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Determinants of Recent Online Purchasing and the Percentage of Income Spent Online

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ABSTRACT

The recent stagnation of electronic commerce highlights the need to understand contemporary online consumer behavior. This study incorporates current user demographics and emerging Internet activities to dynamically model the determinants of two key measurements of recent online shopping, a purchase within the last year and the novel dependent variable, percentage of income spent online in the last three months. Logistic regression is applied to a nationally representative 2007 survey of the U.S. online population. Determinants of a recent online purchase include, ownership of a credit card, an online payment account (PayPal™), listening to podcasts, participating in online auctions, and for the first time, female gender. In a second regression, positive determinants for the percentage of income spent online include male gender, educational attainment, online auctions, instant messenging and online dating. Online spending increases with time online and appears to compete with other forms of online entertainment and social networking.

Stratification of the data by gender yields higher estimates for the explained variance in the percentage of income spent online for men than for women. Males are novelty shoppers, and online purchasing competes with watching television, playing games online and blogging. They strongly prefer products perceived as new and innovative and are not motivated by value. Further stratification by income and age reveals that possession of an online deferred account is the strongest determinant for all men except the highest earners. In contrast, women are convenience-oriented but not novelty or value shoppers. High-spending women are technologically sophisticated, using the Internet to obtain stock quotes, participate in online auctions and make deferred payments. These results produce snapshots of contemporary online shoppers that can be used by electronic retailers to determine which product characteristics to highlight for greatest impact, and to efficiently target specific activities, such as entertainment, podcast and social network websites, to develop new and robust marketing platforms.

Keywords: online consumer behavior, online purchasing, online shopping, e-commerce, online marketing

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1. Introduction

The number of Internet users in the U.S. has almost doubled over the last eight years to approximately 220 million in 2008 (Nielsen 2008) with over 70% purchasing online (Pew Internet 2009a). E-commerce revenue totaled just over $128 billion in 2008 (U.S. Census Bureau 2008; 2009). Since fourth quarter 2006, e-commerce has represented about 3.1% of retail sales, and yearly growth has fallen short of nearly all analysts' predictions for nearly a decade (Bakos 2001). The percentage of online consumers has remained steady at about 70% since late 2004 (Pew Internet 2008b) when online buying represented 2.5% of national retail sales (U.S. Census Bureau 2008). Thus, the bulk of e-commerce growth must come from existing shoppers rather than new adopters (Comiskey 2006).

If current trends hold, the success of electronic retailers will depend on cultivating existing consumers. This study illuminates where to find them and how to best appeal to them. The ability of e-retailers to grow their markets is contingent on a thorough understanding of contemporary online behavior. Most published studies focus on the decision to adopt Internet shopping rather than recent purchasing behavior and utilize data from the 1990's, a period in which online buyers were predominantly older, wealthier, well-educated males (Swinyard and Smith 2003). However, according to Pew Internet (2008a,b) current user demographics have shifted to equal percentages of men and women buying online with decreasing age and levels of income and education (Cummings and Kraut 2002). This study seeks to fill the gap that has developed and analyze more current data in portraying current online purchasing behavior. Information on the demographics, socioeconomics and consumer behavior of Internet shoppers has recently been synthesized into an Online Shopping Acceptance Model (OSAM) by Zhou et al. (2007). Online purchasing appears to be most related to convenience (Zhou et al. 2007) in addition to recreational and economic shopping (Donthu and Garcia 1999; Korgaonkar and Wolin 1999; Li et al. 1999; Swaminathan et al. 1999). The higher efficiency of e-commerce has reduced buyer search costs (Bakos 1997) and produced lower prices for several online goods and services than their offline counterparts (Brown and Goolsbee 2002; Brynjolfsson et al. 2003; Lee et al. 2003), offering the promise of products supplying good value to economic shoppers.

Online purchasing has also been facilitated by enhanced Internet accessibility as prices have steadily dropped and connections have become faster. Through this, online usage has developed into a daily part of nearly all American's lives for email correspondence and to obtain information (Nielsen 2008). In 2008, just over 90% of American home Internet consumers connect using broadband (WebSiteOptimization.com 2008). Higher connection speeds allow

the Internet to be used more heavily for entertainment, placing online gaming, instant messaging and social networking as the top three most time-intensive activities among broadband consumers (Nielsen//NetRatings 2006). Between 32% and 35% of users visit blogs and social network websites such as MySpace, Facebook and others (Pew Internet 2009a). The same study showed that, 28% access or download digital content, 26% participate in eBay and other online auctions, 52% watch video sites including YouTube and its derivatives, and 35% play games online (Pew Internet 2008b). The patronization of entertainment activities represents an unstudied aspect of online purchasing behavior.

To our knowledge, this study is the first in nearly a decade to define the factors that influence contemporary online shopping behavior. Using representative U.S. online consumer data and the current range of Internet activities, two models are developed to explain consumer determinants of online purchasing within the last year and the percentage of income spent online in the last three months, a variable that has never before been studied. There are several elements of this study that both set it apart as a unique contribution and mark it as a valuable addition to the existing literature. First, this study is focused on the specifics of purchasing behavior rather than the decision to adopt Internet shopping. The empirical work also utilizes a new, current dataset which provides insight into online retailing with information that reflects the newly-diverse demographics of online shoppers. The analysis also provides perspective on perhaps which retailers will be the most likely to succeed online and highlights which strategies will be the most successful. Finally, the study suggests that the greatest promise of online retailing, lower prices and reduced search costs, may not actually be its greatest attraction.

2. Methodology

2.1. The Models

Model 1. The first model of online purchasing within the last year (Purchase, y_1) incorporates five categories of variables (demographic, socioeconomic, Internet usage, product perceptions and alternative activities) and is analyzed using a weighted logit regression to ensure the results are nationally representative.[1] Appendix 1 provides a description and statistics of each variable.

[1] "The weight variable is based on 12 demographic variables. The idea behind the weight is to ensure that the sample is representative of the US online adult population, according to Jupiter's definition of what the demographics of that population are. Respondents are invited to take the survey based on specific demographic quotas, and then the weight is applied to the data to ensure that the distributions are precisely in line with the same demos." (Jupiter Research 2007)

(Equation 1) $$y_1 = ß_0 + \sum_{i=1}^{26} ß_i x_i + \varepsilon$$

Model 2. The second model examines the percentage of income spent online within the last three months (Spending, y_2) and incorporates the same five categories of variables as described above. Equation 2 is analyzed as a weighted least squares regression.

(Equation 2) $$y_2 = ß_0 + \sum_{i=1}^{26} ß_i x_i + \varepsilon$$

2.2. Data Set and Sources

The regression models utilize a data set acquired through a leading, publicly traded market research company that specializes in e-commerce and online demographics. [2] Data are compiled from a portion of a forty-two question, closed-end survey in June 2007. The questions focus on demographics, product preferences, and online behaviors, attitudes and activities. The 3,580 participants were selected by Ipsos from their U.S. online consumer panel, and the sample was balanced by demographic and behavioral characteristics derived from the U.S. Census Bureau and research pertaining to the U.S. online population.

Several shortcomings of the data set may slightly reduce the explanatory power for each of the models. The use of median values from bracketed variables for age, amount spent online and income does not assure a constant standard error and can lead to lower explained variance. The data set provides less accuracy since there are ceilings to income ($100,000+) and amount spent online ($5,000+). The questionnaire also lacked key variables regarding demographics (ethnic background or culture), socioeconomics (specific employment, home ownership, number of dependents) and Internet usage (perceptions of risk versus benefit, web apprehension, broader perceptions of Internet and previous online shopping experience). However, these limitations are partially circumvented by integrating previously researched demographic and socioeconomic variables with new variables that align with contemporary Internet usage.

3. Results and Implications for e-Commerce

[2] "In this survey effort, Jupiter Research worked with its research partner, Ipsos Insight…Ipsos Insight is one of the largest market research companies in the US and maintains a general research panel of 400,000 households. Ipsos Insight also has access to the Ipsos US online panel, which comprises two million Internet users." (Jupiter Research 2007)

The models described here incorporate representative U.S. data on 2008 online usage, patronization of Internet activities and user demographics.

3.1. Model 1

The logistic regression used for Model 1 is highly significant ($p < 0.001$) (Table 3.1) with 12 determinants (Table 3.2) of the 26 variables studied. The R-squared value of 0.237 is obtained by replicating the model for each participant and creating a predicted value.[3] Then a weighted, bivariate regression is run with the actual participant's outcome (purchase = 1 or no purchase = 0) as the dependent variable and the predicted values as the independent variable. While close to 24% of the variance is explained by the 26 independent variables studied, demographic variables alone explained only 3.3% of the variance (see Appendix 2).

Table 3.1: Results from Regressions

Model		Adjusted R-Squared	F Statistic (p value)	Number of Observations
Model 1	Purchase	0.237	1115.76 (p<0.001)	3580
Model 2	Spending	0.194	23.277 (p<0.001)	2539
Model 2 with Partitioned Data	Spending by Men	0.315	23.239 (p<0.001)	1213
	Spending by Women	0.086	5.473 (p<0.001)	1197
	Spending by Men with Household Incomes < $35K	0.667	27.000 (p<0.001)	312
	Spending by Men with Household Incomes > $100K	0.291	7.028 (p<0.001)	226
	Spending by Men Aged 45-54	0.791	45.250 (p<0.001)	281

[3] Predicted values are determined by applying the participant's survey answers (such as age, income, high-speed connection, etc.) to the coefficients from the first regression.

Table 3.2: Coefficients and Significance from Regressions Using Partitioned Data

	Model 1	Model 2					
		2A	**2B**	**2C**	**2D**	**2E**	**2F**
	Purchase	Spending	Spending by Men	Spending by Women	Spending by Men <$35K	Spending by Men > $100K	Spending by Men 45-54
Constant	-3.683***	0.684***	0.255	0.750***	-1.033	-1.725**	0.481
Demographic							
Age	0.006	0.002	0.007	-0.003	-0.008	0.009	♦
Gender	0.290**	-0.114*	♦	♦	♦	♦	♦
Education	0.069	0.120***	0.221***	-0.015	0.573***	0.259**	0.079
Socioeconomic							
Income	0.128***	-8E-006***	-8E-006***	-6E-006***	♦	♦	-4E-006
High-Speed Connection	0.183	0.096	0.153	0.205***	-0.429*	0.553**	-0.330*
Credit Card	1.279***						
Online Payment	0.637***	-0.048	-0.155	0.040	-0.065	-0.179	0.029
Online Deferred Payment		1.797***	2.973***	0.498***	4.627***	-0.028	3.614***
Internet Usage							
Weekly Usage	0.003	0.005**	0.001	0.003	0.003	0.011*	0.001
Communication							
Email	0.588***	-0.247*	-0.516**	0.158	-0.237	0.211	-0.036
Instant Messenger	-0.133	0.235***	0.433***	-0.085	0.703***	-0.212	0.478*
Information Retrieval							
Product Research	0.471***	-1.668	-0.101	0.105	-0.542***	-0.147	-0.524**
Search Engine	0.588***	0.125	0.155	0.046	-0.391	0.093	0.119
Download	0.273*	0.112	0.211*	-0.098	0.125	0.050	0.645***
Investigate Travel	0.426***	-0.107	-0.148	0.057	-0.062	0.369*	0.054
Stock Quotes	0.215	0.162*	0.066	0.473***	-0.339	0.230	0.081
Shopping Behavior							
Online Auction	0.877***	0.125*	0.125	0.197**	0.513**	0.696***	-0.134
Classified Ads	-0.008	-0.084	0.029	-0.226*	0.798**	-0.205	0.230
Entertainment							
Podcast	0.403*	0.149*	0.086	0.089	-0.106	0.254	-0.131
Online Gaming	-0.090	-0.233***	-0.343***	-0.089	-0.192	-0.427*	-0.513*
Social Networking							
Social Networks	0.039	-0.126*	-0.129	-0.149	-0.345	-0.296	-0.743***
Online Dating	0.312	0.310***	0.336***	0.057	0.263	0.483*	0.689***
Blogs	0.318	-0.020***	-0.253**	0.100	0.260	0.101	-0.329
Product Perception							
Good Value	0.111	-0.281***	-0.320**	-0.298***	0.184	-0.656***	0.304
New/Innovative	0.391**	0.505***	0.667***	0.153	0.753***	0.439***	1.314***
Alternative Activities							
Weekly Work	-0.266	0.001	-0.001	0.003**	-0.011*	-0.006	-0.003
Weekly Television	0.005	-0.003	-0.007*	0.000	-0.006	0.002	-0.010

♦ These variables were not included when the data were partitioned by gender and/or income.

* $0.01 < p \text{ value} \leq 0.05$

** $0.001 < p \text{ value} \leq 0.01$

*** $0.001 < p \text{ value}$

The only significant demographic determinant of a recent online purchase is the gender of the participant ($p<0.003$, Table 3.2). For the first time ever, female gender is positively correlated with online shopping; in this

case, purchasing within the last year. When adjusted for other variables including household income, females are on average 29.0% more likely than males to have made a recent online purchase. This result aligns with the shifting online demographics as noted by Pew Internet (2008a,b), an increasing percentage of women are online and becoming more sophisticated users. Not surprisingly, this translates into a higher rate of recent online purchasing by women than men at the time of this survey. These results provide a reason for retailers to exclusively target advertising at websites heavily patronized by women.

The majority of socioeconomic variables showed strong, positive correlations with a recent online purchase, providing verification of previous studies (Bellman et al. 1999; Donthu and Garcia 1999; Korgaonkar and Wolin 1999; Li et al. 1999). Even though the regression coefficient is small, household income is positively correlated with recent online buying. For every income level increase the user is, on average, 12.8% more likely to have purchased an item online within the last year. Users with a payment account such as PayPal™ are 64.4% more likely to shop within the last year. Marketing preferentially to high earners and increasing access to credit cards or PayPal™ accounts are expected to increase the adoption of online shopping.

The Internet usage determinants include several previously studied variables on communication and information retrieval. In contrast to the findings of previous studies (Huang 1998; Bellman et al. 1999; Bhatnagar,et al. 2000), weekly Internet usage is not significantly correlated with a recent purchase. Use of email, researching products online, using a search engine, downloading software and investigating travel online are all positive, significant determinants of recent online shopping. Use of Instant Messenger for communication, a previously unstudied variable, is not significantly correlated.

Several novel variables describing contemporary Internet activities such as shopping behavior, entertainment and social networking are also included in the regression models. Of these, participation in online auctions is the most significant determinant, followed by listening to podcasts. The remaining five variables were not found to be significant determinants of recent online purchasing.

These data include measures of product perceptions in order to account for their influence on contemporary online consumer behavior. Recent online purchasing is strongly correlated with a user preference for products that are described as new and innovative. When online consumers are driven by the perception of novelty or innovativeness, the variable for products described as good values is statistically insignificant in determining online

purchasing. These findings indicate that new, dynamic product lines should highlight innovativeness in their descriptions and advertising.

Contrary to Bellman et al.'s (1999) theory of time starvation, time spent working proved insignificant in explaining recent online purchasing. In addition, given that weekly television hours is not a determinant, electronic retailers should be less motivated to advertise on television, at least to heavier watchers. Their resources might be better spent advertising via new channels on the Internet that allow for targeted marketing. Most users apparently do not view Internet shopping as a time- or money-saving activity, but instead shop online for entertainment or novelty.

3.2. Model 2

Model 2 Using All Data. The second model utilizes a novel dependent variable, the percentage of income spent online in the last three months. As reported in Table 3.1, the regression is highly significant especially when analyzed using partitioned data on some subsets of men. Table 3.2 provides the coefficients and describes the significance of the 26 determinants. These variables explain 19.4% of the variance, while demographic variables account for only 2.1% (see Appendix 2).

In contrast to the results from Model 1, the second model reveals that male gender and higher educational attainment are positively correlated with the percentage of income spent online in the last quarter. While demographic factors account for less of the variance than in the first regression, the percentage is statistically significant. Males spend 0.361% more income online than do women, an increase of $160.20 quarterly. This finding is particularly important since it is a far greater spending increase than that previously reported by Lohse et al. (1999) who found men only purchased $3.15 more online annually than did women. College graduation increases the percentage of income spent online by 0.24% compared to someone with just a high school degree. These findings track previous results closely and align with the demographic hypotheses. Targeting an audience that is male and well educated should produce more revenue and allow for highly efficient marketing.

The influences of the socioeconomic determinants are somewhat different in the second regression. There is a significant, though very small, negative correlation between household income and percentage of income spent online because households with lower incomes tend to spend a larger percentage of income online, even though the actual amount spent online is less than that spent by higher income households. Possession of an online deferred payment account is a strong positive determinant of the percentage of income spent online in the last three months.

In contrast, possession of an online payment account such as PayPal™ is not a significant determinant. Online purchasers using deferred payment accounts spend 1.797% more income per year. Although economic data are not available, online deferred purchases are relatively large (usually requiring a purchase of at least $99) and possibly account for an increase in online spending. To generate more revenue, these results suggest that online retailers should provide more methods for buyers to establish and utilize online deferred payment accounts, focusing less on PayPal™and other similar payment systems.

Internet usage determinants also differ across the two models. Positive determinants for percentage of income spent online are high Internet usage and communication via Instant Messenger while email is a negative determinant. None of the information retrieval variables that was significant in Model 1 was significant at any level in Model 2: researching products or travel, use of search engines, downloading software. However, obtaining online stock quotes is positively correlated with the percentage of income spent online only in Model 2. Within both models there are significant correlations with participation in online auctions but not with posting classified ads. The strong positive correlations observed here suggest that heavier Internet users, stock owners and those who participate in online auctions are more likely to spend a higher percentage of their income online, providing target markets for online retailers.

In contrast to the results from the first model, all entertainment and social networking are determinants of percentage of income spent online. Podcasting and online dating are positive determinants while online gaming, visiting social network sites and blogging are negative determinants. These results suggest that online retailers could more profitably shift their advertising to podcasts, communication providers and online dating services.

While perception of a product as new and innovative is a highly positive determinant in both models, good value is a highly significant negative determinant in Model 2. Given these results, product lines that are novel or evolve frequently should be highlighted as such. E-retailers' marketing should align with consumers' perceptions and the Internet provides unparalleled flexibility for retailers to update websites to coincide with their target audience's perceptions and desires.

Alternative activities yield little explanatory power in either model. The lack of significant correlations between weekly television hours and percentage of income spent online suggests electronic retailers should steer marketing projects away from television and towards more profitable advertising channels such as podcasts or other online venues that reach buyers more directly. Given that it is not currently possible to selectively bypass ads in media

viewed on the Internet, advertisers have the opportunity to target marketing to this captive audience or even personalize advertising using viewers' search profiles. There has been a rapid expansion in viewing television shows online, a sevenfold increase between 2006 and 2007, because of increased broadband adoption coupled with the virtually limitless archived and contemporaneous media available from television networks or free from third parties(Pew Internet 2009a,b).

Model 2 Using Partitioned Data. The data set is partitioned to better understand the influence of gender, age and income, the only variables that show non-normal distributions. (Nationally representative information may still be obtained by weighting partitioned categories). The first partitioned data set is stratified by gender; then each data set is applied to the second model (Table 3.1). The results for men (Model 2B) show much more variance explained (31.5%) than for women (Model 2C) (8.6%). The models reveal very different determinants of online spending for men and women. The only commonalities across gender are in the impacts of income (a small, negative effect) and possession of an online deferred account, though the coefficient for men is six-times that of women. The characteristics of this model provide for better explanation of the variance of men than for women, but the reasons for these differences is beyond the scope of this study. For males, educational attainment, deferred online payment, use of instant messaging, downloading software, online dating, and perception of new and innovative products are all significant determinants, with a deferred online payment account providing most of the predictive power (Table 3.2). Interestingly, significant negative determinants are use of email, online gaming and blogging. Men appear to be strongly attracted by novel products and are not value shoppers. Online gaming is a highly significant negative determinant only for men, aligning with the rest of this data suggesting that men use online shopping as a form of entertainment. Deviating from the overall data set, online male shoppers show a significant negative correlation between percent of income spent online and hours watching television.

With its lower explained variance, the regression model for women has fewer significant determinants but unearths some key gender-related differences. The determinants of women's online spending support Bellman et al.'s (1999) theory of time starvation. For women only, work hours and having a high-speed connection are positive determinants. Similarly, none of the entertainment usage or social networking variables is significant. In addition to being more convenience-oriented, women who spend more online do not appear to be drawn to new or innovative products. Sophisticated Internet users, they participate in online auctions and appear to be responsible for producing stock quotes as a significant determinant for Model 2C.

Further partitioning of the data for men by income and age (Models 2D, 2E, 2F) yield improvements in the percentage of variability explained (Table 3.1). In Model 2D, for men with household incomes less than $35,000, 66.7% of the variability is explained by this model. Positive determinants are educational attainment, deferred payment, Instant Messenger, online auctions, classified ads, and new and innovative products (Table 3.2). High-speed connection, product research and weekly work hours are negative determinants. A college graduate at this income level, on average, spends 1.146% more income online quarterly than someone with just a high school degree. The most important factor, the variable with the largest coefficient, is the possession of an online deferred payment account. This result is not surprising and again points to the attention online retails should give to such advertising venues. These results illustrate a profitable target market for retailers: men with household incomes less than $35,000 but with a higher education seem to be novelty-oriented. Men with a household income less than $35,000 spend 1.172% of their income online each quarter, a higher percentage than those earning more.

Although individuals in the highest income bracket (household income of greater than $100,000) spend more online than those in the lower income brackets, their percentage of income spent online is lower, 0.745%. A data set of males with household incomes greater than $100,000 (Model 2E) explains 29.1% of the variance in online spending (Table 3.1). Similar to lower earners, educational attainment, online auctions and novel products are positive determinants but not weekly work hours (Table 3.2). Positive Internet usage determinants are quite different for this economic group; high speed connection, weekly usage, travel research, and online dating. Not surprisingly, possession of an online deferred account is not a determinant of online spending for these highest earning men and good value is actually a negative determinant for this group. Online gaming is also a negative determinant. Given the very distinct results for high-income men, e-retailers would be well advised to give unique attention to this market segment in order to best attract the business of these high earners.

Online retailers need to rely on models that explain large amounts of variance in their target market. Model 2F, applied to men aged 45-54, accounts for 79.1% of the variance at a highly significant level despite the lack of a significant correlation with household income. In this age group, positive determinants are downloading software, instant messaging, online dating, and most significantly, having an online deferred account and products perceived as new and innovative (Table 3.2). The highest observed coefficients in this model are again associated with online deferred payment. Negative determinants are high-speed connection, product research, social networking sites, online gaming and weekly television hours.

4.0 Conclusions

According to the Internet Advertising Revenue Report (2009), Internet advertising grew 10.6% in 2008. In the midst of an economic downturn, and in a year in which cable television advertising was the only other category of advertising to grow, this clearly indicates the importance and potential of this venue (Interactive Advertising Bureau 2009). Recognizing its importance, the issue then becomes how e-retailers can most effectively utilize Internet advertising. Their future growth and success depend on it. To improve marketing efficiency, online retailers must search out new, dynamic venues to advertise to their target market. This study establishes that online auctions, travel research and podcasts have large significant coefficients and provide easily accessible advertising channels. Advertising on these websites allows for especially efficient advertising because it allows online firms to reach exact, targeted demographics without wasting resources on unintended users. The podcast audience is a largely untapped, growing market that will prove beneficial for online firms. Podcast consumers are at least 50% more likely than non-consumers to have made an online purchase in the past week, are avid consumers of other communication technology and are active social networkers (Webster 2008). Possession of an online deferred payment account provided the largest significant coefficient for all groups except the highest earning men. Potential consumers may be encouraged to open a deferred payment account by advertising on highly correlated forums such as products seen as new and innovative, online auctions, downloadable software and podcasts.

Increasing online spending in the higher income brackets, particularly by men, is key to the growth of electronic commerce. This model explains a significant amount of the variance for this key demographic, which electronic retailers can utilize to perform cost-benefit analysis of each potential advertising project. It is speculated that increasing online spending in this group can be achieved through selective online advertising integrated with their preferred online activities. This demographic is well versed in technology and has a higher than average educational attainment. They participate in online auctions and have a high correlation coefficient for podcasting, although it is not statistically significant for this group. Their technological sophistication allows them to block many traditional advertising methods, so advertising via podcasts could target this attractive demographic (Nesbitt 2008).

The models presented here provide actual revenue estimates. For example, a college graduate on average spends 0.24% more of income online than does someone with just a high school degree while increasing time online by 40 hours boosts spending by an average of only 0.2%. If online retailers could increase the percentage of income spent

online by the highest income bracket, their revenues would increase significantly. Increased revenues can then be weighed against advertising costs; the resulting cost-benefit analyses are expected to reduce marketing costs. There are implications for website design as well.

In nearly a decade since a representative population of online buyers was last studied in detail, a more focused picture of the current American online buyer emerges from this research. Women are achieving parity as online shoppers as their technological savvy increases; in some cases, women utilize the Internet at a slightly higher rate than men for professional information or enrichment (Pew Internet 2008b). However, analysis of current data provides evidence that women still appear to be time-starved purchasers. There is a small but significant increase in the amount spent by women as work hours increase. Women with high-speed connections, who research products and who participate in Internet auctions spend more online. By far, though, the largest effect on spending (for both women and men) comes from having an online deferred payment account.

It is hoped that the techniques used here can provide a better understanding of contemporary American online behavior and suggest applications to increase future e-commerce. The Internet provides novel channels to reach perfectly targeted niche users. Online content and marketing can be customized for specific demographics, including gender, needs and interests. This is particularly important given the distinct spending patterns for men and women and the markedly different behavior of men in the highest income bracket established in this study. Marketing to new cultural or underserved ethnic groups is another route that should greatly expand future e-commerce, but specific websites and advertising must be developed to accommodate cultural differences in online perceptions and types of Internet usage (Chau et al. 2002; Singh et al. 2008). The growing base of people who utilize the Internet for entertainment and social networks also provides online retailers with new and robust marketing platforms. E-retailers advertise to grow their markets with the hope that they are not wasting resources on uninterested users. This study sheds light on how to more successfully accomplish this and provides direction for future research that may further illuminate how to best allocate scarce advertising resources.

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APPENDICES

Appendix 1: Description of Variables in Models and Key Statistics

DEPENDENT VARIABLE		DEFINITION OF DEPENDENT VARIABLE
y_1	Purchase	Has purchased a good or service online within the last year (1) or not (0)
		n = 3580; 72% yes, 28% no
y_2	Spending	Percentage of income spent via online purchasing in the last three months (the amount spent online in the last three months [median of bracketed range] by household income for the last three months [median of bracketed range divided by four].
		n = 2539; mean [SD] = 0.682% [1.603%]
CATEGORY AND NAME OF INDEPENDENT VARIABLE		**DEFINITION OF INDEPENDENT VARIABLE**
Demographic		
x_1	Age	Median age of each bracket is applied to data set: 21 (18-24), 29.5 (25-34), 39.5 (35-44), 49.5 (45-54), 55 (55+).
		Mean [SD] = 37.1 [13.9]
x_2	Gender	Male (0) or female (1).
		50% male, 50% female
x_3	Educational Attainment	Highest level of education the respondent completed (1) Grade school (2) Some high school (3) Graduated high school (4) Some College (5) College graduate (6) Post-graduate degree
		The average respondent has completed some college. 6% some high school, 26% graduated high school, 28% some college, 28% graduated college, 12% post-graduate degree
Socioeconomic		
x_4	Household Income	Median value from the bracketed range applied to the data set $ 35K (<$35K), 39.5K (35K-44K), 52K (45K-59K), 67K (60K-74K), 87.5K (75K-100K), 100K (100K+).
		Mean [SD]= $59,130 [$29,891]
x_5	High-speed Connection	Dial-up or no connection at home (0) or high-speed (1).
		63% high-speed connections, 34% dial-up connections, 2% without connection and 1% did not know their connection type
x_6	Credit or Debit Card Ownership	Possession of credit card or debit card that can be used in online purchasing (1) or does not own any form of online payment method (0).
		84% own payment card, 16% without payment card. (This variable is not used in Model 2 since an insignificant number of participants did not possess a payment card)
x_7	Online Payment	Has online payment account such as PayPal™ (1) or not (0).
		37% yes, 63% no
x_8	Online Deferred Payment	Has online deferred payment account (1) or not (0).
		5% yes, 95% no. (This variable is not used in Model 1 because it assumes user has purchased online)
Internet Usage		
x_9	Weekly Internet Usage	Average hours spent online weekly by the user.
		Mean [SD] = 19.3 [21.7]
Communication		
x_{10}	Email	User has sent or received email in last month (1) or not (0).
		90% yes, 10% no
x_{11}	Instant Messenger	User has used AOL Instant Messenger, ICQ, Yahoo or MSN Messenger, or similar instant messaging services in the last month (1) or not (0).
		37% yes, 63% no

Information Retrieval		
x_{12}	Product Research	User has researched product or services online in the last year (1) or has not (0).
		52% yes, 48% no
x_{13}	Search Engine	User searched for information using a search engine within the last month (1) or has not (0).
		78% yes, 22% no
x_{14}	Downloaded Software	User has downloaded software programs for their personal computer in the last year (1) or not (0).
		25% yes, 75% no
x_{15}	Investigated Travel	User has investigated travel arrangements (availability or pricing) online in the last month (1) or not (0).
		41% yes, 59% no
x_{16}	Stock Quotes	User has checked stock quotes online in the last month (1) or not (0).
		14% yes, 86% no
Shopping Behavior		
x_{17}	Online Auction	User has sold or bid for products in an online auction within the last month (1) or has not (0).
		21% yes, 79% no
x_{18}	Classified Ads	User posted classified ads online (e.g. Craig's List, AutoTrader™, etc.) in the last month (1) or has not (0).
		8% yes, 92% no
Entertainment		
x_{19}	Podcast	User has listened to or downloaded a podcast within the last month (1) or not (0).
		12% yes, 88% no
x_{20}	Online Gaming	User played games online such as action games, fantasy, flight simulators, etc. in the last month (1) or has not (0).
		27% yes, 73% no
Social Networking		
x_{21}	Social Networks	User has visited social networking sites like MySpace™, Facebook™, etc. in the last month (1) or has not (0).
		36% yes, 64% no
x_{22}	Online Dating	User has used an online dating service or viewed personal ads in the last month (1) or has not (0).
		15% yes, 85% no
x_{23}	Blogs	User has read a blog in the last month (1) or has not (0).
		26% yes, 74% no
Product Perceptions		
x_{24}	Good Value	User prefers to buy products that are a good value for the money (1) or not (0).
		78% yes, 22% no
x_{25}	New/Innovative	User prefers to buy products that are new and innovative (1) or not (0).
		16% yes, 84% no
Alternative Activities		
x_{26}	Weekly Work	Average hours user works weekly.
		Mean [SD] = 29.6 [27.2]
x_{27}	Weekly Television	Average hours user watches television weekly.
		Mean [SD] = 16.9 [17.6]

Appendix 2: Results from Model #1 & #2 (Demographic Variables Only).

Model		Adjusted R-Squared	F Statistic (p value)	Number of Observations
Model 1	**Purchase**	0.033	123.242 (p<0.001)	3580
Model 2	**Spending**	0.021	17.415 (p<0.001)	2539

	Model 1 Purchase	**Model 2** Spending
Constant	-1.419***	3.341***
Demographic		
Age	0.012***	0.001
Gender	0.217**	-1.272**
Education	0.316***	0.235*

* $0.01 < p \text{ value} \leq 0.05$
** $0.001 < p \text{ value} \leq 0.01$
*** $0.001 < p \text{ value}$