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El Paso's Digital Divide: A Multivariate Analysis of Computer Ownership and Internet Access from Home in El Paso County

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A Multivariate Analysis of Computer Ownership and Internet Access from Home in El Paso County

By

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Overview:

A variety of groups in El Paso, Texas have long been interested in a county-wide technology usage and access survey. In large part, the interest stems from the original *Digital Divide* study conducted by the National Telecommunications and Information Administration (NTIA) in 1995. This first study, *Falling through the Net: A Survey of the "Have Nots" in Rural and Urban America*, showed how African Americans, Hispanics, and—at the time—women trailed behind their white, male, more affluent counterparts in terms of computer ownership and Internet access. Subsequent NTIA studies released in 1998, 2000, and 2002[1] showed significant gains among minorities and low-income groups in terms of improved access; but they still trailed well behind their more affluent non-minority counterparts. More importantly, the limited data available suggest that as an underserved community, El Paso may be at even greater risk as technology becomes a cornerstone of the modern education and workplace environments. Only recently, however, has the funding become available to conduct such a study. The Institute for Policy and Economic Development (IPED) at the University of Texas at El Paso (UTEP), El Paso Electric, El Paso Water Utilities, and El Paso County 911 incurred all costs for this study in order to provide a baseline for technology use in El Paso County.

One year after the most recent NTIA study, El Paso lags behind the rest of the U.S. in terms of computer ownership and Internet access, although local Hispanics are doing at least as well (or better) than Hispanics nationally. More important, however, are the factors that influence computer ownership and Internet access at the local level, where local taxes and local officials, not federal intervention, assist in regional economic development and provide the access many poor children have to technology in school. The findings below suggest that income and education, as at the national level, continue to be the most important factors in determining whether a household owns a computer or has Internet access, while being of Hispanic origin does not. The level to which these factors explain that access in El Paso is surprising.

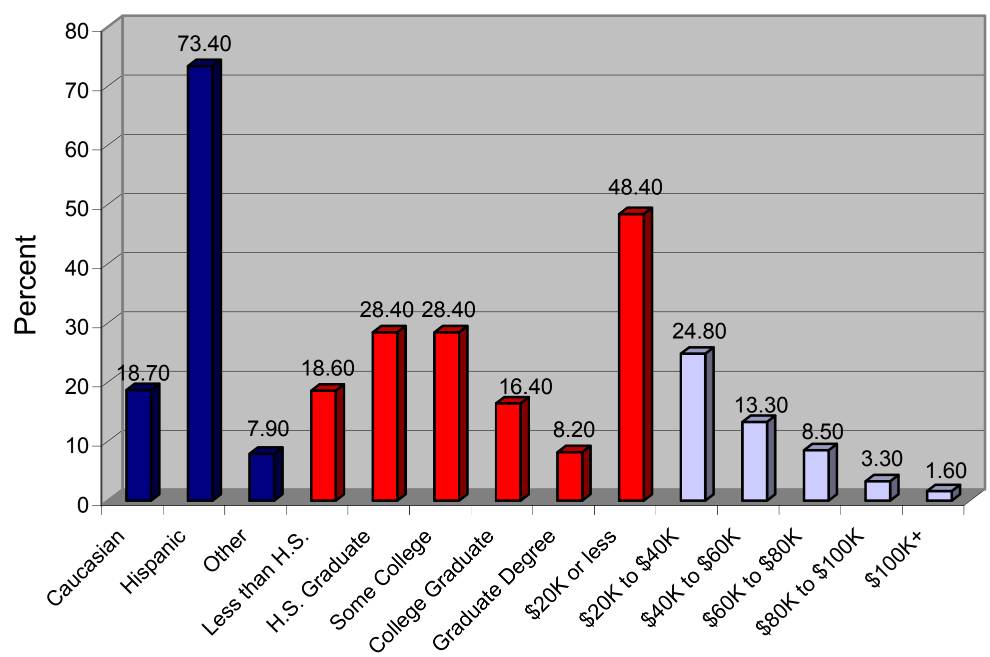
Methodology and Participants:

The survey was conducted from September 16th through the 28th, 2002, using a Random Digit Dialing (RDD) sample of El Paso County phone numbers that was pre-tested for disconnects and fax machines. With random digit dialing, every household with a working phone within a county has an equal probability of being selected, as the numbers are generated *at random* based only on the working prefixes (first three numbers) for a selected area. In total, 609 surveys were completed. All interviewers were bilingual in English and Spanish, and calls were made from 12:00 p.m. to 8:00 p.m. each day, Monday through Sunday. Potential participants were informed of the purpose of the study, that participation was voluntary, and that all responses would remain confidential and reported only in the aggregate.

At the 95 percent confidence level, a county-wide sample of 609 provides an accuracy level of plus or minus four percent of the mean (i.e., a range of 96 percent to 104 percent of the county-wide mean). The ninety-five percent confidence level can be interpreted to mean only that if the above interval was constructed for many different samples of the same sample size, for approximately 95 percent of the samples, the interval would include the unknown population mean. Further, all statistical procedures below have sufficient power at the α = .05 level, as effect sizes (R^2) of .10 have power of .80 with 110 subjects.

Participants generally mirrored the demographic and socioeconomic composition of El Paso County in the 2000 Census (Chart 1). Over 73 percent (73.4) of the sample were Hispanic, followed by Whites, who composed 18.7 percent of the sample. The remainder was made up of 7.9 percent self-identifying as "Other." The largest income group reported a total household income of $20,000 or less (48.4 percent). Twenty-five percent (24.8) had household incomes between $20,000 and $40,000; 13.3 percent earned between $40,000 and $60,000; 8.5 percent earned between $60,000 and $80,000; 3.3 percent earned between $80,000 and $100,000; and 1.6 percent earned above $100,000. The majority of the sample also fell into lower education categories. Nearly a fifth (18.6 percent) had less than a high school education, and 28.4 percent graduated from high school. More than a quarter (28.4 percent) had some college (includes technical school training), followed by 16.4 percent who held at least a bachelor's degree. Eight (8.2) percent of the sample had a graduate degree.

Chart 1: Sample Ethnicity, Education, and Income

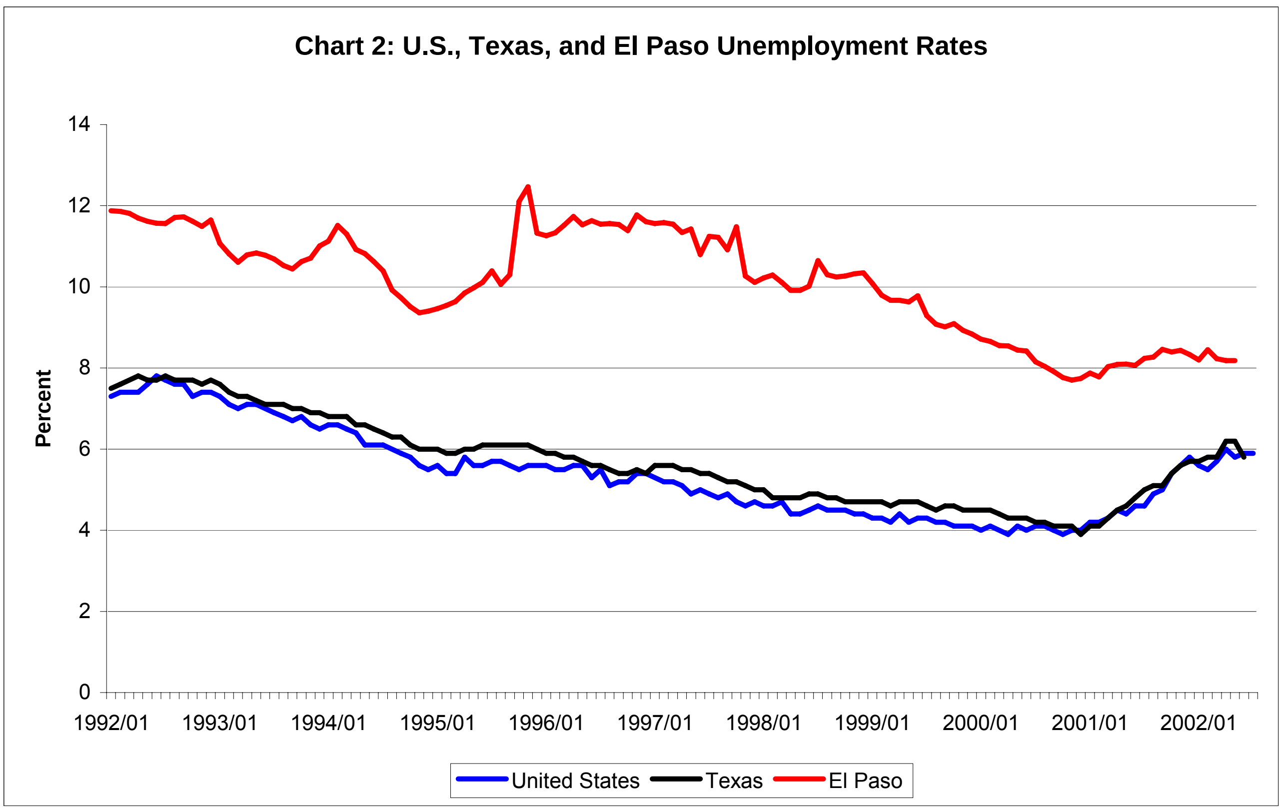


El Paso, Texas

El Paso, Texas is located in far West Texas along the U.S. –Mexico Border and sits just across the Rio Grande from Ciudad Juarez, Chihuahua Mexico. In 2001, just under 690,000 people lived in El

Paso,[2] less than was estimated prior to the 2000 Census when over 700,000 were expected. This mismatch begins to tell part of the El Paso story. From 1990 through about 1994 El Paso experienced relatively strong growth both in terms of birth rates and in-migration. After 1994, however, El Paso actually had a negative migration rate. Explanations for the exodus abound, but many point to higher salaries in other metropolitan areas and El Paso's relatively high unemployment rate, which typically hovers two to three points above the national and state rates (Chart 1). As of December 2002, El Paso's unemployment rate climbed above nine percent (9.1),[3] well above the state rate of 6.5 percent.[4]

El Paso's weak economy was brought about by a variety of factors. For close to two decades (1970s and 1980s), the city hinged its future on the low wage garment industry, and when companies like Levi Strauss finally moved on in search of even lower wages in South America, very few groups were prepared to develop a new economic base. The recovery has been a slow one, but as of yet the13 percent unemployment rates of 1996 have yet to return. This is in part a function of the evolution of the local economy to a service base, but many obstacles must still be overcome if the transition is to be made.



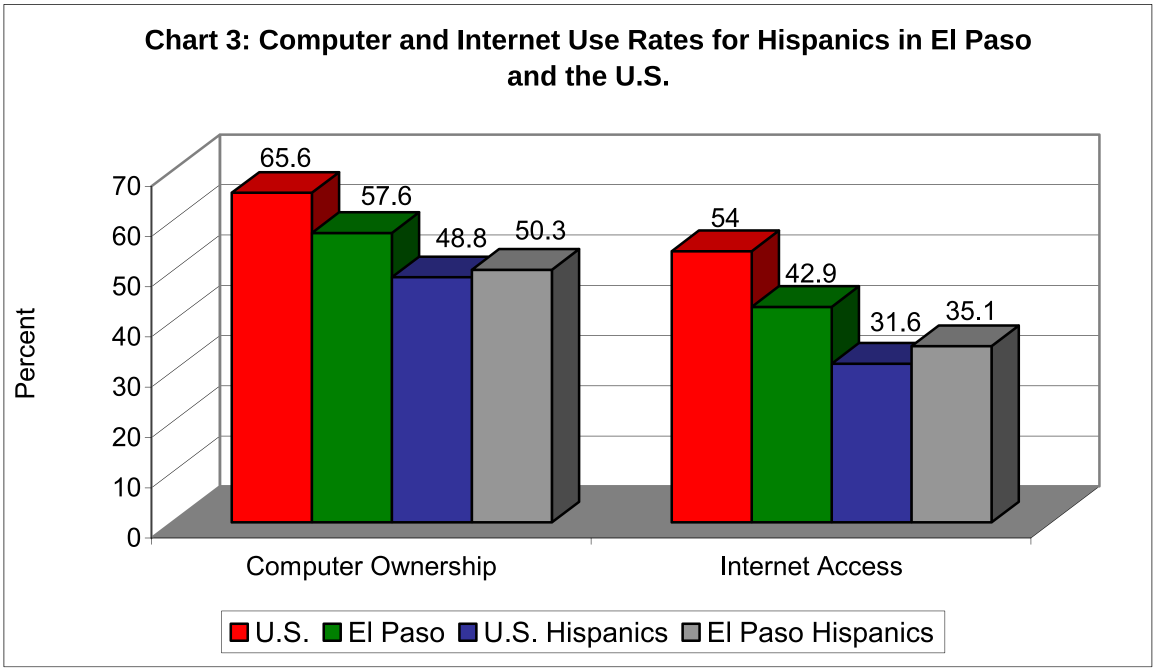
Source: Bureau of Labor Statistics

Most important is El Paso's educational attainment rate. Aside from the strong correlation between education and income along the U.S. Mexico border,[5] a well educated and population ensures that industries that do locate to an area can find trained employees. Thus far, fixing the educational pipeline locally has met with mixed results. As of 2000, El Paso trailed both the state and nation in the percentage of the population with high school degrees. Only 65.8 percent had graduated from high school, compared to 75.7 and 80.4 percent at the state and national level, respectively. The same trend is evident for those with bachelor's degrees or higher. In 2000, only 16.6 percent of El Paso residents had four year college degrees, far less than state (23.2 percent) and national (24.4 percent) averages.

Not surprisingly, the above challenges have led to lower overall income rates and higher poverty rates. El Paso's median household income in 1999 was $31,051, 77 and 74 percent of the state ($39,927) and national ($41,994) totals, respectively. Per capita income figures are even more disturbing, as El Paso's per capita income level is only 62 percent of the national amount. Poverty figures tell a similar story; in the 2000 Census, 23.8 percent of El Paso residents fell below the federal poverty limit. Texas had only 15.4 percent of its population below the poverty level, while the U.S. average was even lower at 12.4 percent.

How El Paso Compares[6]:

Although the most recent NTIA study is over a year old, it is still useful for El Paso to compare itself to the rest of the nation, where income, education, age, and ethnicity each play a significant role in explaining computer ownership and Internet access. Nationwide in 2001, 65.6 percent of households owned computers, compared to 57.6 percent of households in El Paso. Hispanics in El Paso actually fared better than their U.S counterparts, with 50.3 percent reporting that they owned computers, although this figure is well within the margin of error for this study. The same general trend holds true for Internet access. Across the nation, fifty-four percent of homes had Internet access in 2002, compared to 42.9 percent for El Paso. El Paso Hispanics also had somewhat higher Internet use rates (35.1percent) than Hispanics nationally (31.6 percent). Neither of the findings is surprising, however, given that El Paso's Hispanic community is largely heterogeneous, as would be expected in any county where the largest ethnic group makes up 78 percent of the total population.[7]



For El Paso, the real question is whether the same predictors used at the national level (income, education, age, and ethnicity) help to explain computer ownership and Internet access locally. To this same end, the 1999 NTIA study adopted binary logistic regression as its primary explanatory tool. This statistical procedure allows researchers to specify a model that explains, at least in part, the variability of the dependent variable in terms of the probabilities of an attribute being absent or present. For the discussion below, computer ownership and Internet access from home are either absent (coded 0) or present (coded 1).

Statistical Overview:

Income, education, age, and ethnicity variables are fit sequentially to a binary logistic model. The order the variables are added to the model generally follows the importance assigned to each predictor by the NTIA. Unlike traditional multiple regression analysis, logistic regression is used when the dependent variable is dichotomous, coded 0-1, and is intended to indicate the absence or presence of some attribute. Like traditional multiple regression, it can provide the "expected" value of Y. This expected value of Y is "equivalent to the probability of Y."[8] The probability of an event happening (between 0 and 1) is then given by $f(z) = 1/1 + e^{-z}$, where $z = \beta_0 + \sum_{j=1}^{k} \beta_j X_j$ [9].

The statistical significance of both the model as a whole and individual predictors can be evaluated several ways. In the analysis below, overall model significance will be evaluated using the chi-square statistic (χ^2). The Wald statistic, which is given by $\hat{\beta}_1 / \sqrt{\hat{Var}\,\hat{\beta}_1}$ and has a distribution similar to that of the chi square with large samples, functions in the same manner as *t* statistics in traditional multiple regression and will be used to judge the significance of individual predictors.

Statistical significance, however, is simply a function of sample size[10]; what is more important are measures of effect size. Classical multiple regression uses R^2, the closest analog to which in logistic regression is the Nagelkerke R^2.[11] As an analog to classical R^2, this statistic can generally be understood to mean that the given set of predictors explain *x* amount of variability in the dependent variable *Y*. However, one of the strengths of logistic regression is its ability to predict the presence or absence of some attribute. As such, the percentage predicted correct given by the model becomes important as well, so long as the predictors are statistically significant. Significant increases (in a practical, not statistical sense) in the predictive power of the model over the constant suggest that the model is effective.

Findings:

Two different sets of equations were fit for this evaluation. The first includes income, education, age, and ethnicity sequentially as independent variables in models with computer ownership and Internet access from home as dependent variables, respectively. Table 1 provides a summary for each of the models discussed below and can be found at the end of the models discussion. Detailed tables including additional measures of model fit and confidence intervals are included for each step of the analysis below in Appendix 1.

Computer Ownership

Equation one uses only income as a predictor of computer ownership. The income variable had six possible response categories:[12] \$0 to \$20,000; \$20,000 to \$40,000; \$40,000 to \$60,000; \$60,000 to \$80,000; \$80,000 to \$100,000; and \$100,000 and above. This model is presented below, along with the fitted values:

$$logit\ [pr(Y=1)] = \beta_0 + \beta_1(income)$$

$$logit\ [pr(Y=1)] = -1.427 + .965(income)$$

Both the model and income variable are statistically significant beyond the $p = .005$ level (χ^2 [1] = 122.012 $p<.005$; $Wald$[1] = 80.909 $p<.005$). More revealing is the fact that with income alone, the model explains 24.4 percent of the variability in computer ownership (*Naglekerke* R^2) and correctly predicts 70 percent of all cases, which is somewhat better than the 57.6 percent predicted correctly with only the constant included. Not surprisingly, the coefficient for income is positive, suggesting that as income increases the probability of owning a computer also increases.

Equation two adds education to the model. Response categories for education included: less than high school, high school graduate, some college, college graduate, and graduate degree. In this iteration, the model and each individual predictor are again statistically significant beyond the *p = .005* level (χ^2 [2] = 145.754 *p*<.005; Income, *Wald*[1] = 51.650 *p*<.005, Education, *Wald*[1] = 22.580 *p*<.005). The overall variability in computer ownership explained by the equation increases by about 4 percent (*Naglekerke* R^2 = .286), while the model's predictive power increases only slightly to 70.3 percent. While the increase in predictive power is low, the increase in variability explained along with the statistical significance of the education variable would suggest that no heuristic standards for model parsimony are being violated. The coefficients for both independent variables are again positive, which would suggest a positive correlation between income and educational attainment and computer ownership. The fitted equation is presented below.

$$logit\ [pr(Y=1)] = \beta_0 + \beta_1(income) + \beta_2(education)$$
$$logit\ [pr(Y=1)] = -.221 + .799(income) + .423(education)$$

Equation three adds an age variable, which is divided into five possible response categories: 18-25, 25-39, 40-49, 50-59, and 60 and above. The model and each of the individual predictors is statistically significant (χ^2 [3] = 156.592 *p*<.005; Income, *Wald*[1] = 52.556 *p*<.005, Education, *Wald*[1] = 22.820 *p*<.005; Age, *Wald*[1] = 10.595 *p*<.005), while variability explained and percentage predicted correct also increase to 30.5 percent and 70.9, respectively. Examining the fitted model below shows that as people get older, the probability of their owning a computer decreases. This finding is somewhat unexpected in that the correlation between education and income is well-documented, particularly along the border,[13] but each of these is also generally positively correlated with age.

$$logit\ [pr(Y=1)] = \beta_0 + \beta_1(income) + \beta_2(education) + \beta_3(age)$$
$$logit\ [pr(Y=1)] = -1.318 + .796\ (income) + .429(education) - .238(age)$$

The final variable included in this analysis was ethnicity. Since ethnicity cannot serve as a covariate, it was entered into the equation as a set of categorical dummy variables. Given El Paso's overall demographic composition the only ethnicity categories created were Hispanic, Caucasian, and Other. The variable for the Hispanic category was statistically insignificant, which seems contrary to NTIA research which suggests that there are true gaps between ethnic groups, but this is not surprising given the heterogeneity of El Paso's Hispanic population.

Internet Access from Home

As above, the first variable used as a predictor of Internet access from home is income. Both the model and income variable are statistically significant (χ^2[1] = 149.991 *p*<.005; *Wald*[1] = 104.244

p<.005). The variability explained (*Naglekerke* R^2 = .293) is higher than equations one and two above, and the percentage predicted correct (73.7 percent) is higher than in any of the three computer ownership equations (the baseline here is 57.1 percent correct with only the constant in the model). The coefficient is again positive, suggesting that as income increases, so does the probability of having home Internet access.

$$logit\ [pr(Y=1)] = \beta_0 + \beta_1(income)$$

$$logit\ [pr(Y=1)] = -2.2 + .979(income)$$

The education variable is also statistical, as is the model at this step (χ^2 [2] = 176.917 *p*<.005; Income, *Wald*[1] = 67.260 *p*<.005, Education, *Wald*[1] = 25.859 *p*<.005). Both the variability explained by the model (*Naglekerke* R^2 = .338) and the percentage predicted correct (74.4 percent) are higher than any of the computer ownership equations above. The coefficients for both independent variables are positive.

$$logit\ [pr(Y=1)] = \beta_0 + \beta_1(income) + \beta_2(education)$$

$$logit\ [pr(Y=1)] = -3.133 + .817(income) + .461(education)$$

When age is included in equation three, results are similar to those above. The model and each of the three predictors is statistically significant (χ^2 [3] = 183.314 *p*<.005; Income, *Wald* [1] = 68.669 *p*<.005, Education, *Wald*[1] = 26.358; Age, *Wald*[1] = 6.267 *p* =.012), and the coefficient for age is again negative.

$$logit\ [pr(Y=1)] = \beta_0 + \beta_1(income) + \beta_2(education) + \beta_3(age)$$

$$logit\ [pr(Y=1)] = -2.450 + .823\ (income) + .470(education) - .190(age)$$

The remainder of the results, however, are mixed. The *Naglekerke* R^2 value increases to .349, which one would expect from the addition off a statistically significant independent variable; but the percentage predicted correctly drops slightly to 73.1. It should be noted that percentage predicted correct is a qualitative measure of model effectiveness that is determined by the "cut point" in probability of the attribute being present (.5 here). As the other measures described above are statistical, the incongruence, particularly given only a small drop in correctly predicted cases, is of little consequence.

Ethnicity is used as the final predictor of Internet access from home. Entered as a categorical variable, the category for Hispanic is again statistically insignificant. These findings are most likely again due the heterogeneity of El Paso's Hispanic population.

Table 1: Model Summaries

Model	Predictor Variables	B	Wald	Significance	*Naglekerke* R^2 /PPC	Chi-Square	Model Significance
Computer Ownership							
logit [pr(Y=1)] = β_0 *+* β_1*(income)*	Constant Income	-1.427 .965	53.508 80.909	.000 .000	.244/70.0	122.012	.000
logit [pr(Y=1)] = β_0 *+* β_1*(income)+* β_2*(education)*	Constant Income Education	-2.221 .799 .423	69.813 51.658 22.580	.000 .000 .000	.286/70.3	145.754	.000
logit [pr(Y=1)] = β_0 *+* β_1*(income)+* β_2*(education)+* β_3*(age)*	Constant Income Education Age	-1.318 .796 .429 -.238	12.307 52.556 22.820 10.595	.000 .000 .000 .001	.305/70.9	156.592	.000
logit [pr(Y=1)] = β_0 *+* β_1*(income)+* β_2*(education)+* β_3*(age)+* β_4*(Hisp)+* β_5*(White)+* β_6*(Other)*[14]	Constant Income Education Age Hispanic White Other	-.322 .753 .353 -.306 -.636 .186 N/A	.596 46.289 14.285 15.387 .2494 .166 .012	.596 .000 .000 .000 .114 .683 .012	.320/72.6	165.672	.000
Internet Access from Home							
logit [pr(Y=1)] = β_0 *+* β_1*(income)*	Constant Income	-2.2 .979	119.557 104.244	.000 .000	.293/73.7	149.991	.000
logit [pr(Y=1)] = β_0 *+* β_1*(income)+* β_2*(education)*	Constant Income Education	-3.133 .817 .461	116.854 67.260 25.859	.000 .000 .000	.338/74.4	176.917	.000
logit [pr(Y=1)] = β_0 *+* β_1*(income)+* β_2*(education)+* β_3*(age)*	Constant Income Education Age	-2.450 .823 .470 -.190	39.506 68.669 26.358 6.267	.000 .000 .000 .012	.349/73.1	183.314	.000
logit [pr(Y=1)] = β_0 *+* β_1*(income)+* β_2*(education)+* β_3*(age)+* β_4*(Hisp)+* β_5*(White)+* β_6*(Other)*[15]	Constant Income Education Age Hispanic White Other	-1.839 .788 .412 -.248 -.319 .369 N/A	9.744 61.772 18.757 9.475 .739 .797 6.234	.002 .000 .000 .002 .390 .372 .044	.359/74.1	189.575	.000

Discussion

The NTIA studies suggest a number of factors that influence computer ownership and Internet access from home. The most important of these, particularly at the local level, are income, education, age, and ethnicity. Understanding the importance of each of these variables can help to guide local policy implementation.

In attempting to predict computer ownership, there is no more important indicator than income. With only income information, 70 percent of computer owners in the sample were correctly identified.

These findings are not surprising, however, in that most technological tools are expensive, and the higher a household's income the more likely they are to own a computer. What is somewhat surprising is the level of importance that income plays, explaining approximately 25 percent (24.4) of the variability in computer ownership.

While education is also important in predicting computer ownership, its explanatory power is far less pronounced. Once included in the model, predictive power increases by only three tenths of one percent to 70.3, while overall variability explained increases only slightly by about four percent to 28.6. In a practical sense, the influence of education can easily be explained; increasing years of education, particularly in the educational setting of the past decade, have introduced a variety of new technologies to students. As those tools become important in education, the same tools often become an important part of life at home.

Age also plays an important role in predicting computer ownership, but in the opposite direction of income and education. As a person gets older, the probability of his or her owning a computer actually decreases, although not markedly. The predictive power of the computer ownership model only increases by about six-tenths of one percent to 70.9, and the amount of variability explained also increases only slightly to 30.5 percent.

Perhaps the most interesting finding for each of the sets of equations tested was the fact that ethnicity played no role in predicting computer ownership once the effects of income, education, and age had been accounted for. There has long been an interest in increasing minority access to technology, and federal programs at agencies ranging from NASA to the Department of Education have invested significantly in this goal. It would seem, however, that the correlation between income and ethnicity has far more to do how these programs are funded than between the correlation, at least in El Paso, between ethnicity and computer ownership. No doubt these programs are needed, but program implementation at the local level should pay special attention to the fact access should not necessarily be defined by ethnicity.

No one should be surprised that each of the trends discussed above plays out when attempting to predict Internet access from home, nor should they be surprised that the most important predictor is again income. Income alone plays a stronger role in predicting Internet access than it does computer ownership, correctly identifying 73.7 percent of the sample who had Internet access from home. The overall variability explained by income was also higher at 29.3 percent.

When education is entered into the model, predictive power and variability explained increase only slightly to 74.4 and 33.8 percent, respectively. What is somewhat surprising here is the fact that with education and income information, three-quarters of all households with Internet access from home were correctly identified.

The increased predictive power of the model with age included is minimal, but what is again more interesting is the fact that age is negatively correlated with the probability of having Internet access from home, especially given the fact that the predictive power of the model actually decreases slightly.

Not surprisingly, ethnicity again plays no role in predicting computer ownership from home one the effects of income, education, and age have been accounted for. The same conclusions drawn above for computer ownership would seem applicable here.

Conclusions:

Following the release of each of the NTIA studies, a broad range of measures were implemented by both private organizations and the federal government to address the "Digital Divide." A good portion of these measures are aimed at increasing minority access to technology, and programs range from increasing educator training in elementary and secondary schools to increasing specific types of access at the college level.[16] Such programs are well targeted in the sense that there is also a well documented correlation between income and ethnicity, but managers at the implementation (local) level should pay special attention to the fact that computer ownership and internet access seem to be more a function of income and education rather than ethnicity.

For some time, the idea that "softer variables" explain comfort with and use of new technologies has also existed.[17] The premise of this idea is that certain ethnic groups, due to "cultural" reasons, are less likely to own computers or actively use them, which would logically lead one to purchase Internet access. The data above suggest that at least between Hispanics and Whites no such differences exist. This may be unsettling to some, but in an ever changing educational and work environment, the findings above on ethnicity are encouraging, not the opposite.

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- Mathew S. McElroy, MPA, Assistant Director, IPED
- Beto O'Rourke, Vice President, Stanton Street Technology Group
- Raymond Perez, Assistant Director, El Paso County 911 District
- Ray Sanchez, Webmaster, County of El Paso
- Dennis L. Soden Ph.D., Executive Director, IPED
- Brooks Vandivort, Program Manager, Technology Planning and Distance Learning, UTEP

The above individuals assisted in the development of the survey instrument, particularly in terms of validity, as the primary goal of this project was to provide an accurate description of the technologies and tools El Pasoans are using. Comments on initial drafts of the survey were also provided by representatives of El Paso Electric and El Paso Water Utilities representatives.

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[4] Bureau of Labor Statistics. http://data.bls.gov/cgi-bin/surveymost. Seasonally adjusted.
[5] Fullerton, T.M. Jr. (2001). Educational Attainment and Border Income Performance. Federal Reserve Bank of Dallas *Economic and Financial Review*, Third Quarter, 1-10
[6] The initial IPED report for this study, "Survey of Technology Use in El Paso County," provides overall frequencies and percentages for 126 different variables that comprised the original survey instrument. This report can be found at http:.//iped.utep.edu.
[7] U.S. Census Bureau. 2000 Census. http://quickfacts.census.gov/qfd/states/48/48141.html
[8] Kleinbaum, David; Kupper, Lawrence; Muller, Keith; and Nizam, Azhar. (1998). *Applied Regression Analysis and Other Multivariable Methods*. Boston, Mass.: Duxbury Press.
[9] In long form, this formula is similar to that of traditional multiple regression:
logit $[pr(Y=1)] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 ... \beta_k X_k$
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[11] This value is reported in each of the analyses below instead of the Cox and Snell R^2, as the former has been corrected to take on values for the full range between 0 and 1.
[12] Scale items with 4 or more "equally" spaced options are generally considered linear and are widely accepted as appropriate for use as covariates in regression applications.
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[14] The actual model does not contain three categorical variables. The additional dummy included here is for reporting purposes only. In actuality, *k*-1 dummies are included for any variable with *k* groups.
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