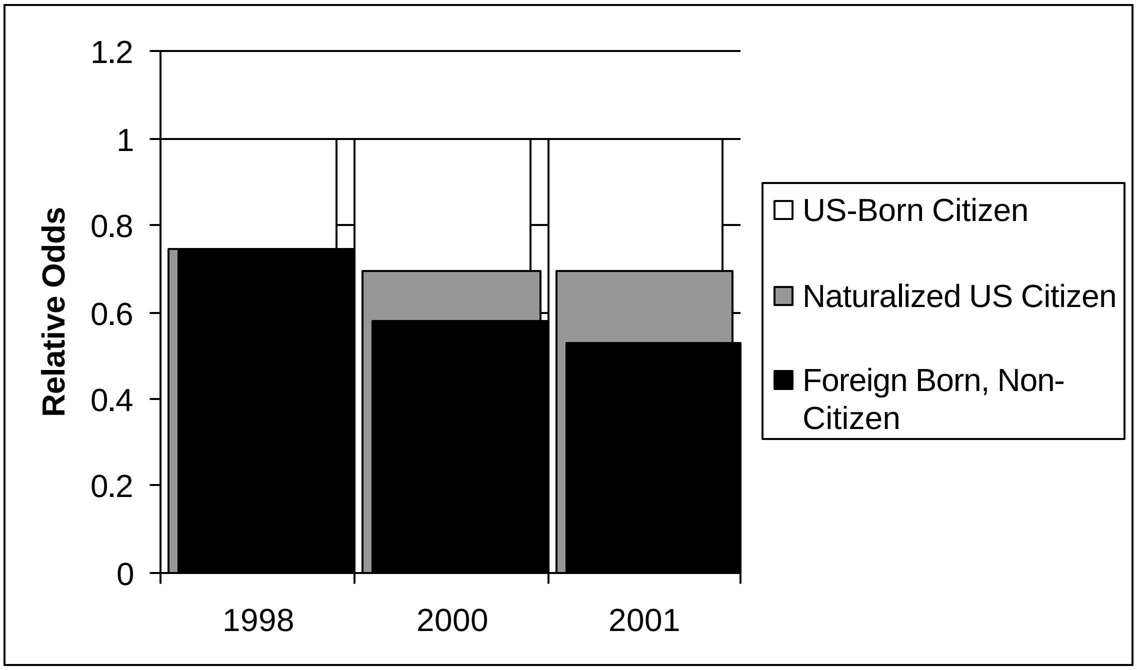


Figure A5: Trends in Relative Odds of Internet Use Across Age Categories.

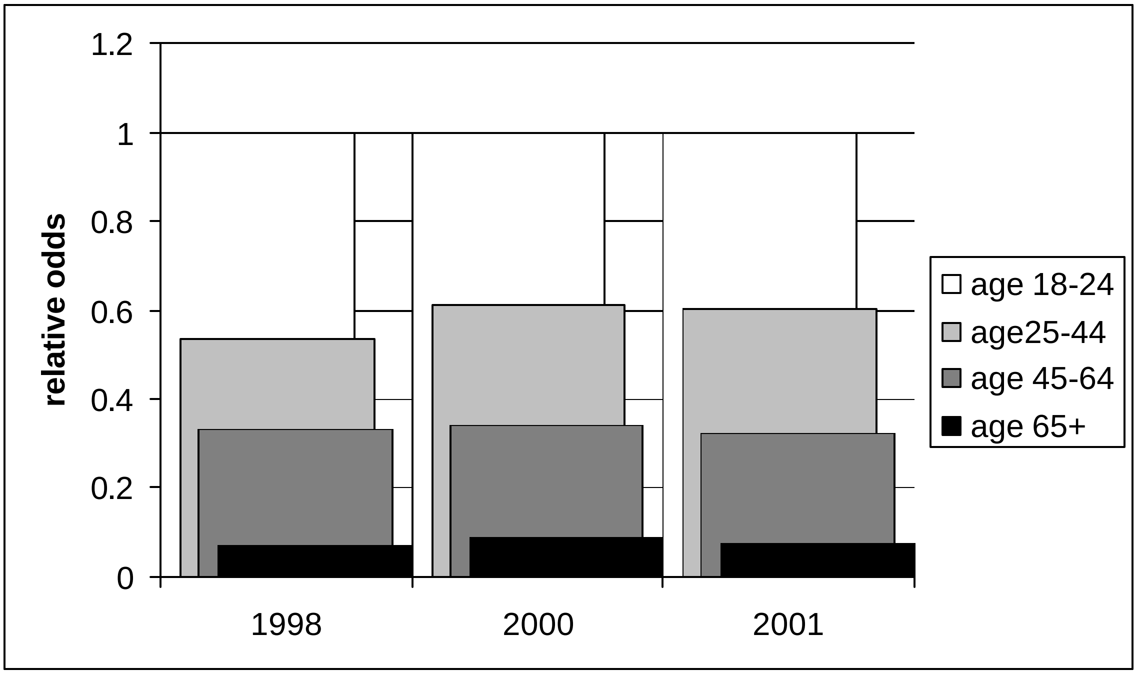
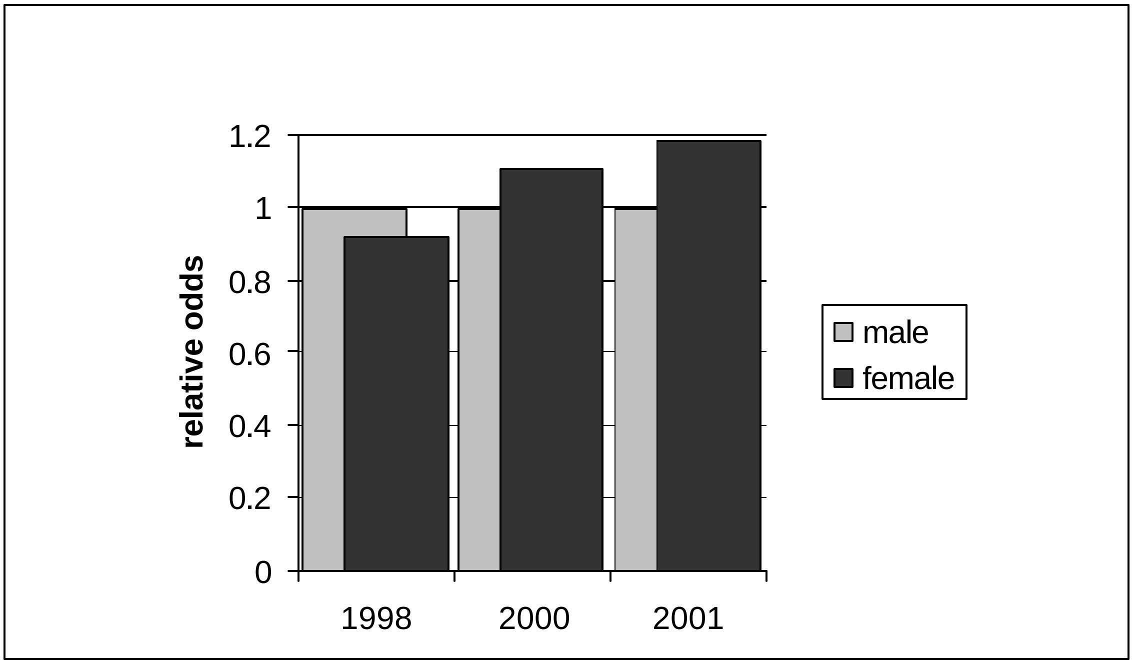


Figure A6: Trends in Relative Odds of Internet Use, By Sex.



Source: Current Population Surveys for December 1998, August 2000, and September 2001.