June 2003

SALES TAXES AND THE DECISION TO PURCHASE ONLINE

James Alm and Mikhail I. Melnik*

* Andrew Young School of Policy Studies, Georgia State University. Please address all correspondence to James Alm, Chair, Department of Economics, Andrew Young School of Policy Studies, Georgia State University, Atlanta, GA 30303-3083 (phone – 404 651 0420; email – jalm@gsu.edu).

I. Introduction

Rapid growth in ecommerce coupled with the recent economic slowdown has put significant pressures on state governments' abilities to generate sales tax revenues. The growing use of ecommerce carries much potential danger for the ability of state and local level governments to collect revenues, due to the current legal practice that does not require out-of-state vendors to collect state and local sales taxes on behalf of any state where they have no legal presence (or "nexus").[1]

The threat emerging from ecommerce has sparked a number of debates among public policy makers. For example, the National Governors Association has advocated a more uniform sales tax structure in the U.S., one that would be more easily adaptable by out-of-state vendors.[2] While the uncertainty about the implementation of such reform still exists, most states continue to experience ongoing budgetary problems, and are forced to look for immediate solutions. Some states have begun to consider increases in sales tax rates as a response to the shrinking tax revenue problem.[3] However, it is feared that such a response in light of the current tax treatment of ecommerce may cause a further deterioration in the sales tax base.

The relevance of this fear depends largely upon the sensitivity of consumers to a change in the sales tax rate, in the presence of an alternative that has a zero (effective) tax rate. However, while hotly debated, this issue has received little formal study, largely because of the absence of data that would permit a systematic empirical examination of

[1] See Quill vs. North Dakota, 112 US 298 (1992). Such internet transactions are in principle still subject to a state use tax, imposed at the same rate as the state sales tax. However, the extent of noncompliance with state use taxes is believed to be quite large.
[2] The National Governors Association can be accessed online at http://www.nga.gov.
[3] One example of the actual use of this strategy is in Tennessee, which enacted a one percentage point increase in the state sales tax rate in summer 2002.

the consumer responses. Although aggregate online retail spending data are now being gathered and analyzed by a number of different consulting firms[4], the lack of information at the individual consumer level, especially about the specific location of the consumer, makes an investigation into the impact of the tax rates on retail ecommerce quite difficult. In an important contribution, Goolsbee (2000) uses individual survey data from Forrester Research to estimate the impact of sales tax rates on the likelihood that individual consumers purchase online. He finds that sales tax rates have a positive and statistically significant impact on the amount of spending the consumer makes online, and concludes that taxing internet sales could reduce the number of online buyers by 24 percent. However, more recent, larger, and more representative data sets are now available, especially a special supplement to the Current Population Survey conducted and published by the Bureau of Labor Statistics and the Department of Census. The existence of this information allows us to reexamine the impact of state sales tax rates on the likelihood of online purchases. Like Goolsbee (2000), we find that a higher sales tax rate reduces the probability that consumers purchase online, and this result is quite robust across a wide variety of specifications and empirical approaches (including some that control for various selection issues that are likely to be present). However, we also find that this impact is typically much smaller than the Goolsbee (2000) estimate. In our preferred model, the elasticity of the probability of online purchases with respect to the tax price of online purchases is only 0.52, or roughly one-fourth the size of Goolsbee (2000). According to our estimates, taxing internet sales would therefore reduce online purchases, but by only 6 percent.

[4] For example, see estimates provided by Forrester Research (http://www.forrester.com), GartnerG2 (http://www.gartnerg2.com), and Jupiter Media Matrix (http://www.jupiterresearch.com). Also, see the eMarketer website (http://www.emarketer.com) and the ePayments website (http://www.epayments.com).

II. Theoretical Considerations

Online commerce presents internet users with another method for purchasing goods. Most all goods traded online can also be purchased in traditional brick and mortar commerce; for example, books sold by Amazon.com can be purchased at a local store, just like computer components, clothing, collectible coins, and the like can be purchased either online or in traditional stores. In this respect, the internet presents simply another venue for purchasing the same goods, and hence internet-purchased goods can be considered as perfect substitutes to some goods purchased in traditional commerce.

We can therefore structure the consumer decision to purchase goods online in the following way. First, we assume that the consumer maximizes a standard, well-behaved utility function subject to a budget constraint, or

Max $U=U(X, Y, Z)$

subject to $M \geq \pi_x \bullet X + \pi_y \bullet Y + Z$,

where X and Z represent goods that can be purchased in traditional commerce, while Y represents a good that can be purchased in online commerce only.[5] The Y and X goods are assumed to be perfect substitutes to each other, while there are no substitutes for the Z good in online commerce.[6] The π's represent the total per unit costs of the respective good, with Z assumed to be the numeraire good. We assume that X is subject to a state

[5] (X, Y, Z) are each assumed for simplicity to represent a single good, but they could also represent vectors of goods.
[6] Some goods available in traditional commerce may have no substitutes online. These are likely to be mainly services (e.g., a haircut) or even some goods (e.g., restaurant meals).

sales tax (and that this sales tax is always paid) and that the *Y* good purchased online is not subject to a sales tax, so that π_i can be represented as

$$\pi_x = P_x(1+t) + \tau_x$$

$$\pi_y = P_y + \tau_y$$

where P_i (i=X, Y) represents the per unit price of good i, t represents the sales tax rate on good X, and τ_i (i=X, Y) represents any additional per unit costs associated with the purchase of good i (e.g., travel costs).[7] The solution to the maximization problem can be presented by the indirect utility function $V(.)$, which can assume two forms[8]:

$$V_1 = V(M, \pi_x, \pi_z) \qquad \text{if} \qquad X>0 \text{ and } Y=0$$

$$V_2 = V(M, \pi_y, \pi_z) \qquad \text{if} \qquad X=0 \text{ and } Y>0$$

Therefore, the probability of purchasing goods online can be structured as a function of the indirect utility function:

$$\Pr(EPurchase) = \Pr(V_2 - V_1 > 0),$$

where *EPurchase* denotes online purchase and Pr denotes probability. The consumer will experience a benefit from buying online if $V_2 > V_1$, which occurs only when $\pi_y < \pi_x$. Importantly, note that an increase in the tax rate increases the probability of *EPurchase* by increasing the price of good *X* relative to that of good *Y*; that is,

---

[7] We follow convention in assuming that, in the absence of any sales taxes, the ratio P_X/P_Y equals unity. See, for example, Goolsbee (2000).

[8] Since *X* and *Y* are perfect substitutes, the consumer will purchase the good with the lowest total per unit cost and zero of the good with the higher per unit cost. Note that we assume for simplicity that Y=0 if $\pi_x = \pi_y$.

$$\frac{\partial \Pr(EPurchase = 1)}{\partial t} = \frac{\partial V_2}{\partial \pi_y}\frac{\partial \pi_y}{\partial t} - \frac{\partial V_1}{\partial \pi_x}\frac{\partial \pi_x}{\partial t} > 0$$

since $\partial\pi_x/\partial t > 0$ and $\partial\pi_y/\partial t = 0$. Simply put, an increase in the sales tax rate increases the relative price of the good purchased in traditional stores, and so increases the payoff to buying online and thereby avoiding the sales tax. The next section presents our empirical strategy for estimating this response.

III. Data and Empirical Specification

A. Data

Consumer data are obtained from one of the most comprehensive U.S. population surveys, the Current Population Survey (CPS), conducted jointly by the Department of the Census and the Bureau of Labor Statistics. The dataset is from the December 2001 "Computer Use and Internet Access Supplement" of the CPS survey. The Supplement includes 143,300 observations with their corresponding probability weights.[9] Because our objective is to estimate the impact of the sales tax rate on the probability of purchasing goods online, we limit our analysis to the adult population only (age 16 and older), or 109,103 observations. Table 1 presents descriptive statistics for the variables used in our analysis.

We construct several dummy variables that measure a consumer's use of, or access to, the internet, a computer, or online shopping. One of these is *EPurchase*, which equals one if the consumer used the internet to conduct online shopping and zero

[9] All results reported in this paper are those of weighted estimations. Note that the sum of all weights is equal to the total corresponding population. We have also used unweighted data to estimate our various specifications.

otherwise. *InternetUse* represents internet use, and is equal to one if the consumer used the internet regardless of the access method and zero otherwise. Nearly two-thirds of all adults used the internet in some way in 2001. In addition, two other internet access measures are also constructed: *InternetAtHome*, a dummy variable that assumes the value of one if the internet is accessed from home and zero otherwise; and *InternetOutsideHome*, a dummy variable that is equal to one if the internet is accessed from outside of home and zero otherwise. Two other variables capture computer use: *PCHome*, equal to one if a computer is present at home in the household and zero otherwise; and *PCWork*, equal to one if a computer is used at work and zero otherwise. Figure 1 presents a structured view of these variables.

We use several sets of variables to estimate the determinants of online shopping. The first group of variables represents income categories for household income. The dataset contains no information about the precise level of earnings of each individual, but rather contains information on household income level within ranges. The income levels up to $60,000 are categorized in six $10,000-dollar brackets; households with income levels between $60,000 and $75,000 are grouped into one category, as are all households with income levels in excess of $75,000. Note that the first column in Table 1 presents the mean values of the variables based on the number of the observations in the dataset, while the last column represents the weighted average of the variable. The weighted average can be interpreted as the average for the total population of the U.S., as the dataset is calibrated to produce aggregate statistics for the entire U.S. population.

Roughly one-sixth (or 16.0 percent) of the observations are missing income data, and these are represented by the dummy variable *NoIncomeReport*. Because of the large number of these observations, income for these observations is imputed using the "hotdeck" imputation technique (Lessler and Kalsbeek, 1992). The hotdeck procedure is based on all household characteristics available in the dataset (e.g., household size, location, number of children, property owner), and on the individual characteristics of the head of household, including many of the characteristics given in Table 1 plus marital status, employment status, and occupational identifier. Table 2 presents summary statistics for income category variables with the imputed income values.

Another group of variables represents demographic characteristics. *Age* is between 16 and 90; the CPS censors age at 90 for those individuals who are 90 and older. The average age is 44 years, and only 0.5 percent of the population is in the over-90 age group. *HouseholdSize* is the number of individuals in the household. *AmericanIndian*, *Asian*, *Black*, *White*, and *Hispanic* are dummy variables that equal one if the individual belongs to the relevant ethnic group and zero otherwise. It is worth noting that the Bureau of Labor Statistics defines "Hispanic" on the basis of origin and not on the basis of race; therefore individuals with Hispanic origin will have *Hispanic* equal to one, and will also have a value of one for their corresponding race variable (*AmericanIndian*, *Asian*, *Black*, or *White*). *Female* is also a dummy variable that equals one if the individual is a female and zero otherwise. Based on the weighted statistics, women are slightly over one-half of the population.

We include another group of control variables to measure education. The dummy variable *AtSchool* is equal to one if the individual is currently attending college and zero otherwise; *SomeCollege* is equal to one if the individual attended college but never earned a degree; *AssociateDegree* is equal to one if the individual has an Associate's degree; *BachelorsDegree* is equal to one if the individual has a Bachelor's degree; and *GraduateDegree* is equal to one if the individual has a graduate (e.g., M.S., M.A., Ph.D.) or a professional (e.g., M.D., D.D.S, M.B.A.) degree. Of the total adult population, 18.6 percent have attended some college but never earned a degree, 15.4 percent received a bachelor's degree as their highest level of education, and only 7.7 percent have graduate degrees. *AssociateDegree* appears to be the least popular option, with only 7.5 percent of the adult population having that degree.

The variable *Metro* equals one if the individual resides in a metropolitan area and zero otherwise. Nearly five-sixths of all adults in the U.S. reside in metropolitan areas. This variable is important because education centers and high-tech employment are more likely to be concentrated in metropolitan areas and both may expose the individual to the internet.

Lastly, *SalesTaxRate* is constructed using data on state sales tax rates and local sales tax rates for 2001 from the Sales Tax Institute.[10] CPS data contain information on the state of residence of each surveyed individual, but not on the county of residence. Because of this, *SalesTaxRate* is constructed as the sum of the state sales tax rate and the sales tax rate imposed by the local jurisdiction with the lowest tax rate in the state, so that *SalesTaxRate* represents the lowest sales tax rate available to the consumer in the state of residence.[11] Table 3 presents a summary of state sales tax rates along with the range in local jurisdiction sales tax rates in each state. Only five states do not employ a sales tax: Alaska, Delaware, New Hampshire, Montana, and Oregon. Sixteen states do not allow

[10] The Sales Tax Institute website is http://www.salestaxinstitute.com.
[11] We do not want to imply that *SalesTaxRate* is the actual tax rate paid by the consumer, since without the knowledge of the locality in which the consumer resides it is impossible to determine the actual value for states with variations in local sales tax rates.

local governments to impose sales taxes, and one state has a fixed local government sales tax rate (Virginia). For these states there is no variation in local sales tax rates across the state. We enter the tax rate in our estimations as the "tax price" of traditional store purchases, or (1+*SalesTaxRate*), with the tax rate entered as a fraction.

B. Empirical Specification

Our main intent is to determine the impact of sales taxes on the probability of online shopping. The dependent variable in this analysis is the consumer decision to purchase online. *EPurchase* is a binary variable that assumes the value of one if the consumer uses the internet for shopping purposes and zero otherwise.[12] The assumption is made that the decision to purchase online may be influenced by a number of different economic and demographic characteristics of the consumer along with the lowest sales tax rate available to the consumer in the state of residence. Therefore the latent variable $EPurchase_i^*$ is defined for individual i as:

$$EPurchase_i^* = X_i \beta + u_i ,$$

where X_i now equals a vector of variables that determine $EPurchase_i$, β is the corresponding vector of coefficients, and u_i is an error term. The observable $EPurchase_i$ is defined as

$$EPurchase_i = \begin{cases} 1 \text{ if } X_i \beta + u_i > 0 \\ 0 \text{ if } X_i \beta + u_i \leq 0 . \end{cases}$$

[12] The actual question on the CPS questionnaire is: "Did you use the internet for shopping the last year?"

However, the problem is complicated by the fact that *EPurchase* is only observable if the consumer has decided to obtain access to the internet; that is, *InternetUse* must equal 1 before *EPurchase* is observable. Failure to recognize this selection issue in a simple binary choice estimation model of *EPurchase* only could lead to selection bias.

As a result, *InternetUse* can be viewed as a selection equation, where the unobserved latent variable $InternetUse_i{*}$ for individual i is defined as

$$InternetUse_i{*} = Y_i\,\gamma + v_i\,,$$

where Y_i is a vector of characteristics of individual i that determines internet use, γ is the corresponding vector of coefficients, and v_i is the error term. Similarly, the observed binary variable $InternetUse_i$ is defined as

$$InternetUse_i \quad \begin{aligned} &= 1 \text{ if } Y_i\,\gamma + v_i > 0 \\ &= 0 \text{ if } Y_i\,\gamma + v_i \leq 0, \end{aligned}$$

so that $InternetUse_i$ is a binary variable that equals one 1 if individual i selects internet access and zero otherwise.

To account for this selection, we follow the procedure suggested by Van deVen and Van Pragg (1981). This procedure is similar to a bivariate probit technique in that it estimates both the *InternetUse* and *EPurchase* equations simultaneously (thereby allowing for correlation across the error terms), but it restricts the estimation of the second-stage *EPurchase* equation only to those observations that have a positive outcome in the first-stage *InternetUse* equation. This method has often been used in discrete choice variable estimation with selection (Painter, 2000; Boyes, Hoffman, and Low, 1989; Alm, Bahl, and Murray, 1993), and results in consistent and efficient estimation of the coefficients.

Note that there are other estimation methods that could be employed here. For example, our procedure resembles the original Heckman (1979) two-step selection approach where the first equation (the selection equation) is estimated first, and then the inverse Mill's ratio from this equation is used as a regressor in the second equation.[13] Another possible approach consists of a two-step estimation with the first step being the estimation of the selection equation using simple probit technique, and then using the predicted probability of a positive outcome in the selection equation as an explanatory variable in the second step equation. In fact, we have estimated all three approaches, and we report these different sets of results. Our results are quite robust across all three methods. Our discussion focuses on the bivariate probit approach of Van de Ven and Van Pragg (1981).

The usual assumptions are imposed on the error terms, or

$$u, v \sim N(0, 1)$$

$$Corr\ (u, v) = \rho,$$

where ρ is the correlation between the error terms. Under these assumptions the log-likelihood can be written as

---

[13] With right-sided censoring, the inverse Mills ratio is $\frac{\phi(X\beta)}{\Phi(X\beta)}$, where ϕ is the probability density function and Φ is the cumulative distribution function.

$$L = \sum_{\substack{i \in J \\ EPurchase_i = 1}} \omega_i \ln\left[\Omega(X_i\beta, Y_i\gamma, \rho)\right] + \sum_{\substack{i \in J \\ EPurchase_i = 0}} \omega_i \ln\left[\Omega(-X_i\beta, Y_i\gamma, -\rho)\right] + \sum_{i \notin J} \omega_i \ln\left[1 - \Phi(Y_i\gamma)\right],$$

where *Ω(.)* represents the bivariate normal cumulative distribution function with both means equal to zero*, Φ(.)* represents the standard cumulative normal, *J* is the set of observations for which *InternetUse* equals one, and ω_i is the sampling weight of observation *i*.

Identification is achieved by functional form and, more importantly, by exclusion restrictions. Several variables are included in the *InternetUse* equation and excluded from the *EPurchase* equation: *PCWork*, *PCHome*, and *AtSchool*. Table 4 presents correlation coefficients between these variables and the dependent variables. All of these are expected to be correlated with the internet use but not with the decision to purchase online. Any correlation between *EPurchase* and these variables is through *InternetUse*. Computer use at work exposes an individual to the possibility of accessing the internet, just as computer ownership may act as the first step in accessing the internet from home. Similarly, school enrolment may enable an individual to access the internet in the same way as the presence of a computer at the workplace.

Our analysis concentrates on the individuals. However, these individuals come from households of various sizes, from 1 to 16 members. To correct for potential heteroskedasticity, we use Huber-White estimation of the variance-covariance matrix throughout the estimations. All reported t-statistics are based on robust standard errors.

IV. Empirical Findings

A. Estimation Results (I): Basic Findings

Table 5 presents the estimation results of our basic bivariate probit model. Recall that income values were imputed for 16.0 percent of all observations. For this reason, we compare the results across specifications that include and exclude observations with imputed income. The first specification in Table 5 excludes all income variables, and is estimated on the entire dataset. Specification 2 includes all income variables, but is restricted to those observations for which income values were reported in the survey. Specification 3 is our preferred estimation and is performed on the entire dataset, inclusive of the observations with imputed income values. We report in Table 5 (and elsewhere) the probit coefficient, with t-statistics based on robust standard errors in parentheses; we also report in italics the marginal effects (evaluated at mean values) of the covariates on the relevant probability, either *InternetUse* or *EPurchase*.

In all specifications Table 5, *SalesTaxRate* has a statistically significant and positive impact on the probability of purchasing goods online. The average magnitude of the marginal effect on the tax price (or (1+*SalesTaxRate*)) in Table 5 is 0.2025, and can be interpreted as an increase in the probability of buying online that would result from a one percent decline in the tax price. Given the average magnitude of this marginal effect, we can conclude that an individual with average characteristics in the dataset would increase the probability of purchasing online by 3.8 percent if he or she relocated from a jurisdiction with a 7.5 percent tax rate to one with a jurisdiction with a 0 percent tax rate. Similarly, the estimated elasticity of the probability of online purchases (conditional on internet access) with respect to the tax price, or (1+*SalesTaxRate*) is 0.52, again evaluated at the average values.[14] The direction of the impact of sales taxes is the same as Goolsbee (2000), but our estimated magnitude is significantly lower, roughly one-quarter the size. This difference may in part be explained by the increased penetration of the internet between 1997 and 2001, as well as by our correction for possible self-selection among internet users.

It is noteworthy that internet access (*InternetUse*) is largely unaffected by sales taxes, with the exception of specification 2 in Table 5 where the coefficient on the tax price is negative and statistically significant. Recall, however, that this specification excludes all observations with missing income data.

As for other variables, income tends to have a positive impact on the decision to buy online, conditional on internet access, with the magnitude of the coefficient on income generally increasing as income increases, relative to the omitted income category of [0-10000]. However, only income categories above $50,000 consistently have statistically significant coefficients. This result is important, since it suggests that the wealthy segments of the population are more likely to benefit from the lack of sales taxation of online purchases. Also, income has a statistically significant and positive impact on the decision to obtain internet access. Individuals coming from households with income levels in excess of $75,000 are about 12 percent more likely to use the internet than individuals with household income levels under $10,000.

Individuals located in metropolitan areas are more likely to access the internet and then to use the internet for consumption purposes than their rural counterparts. Metropolitan status makes an individual nearly 4 percent more likely to access the

---

[14] The elasticity is calculated as $\varepsilon = \dfrac{\%\Delta \Pr(EPurchase \mid InternetUse)}{\%\Delta(1 + SalesTaxRate)}$.

internet and nearly 2 percent more likely to purchase online. One of the arguments behind the growing retail use of the internet is to help extend retail services from urbanized centers into rural areas. Furthermore, individuals located in urbanized areas are more likely to be exposed to a larger number of sellers engaged in traditional commerce, and hence are more likely to find stronger competition for online sellers than individuals located in rural areas. These arguments suggest that rural individuals should be more likely to purchase online. In contrast, individuals in metropolitan areas are more likely to be familiar with the technology, to trust it, and to use it.

With some minor exceptions (e.g., *Asian*), minority groups are less likely to purchase online, and are also less likely to have internet access than *White*. Women are more likely to access the internet, but are less likely to use the internet for shopping purposes, although these latter estimated coefficients are not statistically significant. Age has a negative impact on both internet access and online shopping.[15] Education has a consistently positive and statistically significant impact on the internet access rate and on the probability of buying online across all specifications in Table 5. It should be noted that income categories refer to the *household* income level (not the *individual* income level), while education is for the individual. Nevertheless, education is expected to be correlated with the level of household income.

Inclusion of observations with imputed income values has a minor impact on both the magnitude of the coefficients and the levels of statistical significance. For example, the coefficient on (1+*SalesTaxRate*) in the *EPurchase* estimation declines slightly from 0.55 to 0.47, based on specifications 2 and 3; the level of statistical significance declines

[15] Inclusion of Age in logarithmic form instead of the direct form had no significant impact on any of the coefficients reported in Tables 5 to 7.

slightly as well, as shown by a decline in the t-statistic from 1.59 to 1.43. The coefficients on *Age*, *Female*, the educational variables, *HouseholdSize*, *Metro*, and the ethnic variables remain virtually unaffected by the inclusion of imputed values. The largest impact appears to be on the income variables, with inclusion of observations with imputed income values reducing the magnitude of all income coefficients.

The estimate of ρ is statistically significant and different from zero in all specifications in Table 5. This result indicates that the error terms are correlated across these two equations (*InternetUse* and *EPurchase*). The Wald test statistic [$\chi^2(1)$] for independence of equations (or $\rho = 0$) in specification 1 of Table 5 is 739.63; in specifications 2 and 3, the statistic is 484.03 and 567.51, respectively. All are statistically significant.

B. Estimation Results (II)

Table 6 reports two specifications that exclude educational variables. The first specification in Table 6 excludes the observations with missing income values, while the second specification is performed in the same way as specification 3 in Table 5. As shown by the Wald statistic, excluding these education variables generally lowers the goodness-of-fit of the various specifications. However, the effects on the sign and magnitude of the coefficient estimates are minimal. In particular, the coefficients on (1+*SalesTaxRate*) in Table 6 remain largely consistent with those in the specifications in Table 5, in which education measures are included.

C. Estimation Results (III)

Table 7 compares the results of specification 3 in Table 5 with estimations obtained using the Heckman (1979) two-step procedure (specification 1 in Table 7) and a probit estimation conditional on internet access (specification 2 in Table 7). Comparing these results with those in Table 5 indicates that, for coefficients that are statistically significant at the 90 percent or above level, the changes in the coefficients are quite minor, generally less than 10 percent. The coefficient on (1+*SalesTaxRate*) is within 5 percent of its magnitude in specification 3 of Table 5 in each of the Table 7 estimations, and the level of statistical significance is largely unaffected as well.

D. Estimation Results (IV)

The above results do not differentiate between how the internet is accessed; more importantly, they fail to distinguish between home and outside of home methods of internet access. However, this differentiation is important for many reasons. Individuals who access the internet from home may come from households with higher incomes and may behave differently than those individuals who obtain the internet access outside of home. Furthermore, individuals from low income households may be more likely to seek internet access outside of their homes as a lower cost alternative to home internet access that requires the purchase of the necessary equipment in order to benefit from tax-free consumption. For these reasons, it is important to analyze the effects of sales tax rates on the consumer decision to participate in online commerce on subsets of the data, defined in terms of the location from which the internet is accessed. Table 8 presents the results of these estimations, following the same basic specification 3 of Table 5. These results are performed on the entire dataset (inclusive of the observations with imputed income values).

The first specification in Table 8 restricts the online purchase decision to only those individuals who access the internet from home. The tax price impact remains statistically significant and the marginal effect increases by approximately 10 percent to 0.22. Many other variables also have similar effects. For example, minority groups (except for *Asian*) continue to be less likely to obtain the access, just as earlier, and education measures continue to affect both the probability of internet access and of online purchase in a positive way. *Age* is also unaffected by the change in the specification.

However, the impacts of several other variables change relative to their effects in Table 5. Surprisingly, income now appears to have a negative impact on the decision to buy online, although income remains one of the key factors behind the decision to obtain internet access. Individuals located in metropolitan areas are now less likely to purchase online. The coefficients on *Black* and *AmericanIndian* have lost their statistical significance, and Hispanics appear to be more likely to purchase online.

In specification 2 of Table 8, we look at the factors that determine the decision to access the internet outside of the home and to purchase online using that internet access. The tax price remains a statistically significant and positive factor in the decision to purchase online. Income also seems to have a strong positive impact on the decision to purchase online, as does education. All minority groups are less likely to purchase online given outside-of-home internet access. Other variables – *Age*, *Female*, *Metro*, and *HouseholdSize* – all have similar results to those reported earlier.

E. Estimation Results (V)

It should finally be noted that we have also estimated a range of additional models. For example, we have estimated the various specifications with unweighted sample data rather than weighted data. In another specification we first estimate the determinants of home computer purchase; conditional upon home computer purchase, we then estimate the determinants of home internet access; finally, conditional upon home computer purchase and home internet access, we estimate the determinants of home online purchase. The tax price generally retains its positive and significant impact on online purchase, but the tax price does not affect computer purchase or internet access. Other models give largely similar results.

V. Conclusions

Our results indicate that sales taxes typically have a positive and statistically significant impact on the probability of buying online. The magnitude of the impact tends to be relatively small, though still significant. For example, a one percent change in the tax price reduces the probability of buying online by roughly 0.5 percent, a response that is noticeable but one that is only one-fourth the size of Goolsbee's (2000) estimates. This dependency of the probability to purchase online on the sales tax rate suggests that increases in the sales tax rate may not be an appropriate response to the falling sales tax revenues problem that many states seem to experience, as this remedy will encourage purchases online.

Of some note, our results also generally indicate that the probability of online purchases tends to be higher for higher income groups, but also tends to be lower for most minorities. These results suggest that the failure to tax online purchases benefits mainly higher income whites. However, the exact magnitude of these incidence effects remains unknown. Our study analyzes the impact of the sales taxes on the probability of online purchases, and not on the actual magnitude of online expenditures. Without knowing expenditures, it is impossible to make any incidence calculations. In the absence of expenditure information, it is also impossible to make any revenue predictions that might result from changes in the sales tax rate. Further developments in data collection are needed to assist these lines of future research.

References

Alm, James, Roy Bahl, and Matthew N. Murray (1993). "Audit Selection and Income Tax Underreporting in the Tax Compliance Game". *Journal of Development Economics*, 42, 323-338.

Boyes, William, D. Hoffman, and Stuart A. Low (1989). "An Econometric Analysis of the Bank Credit Scoring Problem". *Journal of Econometrics*, 40, 3-14.

Goolsbee, Austan (2000). "In a World without Borders: The Impact of Taxes on Internet Commerce". *Quarterly Journal of Economics*, 115 (2), 561-576.

Heckman, James (1979). "Sample Selection Bias as a Specification Error". *Econometrica*, 47, 1979, 153-161.

Lessler J. T. and W. D. Kalsbeek (1992). *Nonsampling Error in Surveys* (New York, NY: John Wiley & Sons).

National Governors Association. http://www.nga.gov

Painter, G. (2000). "Tenure Choice with Sample Selection: Differences among Alternative Samples". *Journal of Housing Economics*, 9(3), 197-213.

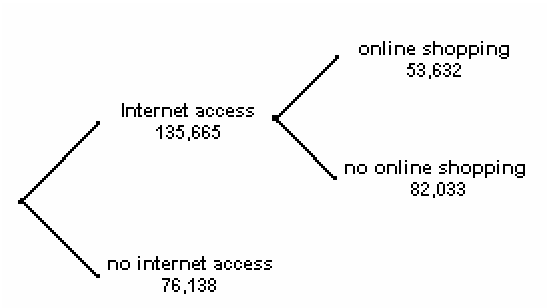
Sales Tax Institute (http://www.salestaxinstitute.com/sales_tax_rates.htm).

Sartori, A. E (2003). "An Estimator for Some Binary-Outcome Selection Models without Exclusion Restrictions". *Political Analysis*, 11 (2), forthcoming.

Tennessee Department of Revenue, http://www.state.tn.us/revenue/

Van de Ven, W. P. M. M. and B. M. S. Van Pragg (1981). "The Demand for Deductibles in Private Health Insurance: A Probit Model with Sample Selection". *Journal of Econometrics*, 17, 229-252.

Figure 1



Source: CPS 2001 December survey. The numbers are weighted numbers, and all numbers are in thousands.

Table 1. Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum	Weighted Average
Income [0-10000]	0.0607	0.2388	0	1	0.0617
Income [10000-20000]	0.0975	0.2966	0	1	0.0970
Income [20000-30000]	0.1143	0.3182	0	1	0.1119
Income [30000-40000]	0.1058	0.3076	0	1	0.1041
Income [40000-50000]	0.0842	0.2777	0	1	0.0825
Income [50000-60000]	0.0840	0.2774	0	1	0.0805
Income [60000-75000]	0.0871	0.2819	0	1	0.0857
Income [75000-up]	0.2061	0.4045	0	1	0.2114
NoIncomeReport	0.1602	0.3668	0	1	0.1651
Age	44.7373	18.0138	16	90	44.0070
AmericanIndian	0.0136	0.1160	0	1	0.0091
Asian	0.0395	0.1949	0	1	0.0404
Hispanic	0.0888	0.2845	0	1	0.1099
Black	0.0960	0.2947	0	1	0.1208
White	0.8508	0.3563	0	1	0.8296
Female	0.5243	0.4994	0	1	0.5191
AtSchool	0.0421	0.2009	0	1	0.0470
SomeCollege	0.1841	0.3876	0	1	0.1863
AssociateDegree	0.0790	0.2698	0	1	0.0751
BachelorsDegree	0.1555	0.3624	0	1	0.1542
GraduateDegree	0.0786	0.2691	0	1	0.0773
EPurchase	0.2578	0.4374	0	1	0.2532
HouseholdSize	2.9974	1.5612	1	16	3.0312
Metro	0.7533	0.4311	0	1	0.8128
InternetUse	0.6470	0.4779	0	1	0.6405
InternetatHome	0.5591	0.4965	0	1	0.5546
InternetOutsideHome	0.3646	0.4813	0	1	0.3611
PCHome	0.6247	0.4842	0	1	0.6166
PCWork	0.3470	0.4760	0	1	0.3401
SalesTaxRate	5.0051	1.8507	0	7.5	5.4505
Sum of weights = 211803532					
Number of observations = 109103					

Table 2. Imputed Income Values

Income Category	Mean	Standard Deviation	Weighted Average
[0-10000]	0.0609	0.2391	0.0795
[10000-20000]	0.0977	0.2968	0.1191
[20000-30000]	0.1143	0.3181	0.1364
[30000-40000]	0.1055	0.3073	0.1253
[40000-50000]	0.0839	0.2773	0.0985
[50000-60000]	0.0839	0.2773	0.0956
[60000-75000]	0.0870	0.2819	0.0998
[75000-up]	0.2063	0.4046	0.2456

Table 3. State Sales Tax Rates[a]

State	State Rate	Range of Local Rates	State	State Rate	Range of Local Rates
Alabama	4.00%	0% - 7%	Montana	0.00%	0.00%
Alaska	0.00%	0% - 7%	Nebraska	5.00%	0% - 1.5%
Arizona	5.60%	0% - 4.50%	Nevada	4.25%	0% - 3%
Arkansas	5.13%	0% - 4.75%	New Hampshire	0.00%	0.00%
California	6.00%	1.25% - 2.75%	New Jersey	6.00%	0.00%
Colorado	2.90%	0% - 6%	New Mexico	5.00%	.125% - 2.1875%
Connecticut	6.00%	0.00%	New York	4.00%	0% - 4.5%
Delaware	0.00%	0.00%	North Carolina	4.50%	2% - 2.5%
District of Columbia	5.75%	0.00%	North Dakota	5.00%	0% - 2.5%
Florida	6.00%	0 - 1.5%	Ohio	5.00%	.25% - 2%
Georgia	4.00%	1 - 3%	Oklahoma	4.50%	0% - 6%
Hawaii	4.00%	0.00%	Oregon	0.00%	0.00%
Idaho	5.00%	0% - 3%	Pennsylvania	6.00%	0% - 1%
Illinois	6.25%	0% - 2.75%	Rhode Island	7.00%	0.00%
Indiana	5.00%	0.00%	South Carolina	5.00%	0% - 2%
Iowa	5.00%	0% - 2%	South Dakota	4.00%	0% - 2%
Kansas	4.90%	0% - 3%	Tennessee	6.00%	1.5% - 2.75%
Kentucky	6.00%	0.00%	Texas	6.25%	0% - 2%
Louisiana	4.00%	0% - 6.75%	Utah	4.75%	1% - 3.25%
Maine	5.00%	0.00%	Vermont	5.00%	0% - 1%
Maryland	5.00%	0.00%	Virginia	3.50%	1.00%
Massachusetts	5.00%	0.00%	Washington	6.50%	.5% - 2.4%
Michigan	6.00%	0.00%	West Virginia	6.00%	0.00%
Minnesota	6.50%	0% - 1%	Wisconsin	5.00%	0% - 1%
Mississippi	7.00%	0% - .25%	Wyoming	4.00%	0% - 2%

Table 4. Correlation Coefficients

Variable	InternetUse	EPurchase
School	0.0870	-0.0188
PCWork	0.4146	0.3540
PCHome	0.7420	0.3675

Table 5. Estimation Results (I)*

Independent Variable	1		2		3	
	InternetUse	EPurchase	InternetUse	EPurchase	InternetUse	EPurchase
(1+Sales Tax Rate)	-0.4709 (1.18) *-0.1474*	0.5662 (1.75) *0.2176*	-0.8559 (1.97) *-0.2521*	0.5548 (1.59) *0.2126*	-0.3926 (0.98) *-0.1222*	0.4657 (1.43) *0.1773*
Income (10000-20000)			-0.0218 (0.66) *-0.0065*	-0.0150 (0.33) *-0.0058*	-0.0315 (1.07) *-0.0099*	-0.0130 (0.35) *-0.0050*
Income (20000-30000)			0.1302 (4.12) *0.0369*	-0.0187 (0.45) *-0.0072*	0.0672 (2.40) *0.0206*	-0.0073 (0.21) *-0.0028*
Income (30000-40000)			0.2458 (7.55) *0.0670*	0.0508 (1.23) *0.0195*	0.1621 (5.64) *0.0482*	0.0234 (0.69) *0.0089*
Income (40000-50000)			0.3270 (9.40) *0.0862*	0.0686 (1.64) *0.0265*	0.2030 (6.60) *0.0594*	0.0470 (1.36) *0.0180*
Income (50000-60000)			0.3470 (9.81) *0.0908*	0.0989 (2.38) *0.0383*	0.2282 (7.30) *0.0663*	0.0788 (2.31) *0.0303*
Income (60000-75000)			0.4819 (13.30) *0.1200*	0.1070 (2.59) *0.0415*	0.3576 (11.20) *0.0995*	0.0796 (2.35) *0.0306*
Income (75000 and up)			0.6407 (18.94) *0.1637*	0.2487 (6.27) *0.0966*	0.4152 (14.69) *0.1188*	0.2236 (7.02) *0.0864*
Metro	0.1625 (10.03) *0.0523*	0.0725 (4.83) *0.0277*	0.1171 (6.56) *0.0353*	0.0400 (2.44) *0.0153*	0.1288 (7.86) *0.0410*	0.0487 (3.21) *0.0185*
HouseholdSize	-0.0071 (1.53) *-0.0022*	-0.0680 (16.37) *-0.0261*	-0.0341 (6.47) *-0.0101*	-0.0865 (18.49) *-0.0331*	-0.0233 (4.91) *-0.0072*	-0.0810 (18.88) *-0.0309*
Asian	0.0099 (0.29) *0.0031*	-0.2308 (8.36) *-0.0855*	0.0631 (1.64) *0.0182*	-0.2081 (6.93) *-0.0771*	0.0403 (1.17) *0.0124*	-0.2183 (7.85) *-0.0801*
AmericanIndian	-0.0666 (1.13) *-0.0213*	-0.1425 (2.28) *-0.0535*	0.0379 (0.61) *0.0109*	-0.1369 (2.05) *-0.0513*	-0.0359 (0.61) *-0.0113*	-0.1253 (2.00) *-0.0467*
Black	-0.2668 (12.62) *-0.0893*	-0.3540 (15.20) *-0.1289*	-0.1850 (7.79) *-0.0576*	-0.3476 (13.69) *-0.1262*	-0.2238 (10.49) *-0.0738*	-0.3376 (14.41) *-0.1217*
Hispanic	-0.4569 (20.71) *-0.1591*	-0.2418 (9.76) *-0.0898*	-0.3812 (15.82) *-0.1248*	-0.2165 (8.18) *-0.0804*	-0.4027 (18.09) *-0.1383*	-0.2203 (8.83) *-0.0811*
SomeCollege	0.2911 (16.11) *0.0850*	0.2630 (16.70) *0.1027*	0.2768 (13.83) *0.0759*	0.2675 (15.66) *0.1043*	0.2645 (14.50) *0.0773*	0.2570 (16.23) *0.0997*
AssociateDegree	0.2197 (8.44) *0.0641*	0.3632 (17,41) *0.1431*	0.1980 (6.94) *0.0544*	0.3582 (15.93) *0.1409*	0.1817 (6.92) *0.0534*	0.3540 (16.88) *0.1388*
BachelorsDegree	0.6119 (26.97) *0.1613*	0.6222 (38.37) *0.2439*	0.5099 (19.92) *0.1290*	0.5845 (32.96) *0.2291*	0.5505 (23.84) *0.1469*	0.5920 (36.21) *0.2316*
GraduateDegree	0.7178 (22.92) *0.1738*	0.7252 (35.73) *0.2830*	0.5715 (15.95) *0.1358*	0.6690 (30.10) *0.2620*	0.6299 (19.81) *0.1568*	0.6784 (33.01) *0.2655*
Female	0.0124 (0.94) *0.0039*	-0.0151 (1.34) *-0.0058*	0.0450 (3.08) *0.0133*	-0.0093 (0.76) *-0.0036*	0.0267 (2.01) *0.0083*	-0.0106 (0.94) *-0.0040*
Age	-0.0153 (37.20) *-0.0048*	-0.0080 (20.43) *-0.0031*	-0.0164 (35.40) *-0.0048*	-0.0088 (20.17) *-0.0034*	-0.0156 (37.75) *-0.0049*	-0.0086 (21.59) *-0.0033*
AtSchool	0.5638 (14.31) *0.1424*		0.5630 (12.27) *0.1313*		0.5578 (13.78) *0.1402*	
PCWork	1.2172 (63.00) *0.3245*		1.0861 (51.88) *0.2799*		1.1701 (59.59) *0.3121*	
PCHome	2.1811 (152.26) *0.6821*		2.0529 (128.76) *0.6417*		2.1331 (146.20) *0.6685*	
Constant	-0.1959 (0.47)	-0.5155 (1.52)	0.1773 (0.39)	-0.4945 (1.35)	-0.3344 (0.80)	-0.4299 (1.26)
Observations	109103	70540	91593	60935	109103	70540
Sum of Weights	211803532	135665305	176834253	116331158	211803532	135665305
Chi-square (degrees of freedom)	29860.78 (16)	2854.60 (13)	25215.73 (23)	2627.41 (20)	29953.45 (23)	3047.98 (20)
Rho (standard error)	-0.4844 (0.0149)		-0.4644 (0.0179)		-0.4454 (0.0160)	

* t-statistics based on robust standard errors are in parentheses. Marginal effects, or the impact of the covariate on the relevant probability, are in italics.

Table 6. Results (II)*

Independent Variable	1		2	
	InternetUse	EPurchase	InternetUse	EPurchase
(1+SalesTaxRate)	-0.6876 (1.61) *-0.2064*	0.6008 (1.75) *0.2351*	-0.2463 (0.63) *-0.0781*	0.4845 (1.52) *0.1891*
Income (10000-20000)	-0.0291 (0.90) *-0.0088*	-0.0500 (1.13) *-0.0195*	-0.0407 (1.42) *-0.0130*	-0.0346 (0.96) *-0.0134*
Income (20000-30000)	0.1416 (4.59) *0.0408*	-0.0466 (1.14) *-0.0182*	0.0718 (2.62) *0.0223*	-0.0285 (0.85) *-0.0111*
Income (30000-40000)	0.2696 (8.49) *0.0745*	0.0408 (1.02) *0.0160*	0.1737 (6.18) *0.0525*	0.0113 (0.34) *0.0044*
Income (40000-50000)	0.3668 (10.74) *0.0974*	0.0731 (1.80) *0.0288*	0.2271 (7.53) *0.0674*	0.0463 (1.38) *0.0181*
Income (50000-60000)	0.3987 (11.54) *0.1046*	0.1193 (2.95) *0.0470*	0.2660 (8.69) *0.0779*	0.0954 (2.86) *0.0375*
Income (60000-75000)	0.5480 (15.57) *0.1362*	0.1565 (3.88) *0.0618*	0.4029 (13.00) *0.1129*	0.1205 (3.65) *0.0474*
Income (75000 and up)	0.7694 (23.60) *0.1949*	0.3610 (9.32) *0.1425*	0.5142 (18.82) *0.1470*	0.3263 (10.51) *0.1286*
Metro	0.1403 (7.92) *0.0432*	0.0731 (4.56) *0.0285*	0.1601 (9.88) *0.0521*	0.0877 (5.90) *0.0340*
HouseholdSize	-0.0506 (9.80) *-0.0152*	-0.1181 (25.71) *-0.0462*	-0.0379 (8.15) *-0.0120*	-0.1110 (26.37) *-0.0433*
Asian	0.1237 (3.31) *0.0355*	-0.1090 (3.75) *-0.0421*	0.1024 (3.04) *0.0314*	-0.1254 (4.65) *-0.0482*
AmericanIndian	0.0200 (0.33) *0.0060*	-0.1562 (2.40) *-0.0600*	-0.0583 (1.00) *-0.0188*	-0.1468 (2.40) *-0.0562*
Black	-0.1903 (8.17) *-0.0603*	-0.3188 (12.95) *-0.1201*	-0.2361 (11.29) *-0.0794*	-0.3125 (13.76) *-0.1174*
Hispanic	-0.4108 (17.27) *-0.1374*	-0.2244 (8.66) *-0.0858*	-0.4382 (19.91) *-0.1535*	-0.2361 (9.66) *-0.0897*
Female	0.0506 (3.52) *0.0152*	-0.0128 (1.08) *-0.0050*	0.0270 (2.07) *0.0086*	-0.0176 (1.59) *-0.0069*
Age	-0.0162 (35.31) *-0.0049*	-0.0066 (15.79) *-0.0026*	-0.0152 (32.79) *-0.0048*	-0.0063 (16.69) *-0.0025*
AtSchool	0.5165 (11.08) *0.1261*		0.5091 (12.39) *0.1339*	
PCWork	1.1776 (58.53) *0.3061*		1.2767 (67.61) *0.3423*	
PCHome	2.0595 (129.74) *0.6486*		2.1404 (147.45) *0.6755*	
Constant	0.1073 (0.24)	-0.2880 (0.80)	-0.3857 (0.94)	-0.2005 (0.60)
Observations	91593	60935	109103	70540
Sum of Weights	176834253	116331158	211803532	135665305
Chi-square (degrees of freedom)	25269.80 (19)	1388.78 (16)	30074.75 (19)	1532.98 (16)
Rho (standard error)	-0.5485 (0.0154)		-0.5279 (0.0138)	

* t-statistics based on robust standard errors are in parentheses. Marginal effects, or the impact of the covariate on the relevant probability, are in italics.

Table 7. Results (III)*

	1		2
Independent Variable	**InternetUse**	**EPurchase with Inverse Mills'Ratio from IntenretUse equation**	**EPurchase with Pr(InternetUse=1)**
(1+SalesTaxRate)	-0.3095 (0.77) *-0.0970*	0.4851 (1.47) *0.1851*	0.4876 (1.47) *0.1860*
Income (10000-20000)	-0.0332 (1.12) *-0.0105*	-0.0153 (0.40) *-0.0058*	-0.0134 (0.35) *-0.0051*
Income (20000-30000)	0.0697 (2.47) *0.0215*	-0.0097 (0.27) *-0.0037*	-0.0063 (0.18) *-0.0024*
Income (30000-40000)	0.1609 (5.57) *0.0482*	0.0190 (0.54) *0.0073*	0.0214 (0.61) *0.0082*
Income (40000-50000)	0.2056 (6.66) *0.0606*	0.0424 (1.19) *0.0162*	0.0442 (1.25) *0.0169*
Income (50000-60000)	0.2325 (7.36) *0.0679*	0.0740 (2.11) *0.0285*	0.0755 (2.15) *0.0291*
Income (60000-75000)	0.3684 (11.40) *0.1029*	0.0732 (2.10) *0.0281*	0.0741 (2.13) *0.0285*
Income (75000 and up)	0.4318 (15.15) *0.1243*	0.2179 (6.64) *0.0838*	0.2188 (6.68) *0.0842*
Metro	0.1335 (8.08) *0.0430*	0.0482 (3.11) *0.0183*	0.0478 (3.08) *0.0182*
HouseholdSize	-0.0269 (5.63) *-0.0084*	-0.0838 (19.07) *-0.0320*	-0.0844 (19.19) *-0.0322*
Asian	0.0268 (0.78) *0.0083*	-0.2240 (7.93) *-0.0824*	-0.2241 (7.93) *-0.0824*
AmericanIndian	-0.0217 (0.36) *-0.0068*	-0.1255 (1.97) *-0.0469*	-0.1251 (1.97) *-0.0467*
Black	-0.2294 (10.71) *-0.0759*	-0.3437 (14.32) *-0.1240*	-0.3417 (14.24) *-0.1233*
Hispanic	-0.4050 (18.09) *-0.1392*	-0.2231 (8.70) *-0.0822*	-0.2202 (8.59) *-0.0812*
SomeCollege	0.2777 (15.09) *0.0815*	0.2623 (16.36) *0.1018*	0.2610 (16.29) *0.1013*
AssociateDegree	0.2002 (7.56) *0.0589*	0.3623 (17.07) *0.1422*	0.3614 (17.02) *0.1418*
BachelorsDegree	0.5806 (24.95) *0.1546*	0.5978 (36.31) *0.2332*	0.5975 (36.32) *0.2331*
GraduateDegree	0.6696 (20.72) *0.1654*	0.6837 (33.08) *0.2674*	0.6829 (33.07) *0.2671*
Female	0.0265 (1.98) *0.0083*	-0.0111 (0.96) *-0.0042*	-0.0108 (0.94) *-0.0041*
Age	-0.0157 (37.94) *-0.0049*	-0.0087 (21.42) *-0.0033*	-0.0086 (21.19) *-0.0033*
AtSchool	0.6076 (14.71) *0.1512*		
PCWork	1.1406 (56.67) *0.3055*		
PCHome	2.1535 (147.28) *0.6724*		
Constant	0.4212 (1.00)	-0.4264 (1.23)	-1.3886 (3.97)
Observations	109103	70540	70540
Sum of weights	211803532	135665305	135665305
Chi-square (degrees of freedom)	29953.45 (23)	5168.81 (21)	5258.72 (21)

* t-statistics based on robust standard errors are in parentheses. Marginal effects, or the impact of the covariate on the relevant probability, are in italics.

Table 8. Results (IV)*

Independent Variable	1		2	
	InternetatHome	EPurchase	InternetOutsideHome	EPurchase
(1+Sales Tax Rate)	-0.3385 (1.19) *-0.1330*	0.5613 (1.80) *0.2170*	-0.6076 (1.77) *-0.1940*	0.8833 (2.05) *0.3524*
Income (10000-20000)	0.0973 (4.22) *0.0379*	-0.0715 (2.04) *-0.0278*	-0.0559 (1.80) *-0.0176*	-0.0460 (0.95) *-0.0184*
Income (20000-30000)	0.2751 (12.41) *0.1054*	-0.1489 (4.56) *-0.0582*	-0.0375 (1.27) *-0.0119*	-0.0174 (0.39) *-0.0070*
Income (30000-40000)	0.5066 (22.58) *0.1873*	-0.2482 (7.63) *-0.0975*	-0.0646 (2.16) *-0.0203*	0.0152 (0.34) *0.0061*
Income (40000-50000)	0.6708 (28.36) *0.2388*	-0.3018 (9.08) *-0.1189*	-0.0229 (0.75) *-0.0073*	0.0605 (1.34) *0.0241*
Income (50000-60000)	0.7744 (32.50) *0.2693*	-0.3114 (9.35) *-0.1228*	-0.0269 (0.89) *-0.0085*	0.0944 (2.13) *0.0376*
Income (60000-75000)	0.9080 (37.90) *0.3060*	-0.3562 (10.69) *-0.1405*	-0.0446 (1.47) *-0.0141*	0.1217 (2.78) *0.0484*
Income (75000 and up)	1.0421 (48.23) *0.3629*	-0.2811 (8.84) *-0.1100*	0.0872 (3.16) *0.0283*	0.2518 (6.13) *0.0999*
Metro	0.1501 (12.31) *0.0593*	-0.0329 (2.27) *-0.0127*	0.0080 (0.52) *0.0025*	0.0965 (4.70) *0.0385*
HouseholdSize	0.1165 (31.13) *0.0458*	-0.1210 (29.47) *-0.0468*	-0.0579 (13.59) *-0.0185*	-0.0535 (9.40) *-0.0213*
Asian	0.0951 (3.61) *0.0370*	-0.2382 (8.89) *-0.0938*	-0.1098 (3.75) *-0.0339*	-0.1026 (2.73) *-0.0409*
AmericanIndian	-0.3010 (5.89) *-0.1196*	0.0797 (1.29) *0.0305*	0.0611 (1.01) *0.0199*	-0.2368 (2.90) *-0.0936*
Black	-0.5615 (33.94) *-0.2208*	-0.0259 (1.09) *-0.0100*	-0.0994 (4.85) *-0.0309*	-0.3899 (13.32) *-0.1528*
Hispanic	-0.6272 (35.08) *-0.2454*	0.0664 (2.66) *0.0255*	-0.2328 (10.65) *-0.0693*	-0.2004 (6.02) *-0.0796*
SomeCollege	0.3346 (25.29) *0.1277*	0.0666 (4.05) *0.0256*	0.3199 (19.95) *0.1084*	0.2118 (9.59) *0.0841*
AssociateDegree	0.3675 (19.74) *0.1381*	0.1230 (5.71) *0.0468*	0.1677 (7.48) *0.0559*	0.3158 (10.68) *0.1244*
BachelorsDegree	0.4971 (32.29) *0.1850*	0.2879 (15.51) *0.1077*	0.5201 (30.80) *0.1826*	0.4883 (20.84) *0.1902*
GraduateDegree	0.5925 (28.36) *0.2133*	0.3351 (14.72) *0.1233*	0.7042 (32.13) *0.2577*	0.5452 (19.18) *0.2093*
Female	-0.0130 (1.34) *-0.0051*	0.0124 (1.15) *0.0048*	-0.0331 (2.85) *-0.0106*	-0.0449 (2.97) *-0.0179*
Age	-0.0081 (25.81) *-0.0032*	-0.0036 (8.73) *-0.0014*	-0.0254 (55.23) *-0.0081*	-0.0010 (1.60) *-0.0004*
AtSchool	-0.0365 (1.46) *-0.0144*		1.1489 (43.88) *0.4305*	
InternetOutsideHome	0.5378 (51.44) *0.2053*			
InternetatHome			0.4040 (29.26) *0.1265*	
PCWork			1.7632 (140.12) *0.5850*	
Constant	-0.4500 (1.50)	0.3431 (1.05)	0.2376 (0.66)	-0.9716 (2.14)
Observations	109103	60904	109103	38379
Sum of weights	211803532	117455191	211803532	73358618
Chi-square (degrees of freedom)	20199.19 (22)	1942.85 (20)	32042.99 (23)	1257.12 (20)
Rho (standard error)	-0.7985 (0.0118)		-0.3237 (0.0177)	

* t-statistics based on robust standard errors are in parentheses. Marginal effects, or the impact of the covariate on the relevant probability, are in italics.