CONSUMER BUYING BEHAVIOR ON THE INTERNET: FINDINGS FROM PANEL DATA

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Online retailing became big business in late 1998, as millions of people placed orders for holiday gifts online and retailers scrambled to upgrade their distribution networks to cope with the growth (Cyberatlas.com, 1999). Companies planning for the growth of online retailing need reliable estimates of the growth of online shopping. Data about online consumer purchasing behavior are also needed to help companies define their online retail strategies for Web site design, online advertising, market segmentation, product variety, inventory holding, and distribution. Forecasts are more likely to be reliable if they are based on the behavior of online consumers, rather than consumers' stated intentions, or worse, the guesses offered by Web marketing "experts."

JOURNAL OF INTERACTIVE MARKETING
VOLUME 14 / NUMBER 1 / WINTER 2000

TABLE 1
Advantages and Disadvantages of Panel Data for Survey Research

Advantages	*Disadvantages*
Additional measurement precision by matching responses from one time period to another	Panel "conditioning" may bias responses (also called "testing effect") in that panel members become atypical as a result of being on the panel
Observe changes in *individual* behavior over time as well as monitor behavior of particular cohorts over time	Panel attrition may cause response bias although incentives can reduce this
Panel data are generally more accurate than cross-sectional data	Panel selection bias—respondents are not representative of the underlying population (e.g., exclude very rich or very poor or transitory)
Although expensive to establish initially, the costs of panels can be lower over the long term.	
More information can be collected since existing background information need not be repeated each time period.	

The Wharton Virtual Test Market[1] (WVTM), started in November of 1997, is both an ongoing survey of Internet users concentrating on electronic commerce and an online-laboratory that can help gauge customer reactions to new strategies and products. It offers an inexpensive and efficient way to estimate the size and composition of the online consumer population and a means to gain feedback on new products and approaches. Because the WVTM is also providing one of the few sources of panel data measuring changes in the behavior of online consumers over time, it is as—we will argue later—particularly useful for understanding trends.

This paper reports the findings from the second year of the WVTM survey—the first opportunity to examine how individual panel members have changed over time. We first summarize the advantages and disadvantages of using panels for collecting data, and then describe the techniques used to create an online panel (the WVTM) to collect data about consumer purchasing behavior on the Internet. Our major contribution is the results of the second survey of WVTM panelists (hereinafter referred to as the WVTM2)—in particular the changes over time within individuals that only a panel such as the WVTM can reveal. We then close by modeling changes over time within individuals to forecast total online spending for the year 2000 using a Monte Carlo simulation.

Panel Data

Panels are used widely in market research to study consumer purchase patterns, test new products, and evaluate promotional campaigns. Panel surveys use longitudinal data comprising responses to the same or similar questions by the same participants over more than one time period.

Dynamic panels rotate panel members to maintain a representative sample of the population and to reduce testing effects or panel conditioning (dynamic panels provide the audience estimates for TV ratings). In contrast, static panels only retain the original panel members and, apart from unavoidable attrition, do not change over time (e.g., a study of the careers of people who graduated from high school in 1972).

The advantages and disadvantages of panel data are listed in Table 1. Panel data have three major disadvantages, or unique sources of bias: attrition bias, panel selection bias, and condi-

[1] The Wharton Virtual Test Market is one of the major research projects sponsored by the Wharton Forum on Electronic Commerce, a research group funded entirely by corporate sponsors.

tioning effects. *Panel attrition* is the loss of panel members over time, which can result in a final panel that is unrepresentative of the population. Panel attrition can be very large. On average, 50% of panel members will drop out by the second survey (Sudman & Ferber, 1979). While incentives can be used to reduce attrition, attrition is rarely random. Incentives can also be used to minimize *panel selection bias*, which can happen when the people who participate in a longitudinal panel survey are very different from the population. *Conditioning effects* happen when the process of conducting the panel survey affects its findings. For example, consumers asked regularly whether they intend to purchase a product may come to the conclusion that they should develop such an intention (Kinnear & Taylor, 1996) and such questions have been shown to actually change subsequent purchases (Morwitz, Johnson, & Schmittlein, 1993). For dynamic panels, recruiting new panel members can reduce conditioning effects as well as biases resulting from differential attrition across market segments in the panel with a loss of continuity.

One problem with using a dynamic panel is the assumption that the "average" panelist is very similar across time periods even though the individuals in each time period are different. Multiple sources of variance are held constant when the same individual is tested (the major advantage of panel data) and this benefit is sacrificed to some extent when a dynamic panel is used (Golany, Phillips, & Rousseau, 1991). All of these sources of bias can be summarized under the heading of *nonresponse bias.* Nonresponse bias will threaten the conclusions of any study when it is plausible that the average member of the population being studied is more likely to be represented by the people who are *not* in a sample, rather than those who are. Assessing the extent of nonresponse bias requires a statistical comparison of the *reporting* sample to the population being studied. Adequate total sample size, in and of itself, is not sufficient to prevent selection bias. Each variable of interest that could affect the conclusions of the study must be adequately represented within the sample.

More recent research suggests another advantage of panel data (Menon, 1997). The report of one's last expenditure on the Internet, asked twice over the course of a year, is more accurate than asking for spending for both last year and the year before.

Most surveys about Internet usage reported in the popular press use cross-sectional data, for example, surveys by Ernst & Young (1998), Forrester Research (Morrisette, Bluestein, & Maraganore, 1999), GVU (Kehoe, Pitkow, & Rogers, 1998), Jupiter Communications (1998), and the Pew Research Center (1998). We believe that panels highlight important changes in individual behavior over time (e.g., "dropouts" and sensitivity to privacy issues on the Web). This is particularly important in the dynamic Internet community, which is constantly changing as more people go online for the first time and those people who are already online become more acclimatized to the World Wide Web. For example, we find that sensitivity to security and privacy is a function of time online.

WVTM1

The first Wharton Virtual Test Market survey panel (WVTM1) closely matched the U.S. online population (Bellman, Lohse, & Johnson, 1999). Responses from 9,738 panelists provided a basis for identifying factors that predict whether a person bought goods or services online, and if they did buy online, how much they spent. Based on logit and regression analysis of these data, two major categories of variables predicted online buying and spending: "*time starvation*" and a "*wired*" lifestyle. Online buyers worked many hours each week (e.g., a single person working over 50 hours per week or a married couple working over 100 hours per week). Because such "time-starved" panelists had fewer hours available for shopping, we believe they made purchases on the Internet to save time. People who buy online also use the Internet more than other people online—they lead a more "wired" lifestyle. They use email to keep in touch with family and friends. They have been on the Internet for years as compared to months for nonbuyers. And, finally, they use the Internet regularly at work and believe it has improved their productivity.

Demographics (e.g., gender, age, income, race, etc.) did not predict differences in online buying, although males spent slightly more than female online shoppers. However, both the WVTM1 and other studies (Kehoe et al., 1998; Kraut et al., 1998a, 1998b) have found that demographics are an important indicator of who is on the Internet in the first place. Based on the spending data reported by panelists during this first time period (WVTM1), we forecasted $23.7 billion of online sales in the United States and Canada for the year 2000. Data from one year later (WVTM2) provide an opportunity to test the veracity of these findings as well as to identify trends that would be more difficult to examine using cross-sectional data.

METHODS

In 1997, 8,174 people from the WVTM1 panel of 9,738 respondents agreed to participate in further surveys. In November 1998, those 8,174 people were recontacted by email and asked to participate in a second round of questions that included replicates of questions they had answered in 1997. Of those 8,174 people, 1,891 (23%) had either unsubscribed from the WVTM1 mailing list or had "dead" email addresses. An email address could be dead for a number of reasons: the person may have changed their email address, had their mailbox closed by their service provider, typed their email address incorrectly, or deliberately provided a false email address. Of the maximum possible sample that could be obtained from the original panel (6,283: those people who had agreed to remain in the WVTM and had a functioning email address) we received 2,549 valid responses, a completion rate of 41%.

In addition, WVTM2 recruited other panel members from around the world. The procedures used to populate the original WVTM1 were duplicated for WVTM2. People were attracted to the survey site by a banner advertising campaign designed to target specific segments of World Wide Web users, as well as by links provided by Wharton Electronic Commerce Forum members' sites and word of mouth. All answers to survey questions are self-reports. Each panelist completed a survey that asked a maximum of 82 questions about their online behavior and attitudes to Internet communication and privacy issues, as well as seven routine demographic questions, a total of 89 questions altogether. Average time to complete the online survey was 7 minutes. Our analysis of the questionnaire data describes the factors associated with buying online, and the amounts of money online buyers spend.

RESULTS

The population frame for the WVTM panel is the total online population. A measure of how accurately the responses of this panel mirror the responses of the online population is a function of selection bias in the panel. To explore potential nonresponse bias problems, due either to attrition or conditioning, we divided the 9,738 WVTM1 panelists into two groups: (1) the 2,549 (26%) respondents who stayed in the panel and completed the WVTM2 survey and (2) the 7,189 (74%) nonrespondents who dropped out of the panel, for whatever reason. Table 2 compares, for these two groups, their values for the 12 variables predicting buying and spending behavior identified in the WVTM1 (Bellman et al., 1999). There was no significant difference between respondents and nonrespondents in either the percentage of panelists that chose to buy online or mean annual online expenditures. This is important since these are the two primary dependent measures in the panel. In addition there were no other statistical differences between respondents and nonrespondents among most of the other variables reported in Table 2. However, there were two differences in variables used to predict buying and spending behavior. WVTM2 respondents were more likely to have ordered from a catalog in the last 6 months compared with WVTM2 nonrespondents ($t(4162) = 2.51$, $p < .050$). There were slightly more females responding to the WVTM2 survey than males ($t(4162) = 6.74$), $p < .0001$). Since this analysis found no differences between respondents and

TABLE 2
Comparison of Nonrespondent Bias of WVTM1 Participants That Did or Did Not Participate in WVTM2 [mean (*std*) and *t* test]

WVTM Variable	*WVTM1 Respondent* $n = 7{,}189$	*WVTM1 & 2 Respondent* $n = 2{,}549$	*Prob* > |*T*|
Buy	0.5430 (0.4982)	.5055 (0.4975)	n.s.
Spend (dollars)	$219.98 ($957.58)	$235.35 ($1054.63)	n.s.
Months on Internet	20.8 (17.2)	20.6 (17.2)	n.s.
Hours online per week	12.3 (9.29)	12.5 (9.27)	n.s.
Ordered catalog 6 months	0.36 (0.48)	0.34 (0.47)	<0.050
Number of emails per day	11.6 (18.6)	11.6 (18.5)	n.s.
Use Internet for news	0.219 (0.414)	0.230 (0.421)	n.s.
Use Internet for finance	0.024 (0.154)	0.027 (0.163)	n.s.
Internet for entertainment	0.130 (0.336)	0.125 (0.330)	n.s.
Use Internet for travel	0.004 (0.066)	0.003 (0.056)	n.s.
Sex (0 = female; 1 = male)	0.580 (0.494)	0.500 (0.500)	<.0001
Income (dollars)	$51,896 ($56,175)	$49,978 ($44,862)	n.s.

nonrespondents in their online buying or spending behavior, we did not correct subsequent analyses of online buying and spending for nonresponse bias.

We compared our online sample to the U.S. Census data for Internet usage (Table No. 917: www.census.gov/statab/freq/98s0917.txt) to explore whether the panel data are representative of all online Internet users in the United States. Although the WVTM1 was representative of the U.S. online population in 1997 (Bellman et al., 1999), it may not have been representative of the U.S. online population in 1998. Table 3 shows data for the Internet user population (people with any online Internet usage) and the panel data. Except for population size, all data in Table 3 are percentages.

There were no differences between the WVTM2 panel and the Internet user population in age, gender, marital status, education, or occupation. Both the panel and the Internet user population are younger, more likely to be male, more likely to have graduated college, and more likely to have a professional occupation compared with the general population of the United States. However, the mean household income is significantly lower for the panel than the income for the Internet user population, although it is still higher than the general population (($\chi^2_{3\mathrm{df}} = 11.95$, $p < .01$).

Who Is Buying Online?

We examined who was and who was not buying on line in three ways. First, we took advantage of the panel structure of the WVTM survey to look at four segments defined by their year-to-year purchase patterns. Second, we similarly examined the effect of time on the Internet on purchasing. Finally, we describe the results of a logistic regression that predicts who will buy.

Buying Segments. Since we have observed the WVTM panelists at two points in time, instead of just once as would be the case with cross-sectional data, we categorized buyer behavior into four segments: (1) "Never Buy," (2) "Dropouts," (3) "Newbies," and (4) "Steadfast Buyers" (Table 4). A multivariate analysis of variance (MANOVA) for 21 independent measures shown in Table 5 simultaneously controlled for the multiple measures and showed that there are significant differences between these four buyer segments (Wilk's $\lambda = .8264$, $F(51, 6056) = 7.85$, $p < .0001$).

Panelists characterized as Never Buy have not made a purchase on the Internet in both time

TABLE 3
Chi Square Test Comparing Demographics of WVTM2 Sample Data with U.S. Census Data for Internet Users

No. 917. June 17, 1998 Internet Access and Usage, and Online Service Usage www.census.gov/statab/freq/98s0917.txt	*Any Online/Internet Usage (Adults 18+)* 44,873,000	*WVTM2* $N = 2{,}549$
Age:	23% U.S. pop.	
18 to 34 years old	42.6	54.5
35 to 54 years old	48.8	39.5
55 years old and over	8.6	6.0
		$\chi^2_{2df} = 2.90$ (n.s.)
Sex:		
Male	53.9	49.5
Female	46.1	50.5
		$\chi^2_{1df} = 0.39$ (n.s.)
Marital status:		
Single	29.3	36.7
Married	61.4	47.8
Other	9.3	15.5
		$\chi^2_{2df} = 4.07$ (n.s.)
Education:		
Graduated college plus	46.9	42.2
Attended college	33.9	36.8
Did not attend college	19.2	21.0
		$\chi^2_{2df} = 0.45$ (n.s.)
Occupation:		
Professional	23.4	22.5
Exec./manager/administrator	19.1	11.0
Clerical/sales/technical	27.3	25.4
		$\chi^2_{2df} = 1.35$ (n.s.)
Household income:		
Less than $50,000	31.8	55.3
$50,000 to $74,000	28.2	22.0
$75,000 to $149,000	32.5	19.4
$150,000 or more	7.5	3.4
		$\chi^2_{3df} = 11.34$ ($p < 0.01$)

periods. This segment represents 14% of the panelists. Panelists that made an online purchase in 1997 (WVTM1) but did not purchase online in 1998 (WVTM2) are labeled as Dropouts (14% of respondents). Newbies (31% of respondents) did not make a purchase in 1997 (WVTM1) but did make a purchase in 1998 (WVTM2). Steadfast buyers (41% of respondents) made a purchase online in 1997 (WVTM1) and again in 1998 (WVTM2).

TABLE 4
Classification of 2,524 Online Buyers Based On Online Purchase Behavior

	WVTM1 Not Buy	*WVTM1 Buy*
WVTM2 Not Buy	Never Buy 14%	Dropouts 14%
WVTM2 Buy	Newbies 31%	Steadfast Buyers 41%

TABLE 5
Univariate ANOVA and Comparison of the Means Using Tukey's Test

	Never Buy	*Dropouts*	*Newbies*	*Steadfast*
Months using the Internet	26.4[a]	27.1[a]	32.3[b]	34.2[b]
Search Internet for product information	1.46[a]	1.48[a]	1.80[b]	1.81[b]
No catalog order in last 6 months	0.48[a]	0.47[a]	0.22[b]	0.22[b]
Click on banner advertisement	91%[a]	90%[a]	96%[b]	97%[b]
Online transactions in last 6 months	0[a]	0[a]	5.3[b]	5.4[b]
Dollar amount of last purchase	0[a]	0[a]	$89.62[b]	$86.22[b]
Number of email messages per day	11.9[a]	12.9[a]	19.9[b]	22.4[b]
Percent of email that is spam	14.4%[a]	18.5%[b]	15.5%[a]	15.4%[a]
Hours per week on the Internet	11.9[a]	12.3[a]	14.1[b]	15.4[b]
Use of Internet for work	57%[a]	64%[b]	70%[bc]	73%[c]
Use of Internet for news	73%[a]	76%[a]	87%[b]	87%[b]
Use of Internet for entertainment	84%[b]	80%[a]	87%[b]	87%[b]
Use of Internet to download software	60%[a]	57%[a]	70%[b]	71%[b]
Use of Internet for finance	20%[a]	25%[a]	40%[b]	41%[b]
Use of Internet for travel	29%[a]	32%[a]	46%[b]	48%[b]
Hours worked per week	40.2[a]	43.0[ab]	47.7[bc]	49.7[c]
Household income	$42,800[a]	$44,618[a]	$55,447[b]	$52,968[b]
Sex (0 = female; 1 = male)	.38[a]	.47[a]	.49[b]	.53[b]
Age	33.8[a]	34.6[ab]	35.2[ab]	36.3[b]
Concerned about online monitoring	2.87[a]	2.80[a]	2.59[b]	2.51[b]
Would give phone number online?	0.45[a]	0.41[a]	0.54[b]	0.57[b]

(means with different letters within a row are significantly different at $\alpha = 0.05$).

Compared with those segments that made an online purchase in 1998 (Newbies and Steadfast Buyers), Never-Buy Panelists and Dropouts have a lower income ($42,800 and $44,618 versus $55,447 and $52,968), work fewer hours per week (40.2 and 43.0 versus 47.7 and 49.7), have been on the Internet for a shorter time (26.4 and 27.1 months versus 32.3 and 34.2 months), and spend fewer hours per week on the Internet (11.9 and 12.3 versus 14.1 and 15.4). Never Buys and Dropouts are also slightly more concerned about their privacy online.

Interestingly, Never Buys have not made an online purchase despite increasing their number of hours online each week from 10.7 to 11.9. Dropouts have experienced a decrease in hours online each week (14.7 to 12.3) as well as a decrease in the number of daily email messages. Compared to the other three groups in Table 4, Dropouts have the highest percentage of spam (junk email), have increased their paper-based catalog orders by 20% and have decreased their usage of the Internet for completing their work by 16%. Newbies had an 18% decrease in paper-based catalog orders, received 12 more email messages per day in 1998 compared with 1997, and increased their total hours online per week from 10.2 to 14.1. Steadfast buyers had a 6% decrease in paper-based catalog orders, received 7 more email messages per day in 1998 compared to 1997, and increased their total hours online per week from 13.9 to 15.4.

The Effect of Internet Usage. One additional finding worth noting is that the percentage of panelists making a purchase on the Internet increases as a function of time spent online. The longer the amount of time spent online, the greater the probability of making a pur-

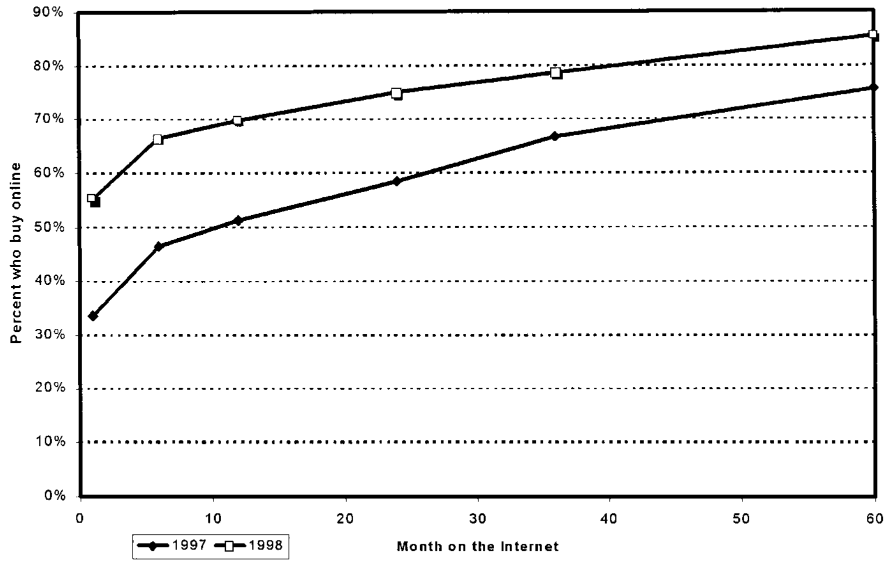

FIGURE 1
Percentage of Respondents Who Make a Purchase on the Internet as a Function of the Number of Months Spent Online

chase online (Figure 1). In 1997, 34% of the respondents who had been online for 1 month had also made an online purchase. In 1998, 84% of the respondents who had been online for 5 years (60 months) made a purchase. More importantly, this trend increased when we compare the two years. There was an across-the-board increase in the rate of adopting online buying. Thus forecasts based upon the a static one-shot study may underestimate the growing size of the Internet marketplace.

Predicting Who Will Buy. The factors that predicted purchasing online were analyzed using logistic regression (Table 6). We combined the returning WVTM panelists with new entrants to the panel and split the WVTM randomly into halves to produce separate calibration and holdout samples. Using the calibration sample, candidate variables were added to a logistic regression equation predicting buying online versus not buying online. The final regression equation for the calibration sample was then

TABLE 6
Results From Logistic Regression Analysis Predicting Online Buying

Variable	*DF*	*Parameter Estimate*	*Standard Error*	*Wald* χ^2	*Pr* $> \chi^2$	*Standardized Estimate*
Intercept	1	−1.0920	0.1861	34.4	0.0001	
Months on Internet	1	0.0111	0.0031	12.8	0.0004	0.1057
Use Internet for product information	1	0.6446	0.0837	59.4	0.0001	0.2030
Catalog order in last 6 months	1	1.0172	0.1028	98.0	0.0001	−0.2546
Gender (1 = male)	1	0.2623	0.1040	6.4	0.0116	0.0723
Emails per day	1	0.0145	0.0027	30.0	0.0001	0.1878
In last 6 months, use Internet for news?	1	0.4648	0.1274	13.3	0.0003	0.0942
In last 6 months, use Internet for finance?	1	0.5489	0.1160	22.4	0.0001	0.1448
In last 6 months, use Internet for health?	1	−0.3004	0.1144	6.9	0.0086	−0.0785
In last 6 months, use Internet for travel?	1	0.4472	0.1078	17.2	0.0001	0.1219

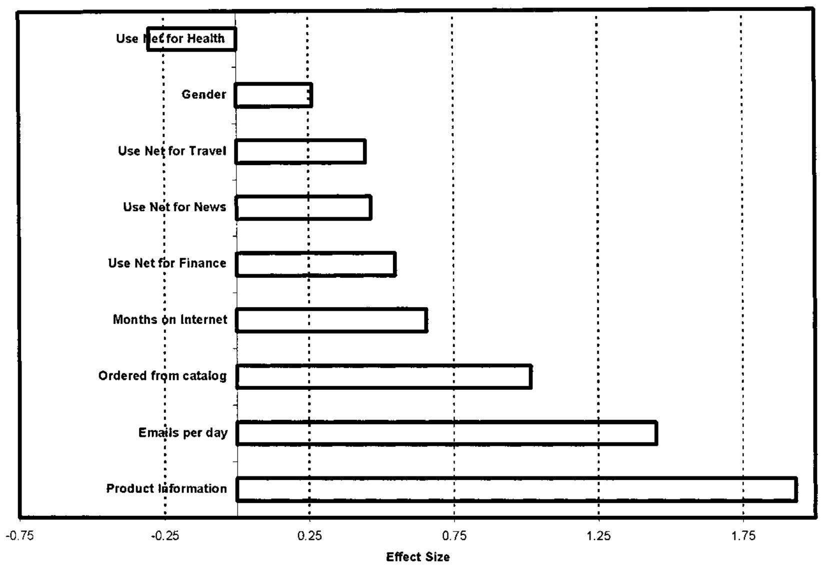

FIGURE 2
Predictors of Buying Versus Not Buying Online, in Increasing Order of Influence
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used to predict whether members of the holdout sample would or would not buy online. This process was repeated, using the original holdout sample to calibrate the regression, and then cross-validating this regression equation in the original calibration sample. The final regression equation, which contains only those variables that were significant in both runs of this double cross-validation procedure, explains a significant amount of buying versus not buying [$\chi^2 = 431.478$ with 9 DF ($p < 0.0001$)], and correctly classifies 77% of panelists.

Figure 2 shows these significant predictor variables. We calculated the impact of each factor by multiplying each variable's range by its parameter in the cross-validated logit. Not surprisingly, the degree of Internet usage to search for product information explained the most variation in whether someone would make an online purchase. The number of email messages per day had the next largest effect on buying behavior. Receiving more email messages is associated with a higher proclivity to buy online. In addition, ordering from a catalog in the last 6 months is an indicator of buying online (in other words, people who buy from catalogs are likely to also buy online). Also, the longer someone has been using the Internet, the more likely they are to make an online purchase. Using the Internet for travel information, financial information, or news and current events are also associated with buying goods and services online.

For these diverse uses of the Internet, there has been a dramatic increase over the past year (Figure 3), demonstrating that in 1998 the "wired lifestyle" was becoming more pervasive. Finally, according to these WVTM2 data, males had a slightly higher proclivity to buy online than females, although the effect size is relatively small.

How Much Are They Spending?

WVTM2 panelists who purchased online were asked how many online transactions they had made over the last 6 months, and the value of their latest online transaction. In 1997, the mean purchase was $49.53, whereas in 1998 the mean purchase was $86.31. The top five categories ranked by median purchase are shown in Figure 4. From 1997 to 1998, buyers increased their average number of online purchases from 4.3 transactions per year to 7.4. The 74% increase in spending per transaction coupled with a 72% increase in the number of transactions

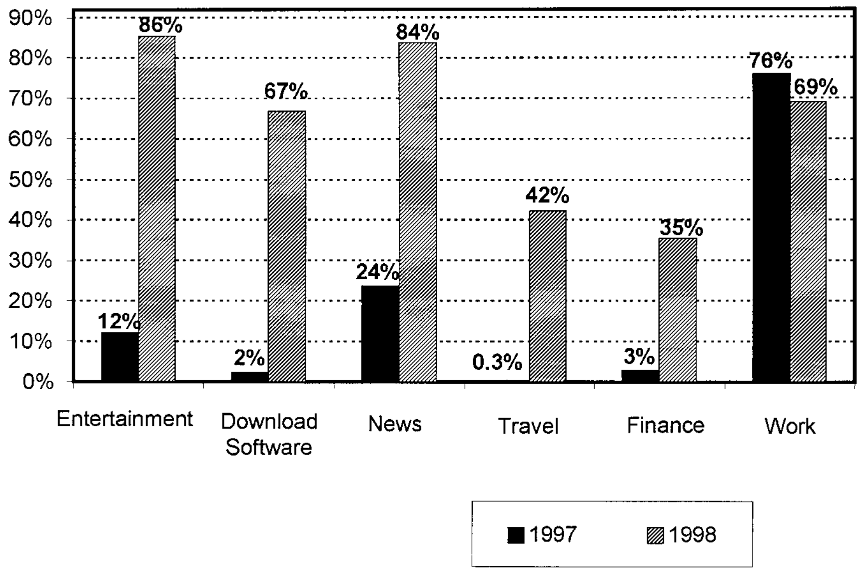

FIGURE 3
Change in Internet Usage From 1997 to 1998 for Selected Categories

translates into a 300% increase in annual expenditures on the Internet from $213 to $639.

A regression model examined factors predicting variance in annual online spending. Annual online spending equals 2 times the number of transactions over the last 6 months multiplied by the amount spent on the most recent online purchase. We applied a log transformation to the dependent measure: annual spending data. A log transformation is justified because the variances within percentiles of the dependent increase in proportion to the mean of the percentile. Again, the subsample of online buyers was split in half randomly, and double cross-validation was used. The final regression equation explained 23% of the variance in annual online spending and was significant ($F(13, 5208) = 57.63$, $p < 0.0001$). Table 7 shows the regression analysis. In addition to the variables noted in the logistic regression to predict buying behavior, another demographic variable (household income) explains a significant por-

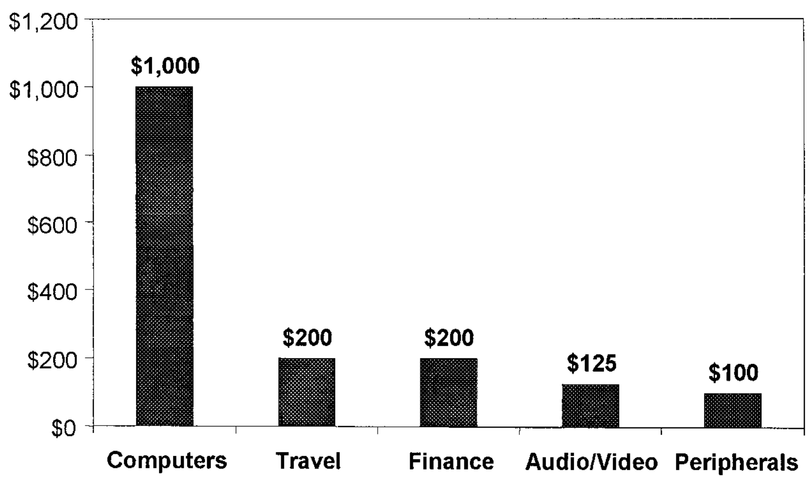

FIGURE 4
Median Dollar Amount of Last Purchase on the Web (top 5 categories)

TABLE 7
Results From Regression Analysis Predicting Online Spending

Variable	*DF*	*Parameter*	*Standard Error*	*T for H_0: Parameter = 0*	*Prob > |T|*	R^2
Intercept	1	0.5851	0.2188	2.67	0.0075	
Months on Internet	1	0.0098	0.0032	3.10	0.0020	0.0062
Use Internet for product information	1	0.8701	0.0932	9.33	0.0001	0.0831
Catalog order in last 6 months	1	1.2195	0.1150	−10.61	0.0001	0.0485
Hours worked/week	1	0.0042	0.0017	2.43	0.0153	0.0024
Household income	1	0.000004	0.000001	3.24	0.0012	0.0044
Emails per day	1	0.0162	0.0023	6.92	0.0001	0.0250
Hours online per week	1	0.0131	0.0055	2.38	0.0174	0.0029
In last 6 months, use Internet for news?	1	0.3357	0.1453	2.31	0.0210	0.0014
In last 6 months, use Internet for software?	1	0.2718	0.1174	2.32	0.0207	0.0019
In last 6 months, use Internet for finance?	1	0.7169	0.1153	6.22	0.0001	0.0328
In last 6 months, use Internet for health?	1	−0.4077	0.1183	−3.45	0.0006	0.0029
In last 6 months, use Internet for travel?	1	0.5249	0.1102	4.76	0.0001	0.0078
Gender (1 = male)	1	0.4982	0.1095	4.55	0.0001	0.0128

tion of the variance in annual online spending. While income did not determine whether someone would make an online purchase, it does influence how much they will spend. Annual household income explains an additional 0.44% of the variance in annual online spending. The greater the annual household income, the more that is spent online (approximately $1.10 a year for every additional $10,000 in household income). Other new variables in this equation that explain differences in spending but not differences in buying versus not buying are the positive influence of downloading software (explains an additional 0.19%), number of hours worked per week (positive, 0.24%), and hours per week online (positive, 0.29%). Sex (coded as 1 for males and 0 for females) explains about 1% of the variance in annual online spending. The positive coefficient indicates that males purchase more online (although only about $3.15 annually) than females.

According to these results, "time starvation" (number of hours worked) and a "wired" lifestyle are still major determinants of the amount of online spending a person does, although time starvation does not seem to influence whether a person buys at all from an online store. One of the unique insights that panel data such as the WVTM1-2 can offer is that individuals achieve a more "wired" lifestyle the more they become acclimatized to the World Wide Web. Although demographics such as gender and income are significant explanatory factors, a person's proclivity to buy and spend on the Internet is not fixed but can change rapidly over time alongside changes in online behavior.

Total U.S. Online Spending Projections

Table 8 shows forecasts for total U.S. online spending (business to consumer) from five in-

TABLE 8
U.S. Business-to-Consumer Online Spending (in billions) From Five Sources

Date	*Mar 99*	*May 97*	*Oct 98*	*Jan 99*	*Jul 99*	*Jul 99*
Source	DMA	Morgan Stanley	Jupiter	Forrester	eMarketer	WVTM
1997	0.7	2.3	3			
1998	1.7	5.9	7	7.8	4.5	
1999	3.4	9.5		18.1		18.8
2000		17.1	17	33.0		29.2
2001				52.2		46.2
2002			41	76.3	26.0	70.5
2003	19.2			108.0		97.0

dustry sources. Forecasts for the year 2000 range from $17–33 billion. Forecasting online business-to-consumer sales depends upon the number of people online (maximum is total U.S. population), the average likelihood of buying, and average annual online spending per person. According to the WVTM2, the longer someone has been using the Internet the more likely they are to buy (Figure 1) and the more they spend (Figure 5). In 1998, for example, buyers that had been using the Internet for 12 months had a median annual purchase amount of $180 whereas buyers that had been using the Internet for 60 months had a median annual purchase of $300. Assuming the number of online Internet users was 55 million in July 1998, we applied our likelihood-to-buy data (Figure 1) and spending data (Figure 5) to forecast total online retail sales in the United States. Estimates for the growth of Internet usage in the United States average 2.5% per month (e.g., Broersma, 1998; Court, 1997; Emmerce, 1998). Accordingly, we assumed that the growth of new Internet users was 2.5% per month. Using Monte Carlo simulation, growth in Internet usage (and therefore the size of the Internet population) is the most critical factor affecting estimates of online retail sales. If more con-

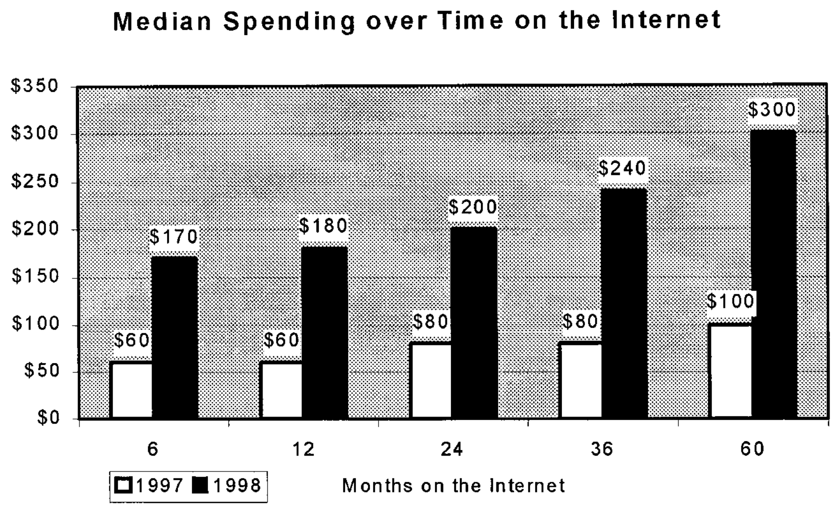

FIGURE 5
Median Annual Purchases as a Function of the Total Number of Months Spent on the Internet

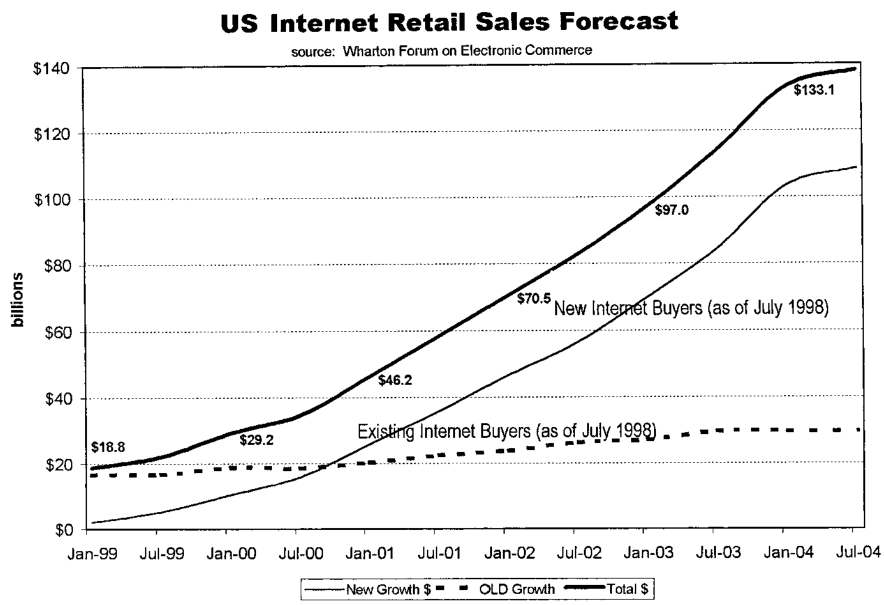

FIGURE 6
U.S. Business-to-Consumer Internet Sales Forecast

servative estimates are used, the final figure drops from $29.1 billion for the generally expected growth rate of 2.5% to $23.6 billion for a growth rate of 1%. In addition, we assumed 14% of online buyers would not purchase from the Web the next year (Table 4). Figure 6 shows the U.S. business-to-consumer Internet sales forecast derived from the WVTM data. Existing online buyers account for all online sales today but new consumers that have never used the Internet will determine the growth of online sales. Assuming their spending matches that of existing online buyers, we predict sales to new buyers will exceed old buyers by the year 2001.

DISCUSSION

The strength of panel data is its ability to provide information about changes in behavior over time for individual consumers. Using the WVTM, we found that over a 12-month period online consumers doubled the number of items bought online and spent nearly three quarters more on each purchase, two facts that together resulted in a tripling of the spending of the average online consumer over time. The size of the online retail market will be driven not only by an increase in the number of people who go online for the first time in the next few years, but also by increases (and, interestingly, decreases) in online shopping by individual consumers already online.

The results of the WVTM2 show that the Internet population is already starting to look more and more like the general population, at least in the United States. Companies will have to plan their Web site design for an audience that is less Web savvy, less educated, earns less, and is possibly less tolerant of new technology. According to our projections, most of the money earned by online retailers in 2 years' time will come from people who have yet to connect to the Internet. However, this research also shows that differences between new online consumers and more experienced online consumers are erased over time by the rapid acclimatization of consumers to this new medium of consumption.

The opportunity to observe differences over time within subjects has also revealed some of the reasons why people change their online shopping behavior. Those people who bought online last year but "dropped out" of online shopping this year seem to have had some bad experiences with online retailers. These people also claim to be getting more spam than other people online. Online retailers will have to provide significant incentives to win these people back to buying online again (news of stockouts and bogus companies will not help). In the meantime, these Dropouts are returning to paper-based catalogs for convenient shopping from home. The people who have never bought are increasing the amount of time they are spending online, and may in time make at least one online purchase.

The WVTM2 offers the chance to observe changes in time over two periods. With two observation points, it is possible to extrapolate a straight line with which to forecast the future. But the growth in Internet shopping seems so dynamic that it is hardly likely to be a simple linear phenomenon. To gauge whether changes over time within individuals are linear, or curvilinear (for example, a tripling each year of the annual spending of each individual), we will need to observe at least three points in time. Even more periods may allow estimates of the limits of this growth, which cannot be infinite, whereas linear and simple curvilinear projections have no asymptotes. With this in mind, the Wharton Forum on Electronic Commerce is collecting a third year of data from the WVTM.

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