individuals (so-called grouped or proportions data).[11] More specifically, we have data that are grouped at the ZCTA level. Accordingly, an observation in our analytical dataset is a vector $\{N_i, \overline{P_i}, T_i, \overline{X_i}\}$, $i = 1,...,N$, where N_i is the number of individuals living in ZCTA *i*, $\overline{P_i}$ is the proportion of those individuals who are SR subscribers (so-called penetration rate), T_i is the number of TR signals in ZCTA *i*, and $\overline{X_i}$ is set of observable characteristics that affect satellite radio penetration.[12] Specifically, we model the aggregate probabilistic relationship between SR penetration and the number of TR signals, accounting for other relevant factors, as a grouped-data probit:

$$\overline{P_i} = \Phi[g(T_i, \theta) + \beta \overline{X_i}] + \overline{\varepsilon_i} \quad (1)$$

where $\Phi[.]$ is the standard normal cumulative distribution, $g(.)$ is a flexible parameterization of the number of terrestrial radio signals, θ and β are parameters to be estimated, and $\overline{\varepsilon_i}$ is an error term.[13]

In our baseline specification, $\overline{X_i}$ consists of variables that we believe affect the demand for SR:

- Median income and median income squared.
- The percentage of people commuting by car.
- The percentage of people who live in urban areas.
- The interaction of the percentage commuting by car and the percentage living in urban areas.
- The percentage of females.

The variable of interest in this analysis is the number of terrestrial radio signals, T_i. We

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[11] At the individual level, the decision to subscribe to SR is a binary choice. Penetration rates at the group level are derived from the aggregation of individual choices.

[12] Satellite radio penetration is defined as number of [redacted] subscribers divided by total ZCTA population. For the limited number of observations for which the computed penetration rate exceeds 100%, we set the penetration rate equal to 100% for our econometric analysis. Out of a total of 31,437 ZCTAs in our dataset, [redacted] Generally these ZCTAs also have small populations and thus will have relatively small impacts on results given the weighting scheme. The results are robust to the exclusion of these observations.

[13] For a discussion of this grouped-data probit specification, see William H. Greene, ECONOMETRIC ANALYSIS, 4th Edition (Prentice Hall, 2000), at 834-7. We note that the log likelihood function, as shown on Greene, p. 836, explicitly includes a weighting scheme such that observations with larger populations at the ZCTA level are given greater weight. Moreover, we note that the use of aggregated data induces heteroscedasticity because the variance of the error term is a decreasing function of population.

use a flexible functional form for $g(.)$ to impose minimal constraints on the way in which the number of TR signals affects SR penetration. For our baseline specification, we choose a fifth-degree polynomial:

$$g(T_i,\theta) = \theta_1 T_i + \theta_2 T_i^2 + \theta_3 T_i^3 + \theta_4 T_i^4 + \theta_5 T_i^5 \qquad (2)$$

Consistent with standard probability models, however, the estimated coefficients cannot be readily interpreted as the marginal effect of a particular variable on SR penetration. Our primary interest is the effect of the number of TR signals on predicted SR penetration, holding constant other factors (in this analysis, at their median values). Accordingly, we focus on the predicted SR penetration rate:

$$\hat{P}(T) = \Phi[g(T,\hat{\theta}) + \hat{\beta}\overline{X}] \qquad (3)$$

where $\hat{\theta}$ and $\hat{\beta}$ are parameters estimated using maximum likelihood and $\overline{X}$ is the vector of right-hand side variables (other than TR signals) evaluated at their median values.[14] We present plots of predicted penetration rates against the number of TR signals.

3. RESULTS FOR BASELINE SPECIFICATION

Figure A2, which corresponds to Figure B2 in our FCC paper, plots the predicted SR penetration based on Equation (3).[15] As in Figure A1, there is a clear inverse relationship between SR penetration and the number of TR signals, which is considerably more pronounced in those areas that receive relatively few TR signals. We find that the availability of TR signals has a substantial effect on predicted SR penetration, holding constant other factors. Predicted SR penetration is [redacted] in those ZCTAs with zero TR signals and [redacted] with one TR signal; it [redacted] with six TR signals and [redacted] with nine TR signals. [redacted]

4. ROBUSTNESS OF BASELINE SPECIFICATION

We now examine whether the results obtained using our baseline specification are sensitive to the inclusion of additional explanatory variables or to alternative functional

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[14] Tables at the end of this Appendix contain detailed regression results for all analyses discussed here. For example, Table A2 contains detailed regression results for the baseline specification that is displayed in Figure A2, Table A3 the results for the predicted penetration rates displayed in Figure A3, and so on. The results plotted here and presented in Table A2 differ from those of Figure B2 and Table B2 of our earlier FCC Report only because [redacted]

[15] As noted above, predicted SR penetration is plotted holding all other variables constant at their median values.

forms.

a) Additional Explanatory Variables

We first examine the sensitivity of the results of our baseline specification to the inclusion of additional explanatory variables.[16] We add to the baseline specification variables measuring the following:

- Age composition by gender.[17]
- Educational attainment.[18]
- The percentage of people who commute more than 45 minutes but do not use public transportation, interacted with percentage of population who go to work by car.[19]

Based on the log-likelihood function values reported in Table A3, the inclusion of the additional variables improves the overall fit of the model. [redacted][20]

Figures A3 plots the predicted total penetration rate, setting the additional variables at their median values. Each figure also plots SR penetration as predicted by the

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[16] As discussed in the body of this report, Sidak claims that our earlier analysis fails to control adequately for demographic heterogeneity. Sidak 3rd Supplemental at ¶30.

[17] As regressors, we use the percentage of population who fall in each of the following gender/age categories: (1) males 0 to 15, (2) males 16 to 21; (3) males 22 to 39; (4) males 40 to 66; (5) males older than 66; (6) females 0 to 15; (7) females 16 to 21; (8) females 22 to 39; and (9) females 40 to 66. Therefore, the omitted category is females older than 66.

[18] As regressors, we use the percentage of population who have a: (1) graduate or professional degree; (2) a bachelor's degree; (3) a high school degree, some college, or an associate's degree. Therefore, the omitted category is the percentage of population with less than a high-school degree.

[19] In this specification, we drop the interaction of the percentage of people commuting by car and the percentage of people who live in urban areas in favor of this interacted variable. We continue to include the percentage of people who live in urban areas.

[20] As with standard probability models, the estimated coefficients of the grouped-data probit are not marginal effects and cannot be compared directly across different specifications. We note that the additional variables generally do not alter the sign and significance of the explanatory variable used in the baseline specification.

corresponding baseline specification. While the overall fit of the model improves, the relationships between SR penetration and number of TR signals remain very similar to those found using the baseline specification, which suggests that the basic empirical finding in the FCC paper is robust.

b) FUNCTIONAL FORM

In our baseline specification, we parameterized the effect of number of TR signals on SR penetration as a fifth degree polynomial. We have confirmed that the finding of a negative relationship between TR signals and SR penetration is not sensitive to this choice of functional form. In this section, we present results based on a still more flexible functional form that uses indicator variables rather than a polynomial. We created a series of indicator variables for each area with zero to 65 TR signals, using a single indicator (which is the omitted category) for those areas with greater than 65 signals. Formally, we specify the function $g(.)$ in Equation (1) to be:

$$g(T_i,\theta)=\sum_{k=0}^{65}\theta_h T_{i,k} \qquad (4)$$

where $T_{i,k}$ is an indicator variable that takes on value one if the number of TR signals in ZCTA is greater than k-0.5 and less than or equal to k+0.5, and zero otherwise. Other regressors are the same as in the baseline specification. As before, the coefficients are estimated using maximum likelihood.[21] Figure A4 plots the predicted value for total SR penetration using the variables in the baseline specification at their median values. The figure also plots the values predicted by the corresponding baseline (polynomial) specification. As can be seen, the results of the revised and benchmark specifications are very similar.

c) ALTERNATIVES TO GROUPED-DATA PROBIT

Finally, we examine whether the finding of a negative relationship between SR penetration and the number of TR signals is robust to our choice of statistical specification and estimation technique. Frequently used alternatives are the grouped-data logit and linear probability models. The grouped-data logit specifies the penetration rate to be:

$$\overline{P_i}=\exp\left[g(T_i,\theta)+\beta\overline{X_i}\right]/\left\{1+\exp\left[g(T_i,\theta)+\beta\overline{X_i}\right]\right\}+\overline{\varepsilon_i} \qquad (5)$$

While the linear probability model specifies it to be:

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[21] Comparing the log-likelihood values in Tables A2 and A4, we note that the use of a more flexible parameterization does not markedly improve the fit of the model.

$$\overline{P_i} = g(T_i, \theta) + \beta \overline{X_i} + \overline{\varepsilon_i} \tag{6}$$

The grouped-data logit model is estimated using maximum likelihood, while the linear probability model is estimated using least squares. We have little basis to prefer the grouped-data logit to the grouped-data probit, absent strong structural or distributional assumptions. On the other hand, we tend to prefer both of these statistical specifications to the linear probability model. In part, this is because the linear probability model can predict probabilities that are outside of the unit interval. More importantly, estimates of the linear probability model may be biased and inconsistent.[22] To address the issue of heteroscedasticity that is common to linear probability models, we estimate the model using ZCTA population as weights.

Figure A5 plots the predicted penetration rate for total penetration using the logit and linear probability models. Again, we have evaluated the variables at their median values. Our basic findings are robust to these alternative statistical specifications.

[22] See William C. Horrace and Ronald L. Oaxaca, *Results on the bias and inconsistency of ordinary least squares for the linear probability model*, ECONOMIC LETTERS, Volume 90, Issue 3, March 2006, pp 321-327.

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Figure A1

Relationship Between SR Penetration Rate and Number of TR Signals

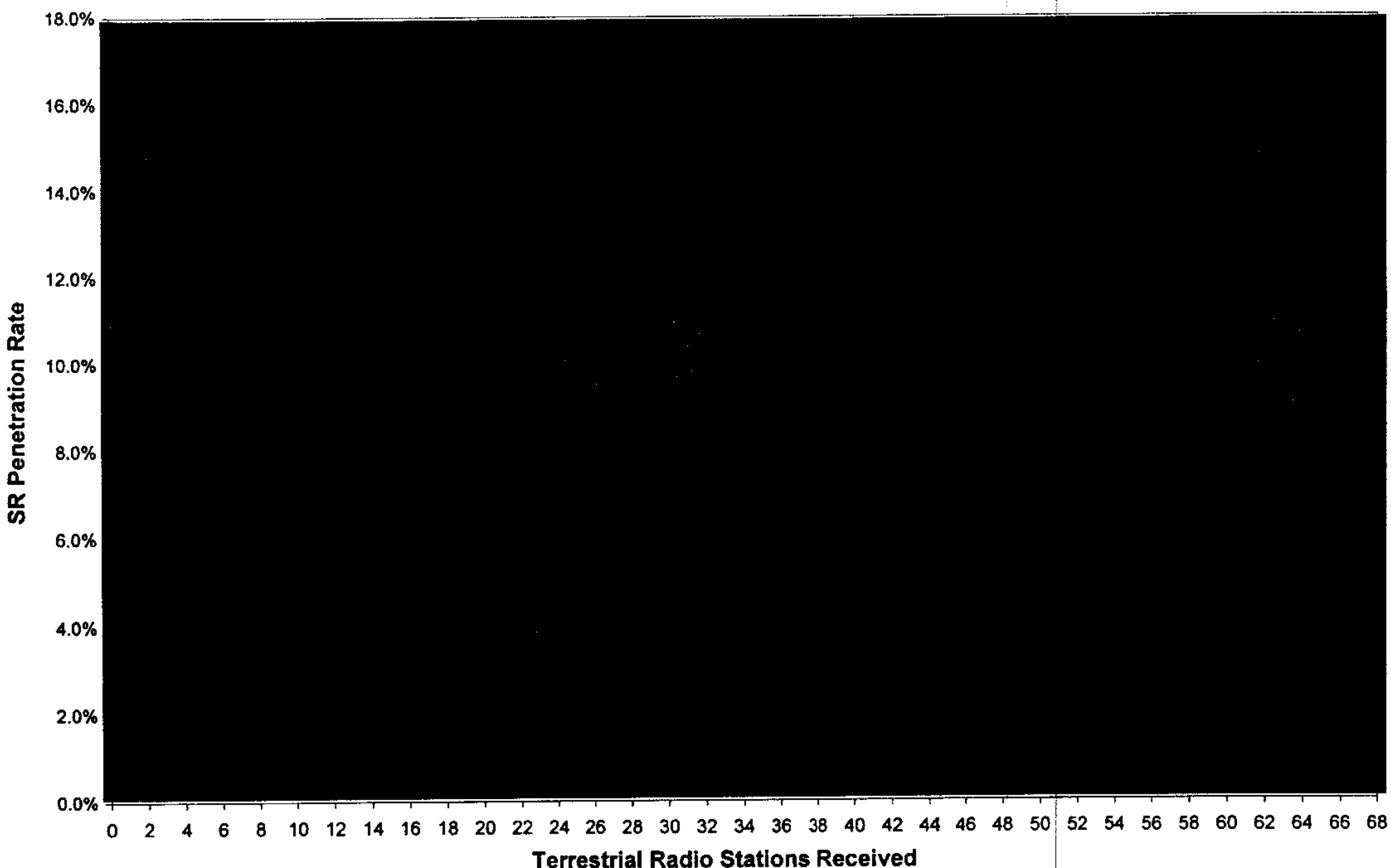

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Figure A2
Relationship Between Predicted SR Penetration Rate and Number of TR Signals
Baseline

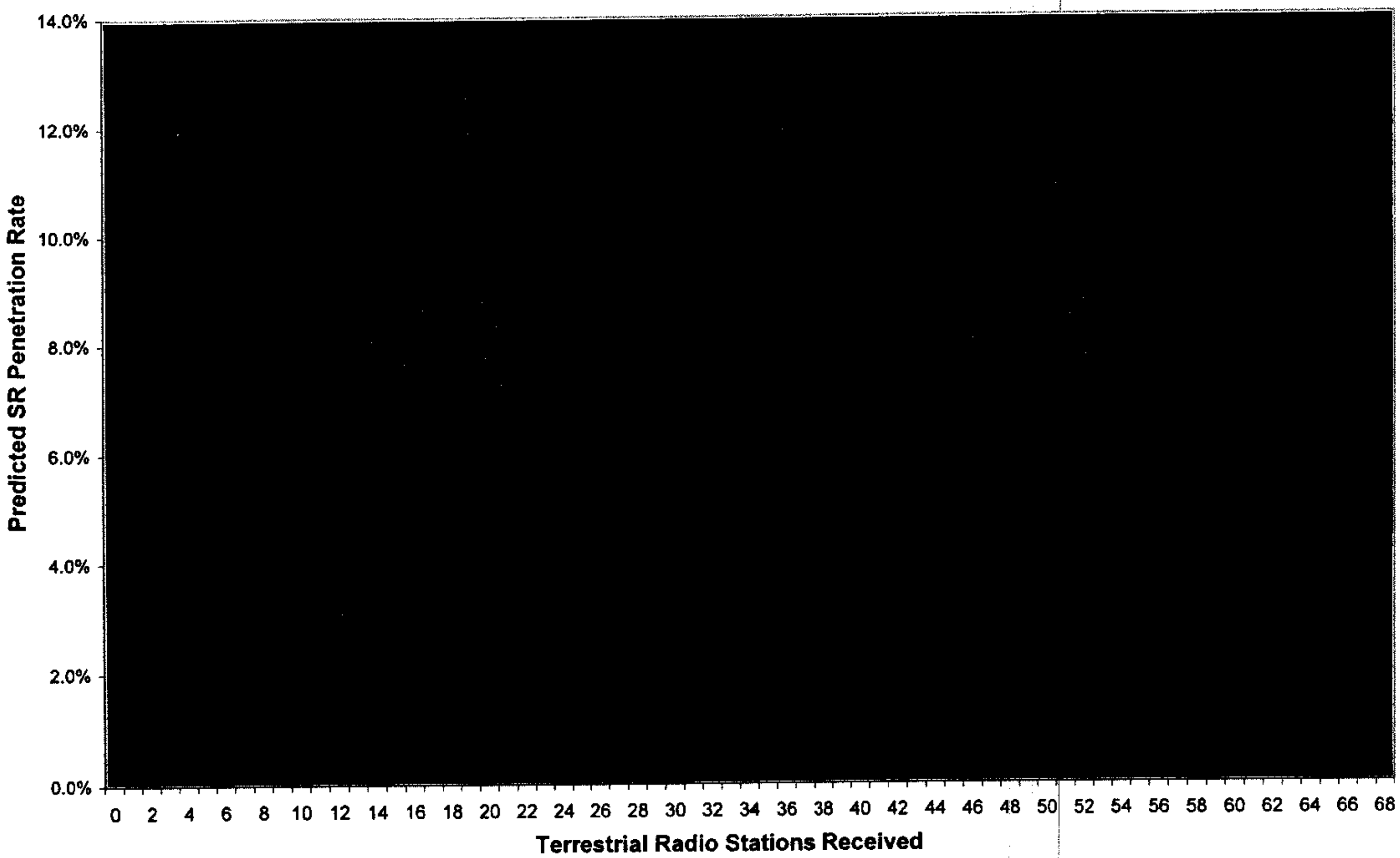

Figure A3
Relationship Between Predicted SR Penetration Rate and Number of TR Signals
Additional Explanatory Variables Included

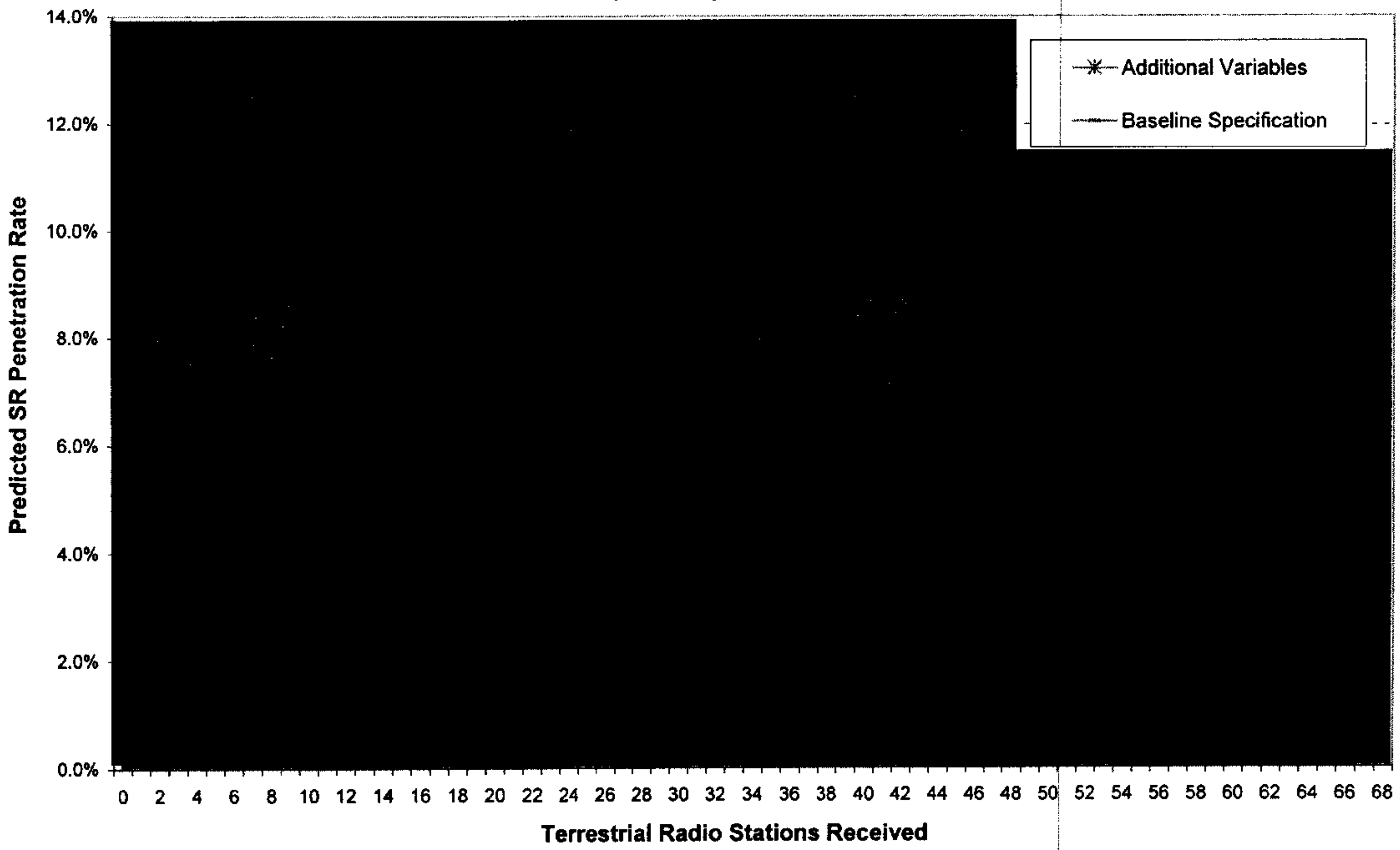

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Figure A4
Relationship Between Predicted SR Penetration Rate and Number of TR Signals
Coverage Dummies Approach

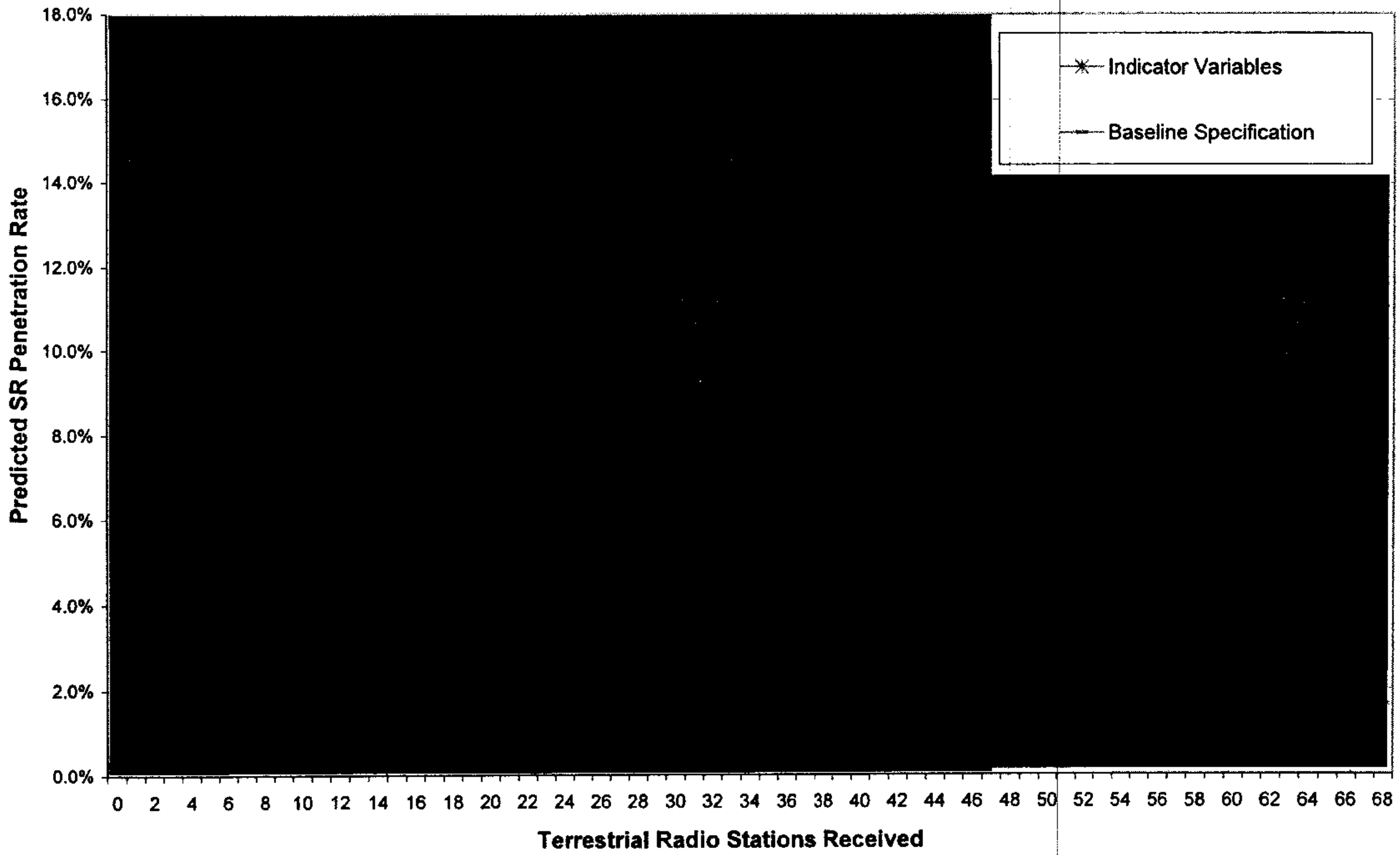
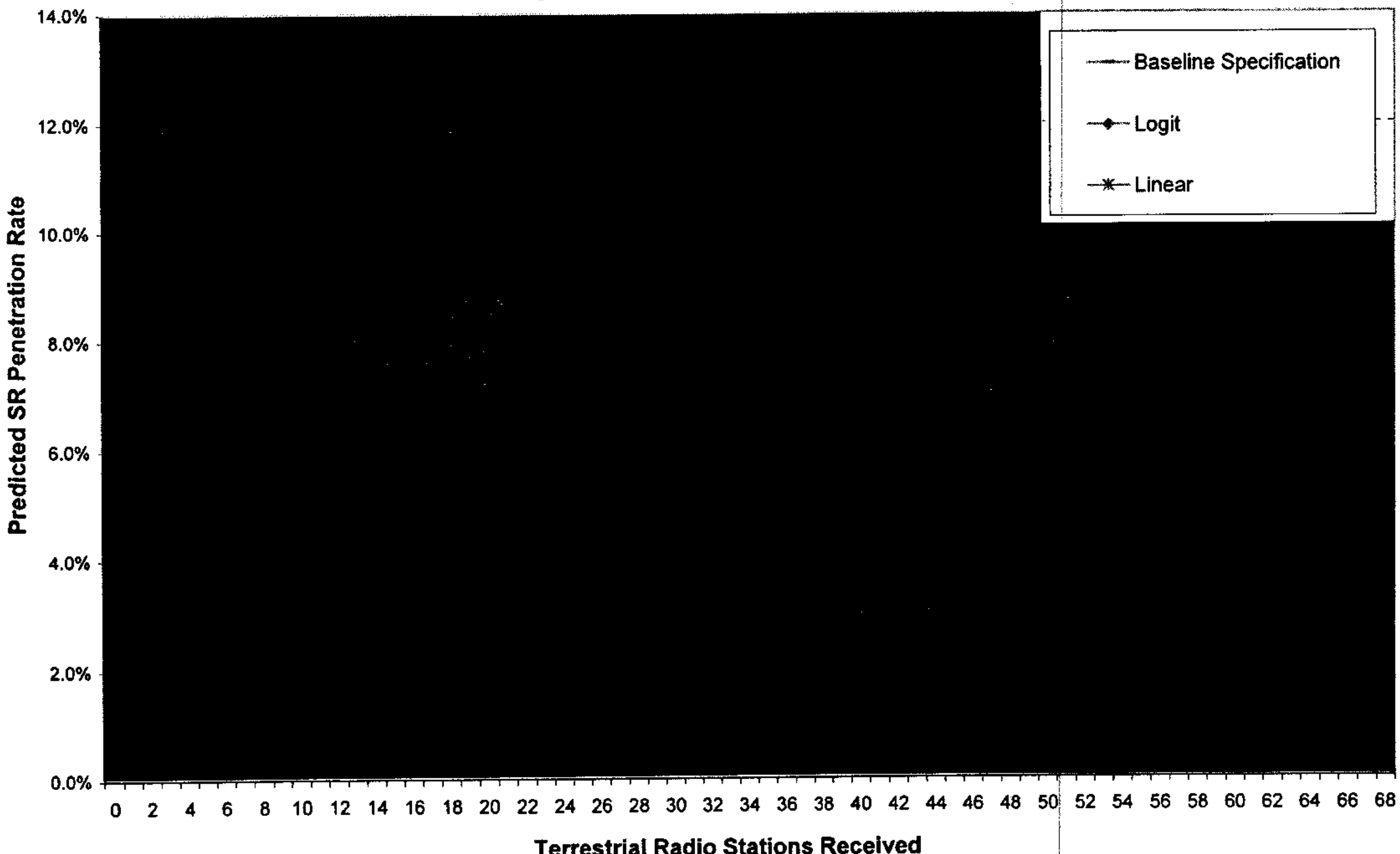


Figure A5
Relationship Between Predicted SR Penetration Rate and Number of TR Signals
Logit & Linear Probability Models



[redacted]

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Table A1: Summary Statistics

Variable	Mean	Median	Standard Deviation
Satellite Radio [redacted] Penetration Rate	[redacted]	[redacted]	[redacted]
Number of TR Signals	19.4	15.6	13.3
Median Household Income	39.7	36.3	16.2
% Go to Work by Car	39.5%	40.6%	9.1%
% Live in Urban Area	35.9%	0.0%	42.9%
[% Go to Work by Car] * [% Commute 45 Minutes or More and do not Use Public Transportation]	2.7%	2.2%	2.4%
% Female	50.2%	50.7%	4.5%
% Male Between Ages 0 and 15	11.4%	11.5%	3.5%
% Male Between Ages 16 and 21	4.2%	3.9%	2.8%
% Male Between Ages 22 and 39	11.8%	11.4%	4.4%
% Male Between Ages 40 and 66	17.0%	16.7%	4.4%
% Male Age 67 or Older	5.5%	5.0%	3.3%
% Female Between Ages 0 and 15	10.8%	10.9%	3.4%
% Female Between Ages 16 and 21	3.8%	3.6%	2.6%
% Female Between Ages 22 and 39	11.5%	11.6%	3.3%
% Female Between Ages 40 and 66	17.0%	16.8%	4.2%
% Have Graduate Degree	4.3%	2.9%	4.7%
% Have Bachelor Degree	8.3%	6.7%	6.2%
% HS Degree or Some College	46.0%	46.8%	9.1%

Source: Terrestrial radio coverage and population data from BIA Research, Inc. Data on XM and Sirius subscribers as of 4/25/2007. Census, ZIP code, ZCTA, and population data from U.S. Census 2000 State Geography Files. For technical documentation on mapping between Census Block, ZIP code, and ZCTA, see Summary File 1, 2000 Census of Population and Housing, Technical Documentation, Issued March 2005.Demographic data are from the U.S. Census 2000 American Fact Finder.

Table A2: Relationship Between Predicted SR Penetration Rate and Number of TR Signals Baseline

	Probit Model
TR Signals	[redacted]
TR Signals^2	
TR Signals^3	
TR Signals^4	
TR Signals^5	
Income	
Income^2	
% Go to Work by Car	
% Live in Urban Area	
[% Go to Work by Car] * [% Live in Urban Area]	
% Female	
Constant	
Observations	
Log-likelihood	

Notes:
Coefficients are in bold, and t statistics are in brackets; * significant at 5%; ** significant at 1%. Standard errors clustered by 3-digit ZCTAs. Probit models estimated by maximum likelihood.

Source: Source data for Table A1.

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Table A3: Relationship Between Predicted SR Penetration Rate and Number of TR Signals Additional Explanatory Variables Included

	Probit Model *Baseline Specification*	Probit Model: Additional Explanatory Variables
	Total	Total
TR Signals	[redacted]	[redacted]
TR Signals^2	[redacted]	[redacted]
TR Signals^3	[redacted]	[redacted]
TR Signals^4	[redacted]	[redacted]
TR Signals^5	[redacted]	[redacted]
Income	[redacted]	[redacted]
Income^2	[redacted]	[redacted]
% Go to Work by Car	[redacted]	[redacted]
% Live in Urban Area	[redacted]	[redacted]
[% Go to Work by Car] * [% Live in Urban Area]	[redacted]	[redacted]
% Female	[redacted]	[redacted]
[% Go to Work by Car] * [% Commute 45 Minutes or More and do not Use Public Transportation]	[redacted]	[redacted]
% Male Between Ages 0 and 15(1)	[redacted]	[redacted]
% Male Between Ages 16 and 21(1)	[redacted]	[redacted]
% Male Between Ages 22 and 39(1)	[redacted]	[redacted]
% Male Between Ages 40 and 66(1)	[redacted]	[redacted]
% Male Age 67 or Older(1)	[redacted]	[redacted]
% Female Between Ages 0 and 15(1)	[redacted]	[redacted]
% Female Between Ages 16 and 21(1)	[redacted]	[redacted]
% Female Between Ages 22 and 39(1)	[redacted]	[redacted]
% Female Between Ages 40 and 66(1)	[redacted]	[redacted]
% Have Graduate or Professional Degree (2)	[redacted]	[redacted]
% Have Bachelor Degree (2)	[redacted]	[redacted]
% HS Degree or Some College (2)	[redacted]	[redacted]
Constant	[redacted]	[redacted]
Observations	[redacted]	[redacted]
Log-likelihood	[redacted]	[redacted]

Notes:
Coefficients are in bold, and t statistics are in brackets; * significant at 5%; ** significant at 1%. Standard errors clustered by 3-digit ZCTAs.
Probit models estimated by maximum likelihood.
(1) Omitted category is "% Female Age 67 or Older."
(2) Omitted category is "% Have Less than High School Degree."

Source: Source data for Table A1.

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Table A4: Relationship Between Predicted SR Penetration Rate and Number of TR Signals
Coverage Dummies Approach

	Probit Model
0 TR Signals (1)	[redacted]
1 TR Signals (1)	
2 TR Signals (1)	
3 TR Signals (1)	
4 TR Signals (1)	
5 TR Signals (1)	
6 TR Signals (1)	
7 TR Signals (1)	
8 TR Signals (1)	
9 TR Signals (1)	
10 TR Signals (1)	
11 TR Signals (1)	
12 TR Signals (1)	
13 TR Signals (1)	
14 TR Signals (1)	
15 TR Signals (1)	
16 TR Signals (1)	
17 TR Signals (1)	
18 TR Signals (1)	
19 TR Signals (1)	
20 TR Signals (1)	
21 TR Signals (1)	
22 TR Signals (1)	
23 TR Signals (1)	
24 TR Signals (1)	
25 TR Signals (1)	
26 TR Signals (1)	
27 TR Signals (1)	
28 TR Signals (1)	
29 TR Signals (1)	
30 TR Signals (1)	
31 TR Signals (1)	
32 TR Signals (1)	
33 TR Signals (1)	
34 TR Signals (1)	
35 TR Signals (1)	
36 TR Signals (1)	

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Table A4: Relationship Between Predicted SR Penetration Rate and Number of TR Signals Coverage Dummies Approach

	Probit Model
37 TR Signals (1)	[redacted]
38 TR Signals (1)	[redacted]
39 TR Signals (1)	[redacted]
40 TR Signals (1)	[redacted]
41 TR Signals (1)	[redacted]
42 TR Signals (1)	[redacted]
43 TR Signals (1)	[redacted]
44 TR Signals (1)	[redacted]
45 TR Signals (1)	[redacted]
46 TR Signals (1)	[redacted]
47 TR Signals (1)	[redacted]
48 TR Signals (1)	[redacted]
49 TR Signals (1)	[redacted]
50 TR Signals (1)	[redacted]
51 TR Signals (1)	[redacted]
52 TR Signals (1)	[redacted]
53 TR Signals (1)	[redacted]
54 TR Signals (1)	[redacted]
55 TR Signals (1)	[redacted]
56 TR Signals (1)	[redacted]
57 TR Signals (1)	[redacted]
58 TR Signals (1)	[redacted]
59 TR Signals (1)	[redacted]
60 TR Signals (1)	[redacted]
61 TR Signals (1)	[redacted]
62 TR Signals (1)	[redacted]
63 TR Signals (1)	[redacted]
64 TR Signals (1)	[redacted]
65 TR Signals (1)	[redacted]
Income	[redacted]
Income^2	[redacted]
% Go to Work by Car	[redacted]
% Live in Urban Area	[redacted]
[% Go to Work by Car] * [% Live in Urban Area]	[redacted]
% Female	[redacted]
Constant	[redacted]
Observations	[redacted]
Log-likelihood	[redacted]

Notes:
Coefficients are in bold, and t statistics are in brackets; * significant at 5%; ** significant at 1%. Standard errors clustered by 3-digit ZCTAs.
Probit models estimated by maximum likelihood.
(1) Omitted category is "More than 65 TR Signals."

Source: Source data for Table A1.

Table A5: Relationship Between Predicted SR Penetration Rate and Number of TR Signals
Logit & Linear Probability Models

	Probit Model *Baseline Specification*	**Logit Model**	**Linear Model**
TR Signals	[redacted]	[redacted]	[redacted]
TR Signals^2	[redacted]	[redacted]	[redacted]
TR Signals^3	[redacted]	[redacted]	[redacted]
TR Signals^4	[redacted]	[redacted]	[redacted]
TR Signals^5	[redacted]	[redacted]	[redacted]
Income	[redacted]	[redacted]	[redacted]
Income^2	[redacted]	[redacted]	[redacted]
% Go to Work by Car	[redacted]	[redacted]	[redacted]
% Live in Urban Area	[redacted]	[redacted]	[redacted]
[% Go to Work by Car] * [% Live in Urban Area]	[redacted]	[redacted]	[redacted]
% Female	[redacted]	[redacted]	[redacted]
Constant	[redacted]	[redacted]	[redacted]
Observations	[redacted]	[redacted]	[redacted]
Log-likelihood	[redacted]	[redacted]	[redacted]

Notes:
Coefficients are in bold, and t statistics are in brackets; * significant at 5%; ** significant at 1%. Standard errors clustered by 3-digit ZCTAs.
Probit and logit models estimated by maximum likelihood. Linear probability models estimated by population weighted least squares.

Source: Source data for Table A1.

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In antitrust analysis, Dr. Savage has extensive experience in the statistical estimation of price and demand relationships to infer market definition. He has evaluated the unilateral and coordinated effects of vertical and horizontal mergers and whether multiproduct discounts are anticompetitive. He also conducted analyses of commonality, typicality, and predominance associated with class certification.

Dr. Savage's published research examines the long-term effects of youth unemployment using complex statistical methods to account for workers' prior labor force and schooling decisions. He has also published empirical analyses of consumers' willingness to pay for haze reduction and visibility improvement.

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2007–Present *Principal*, CRA International, New York.

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2002–2005 *Principal* (2005), *Associate Principal* (2002–2005), *Senior Associate* (1999–2001), CRA International, Washington, D.C.

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"The Long-Term Effects of Youth Unemployment." With Thomas A. Mroz. *Journal of Human Resources*, Vol. 41, No. 2, pp. 259–293.

"Methods and Results from a New Survey of Values for Eastern Regional Haze Improvements." With Anne E. Smith, Michael A. Kemp, and Catherine L. Taylor. *Journal of the Air and Waste Management Association*, Vol. 55, No. 11.

"Finite Sample Overfitting and Biases in Nonparametric Kernel Regressions." With Thomas A. Mroz. Unpublished manuscript, March 2004.

"The Union Wage Gap in the Presence of Endogenous Union Membership." With Thomas A. Mroz. The University of North Carolina Working Paper Series, December 1997.

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Nonuser Valuation of Haze Reduction in Eastern National Parks. Prepared with Anne E. Smith, Ph.D., Michael A. Kemp, and Katherine L. Taylor, September 2005.

"The Availability of Minority and Woman-Owned Businesses for the San Francisco Municipal Railway." Prepared with Mark Berkman, Ph.D., June 2005.

Submission to the U.S. International Trade Commission in the matter of *Softwood Lumber from Canada, Investigation Nos. 701-TA 416 and 731-TA-928, Section 129 Consistency Determination*, on behalf of the Canadian Lumber Trade Alliance regarding analytical and statistical analyses of the domestic effects of the Softwood Lumber Agreement, October 2004. Prepared with Richard D. Boltuck.

Expert Statement in the matter of *Douglas Turner* v. *Applera Corporation*, on behalf of Applera Corporation regarding alleged termination based on age, September 2004.

Deposition testimony in the matter of *Alica Jurisova* v. *D. Andrej Juris*, on behalf of the defendant regarding wage determination and job search efforts, June 2004.

"Disparities in Minority- and Woman-Owned Businesses and Self-Employment Earnings." Prepared for the City and County of San Francisco with Mark Berkman, Ph.D., and Robert Fairlie, Ph.D., March 2004.

Supplemental Expert Rebuttal Report in the matter of *Stephen Sneeringer* v. *National Electronics Warranty Corporation*, on behalf of the National Electronics Warranty Corporation regarding an alleged termination based on age, February 2004.

Expert Rebuttal Report in the matter of *Stephen Sneeringer* v. *National Electronics Warranty Corporation*, on behalf of the National Electronics Warranty Corporation regarding an alleged termination based on age, February 2004.

Expert Witness Rebuttal Report on Damages in the matter of *Tyson Foods, Inc.* v. *ConAgra Foods, Inc.*, on behalf of ConAgra Foods, Inc. regarding a Lanham Act counterclaim, August 2003. Prepared with Mark Berkman, Ph.D. and Phillip Taylor, Ph.D.

Expert Disclosure of Timothy H. Savage in the matter of *Gloria Oliver-Simon* v. *Anthony Principi, Secretary, U.S. Department of Veterans Affairs* on of the Gloria Oliver-Simon regarding alleged failures to promote based on age and race, June 2003.

Expert Witness Report on Damages in the matter of *Tyson Foods, Inc.* v. *ConAgra Foods, Inc.*, on behalf of ConAgra Foods, Inc. regarding a Lanham Act counterclaim, June 2003. Prepared with Mark Berkman, Ph.D. and Phillip Taylor, Ph.D.

"The Availability of Minority and Woman-Owned Businesses for the San Francisco Municipal Railway." Prepared with Mark Berkman, Ph.D., June 2003.

"Comments on the Environmental Protection Agency's Third External Review Draft of Air Quality Criteria for Particulate Matter (April 2002)." Prepared with Anne Smith, Ph.D. on behalf of the Utility Air Regulatory Group, July 2002.

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RESEARCH

"Competition Policy as a Strategic Trade with Differentiated Products," (With Marc Rysman) *Review of International Economics* (in press).

"Exchange Rate Pass-Through in The Italian Car Market: 1990–1996"

"Market Size and Location of Oligopolistic Firms"

"Private Saving Rates in Italy: Differences Between North and South," (in Italian).

PRESENTATIONS

International Industrial Organization Conference, Northeastern University, April 2003, 2004.

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FOR PUBLIC INSPECTION

Appendix B

Technical Analysis of Sidak's Advertising Model

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1. INTRODUCTION

As explained in Section IV of this report, Sidak's advertising welfare analysis is based on three *unreasonable assumptions*. First, Sidak assumes that the merged firm might increase advertising drastically (*e.g.*, *quintupling* of the number of commercials). Second, Sidak assumes that a very large fraction (*e.g.*, half) of the value consumers place on satellite radio results from it being commercial-free. Third, Sidak assumes that the merged firm would increase advertising without also reducing the subscription price. Based on these three assumptions, Sidak's model derives the result that an increase in the number of commercials would lead to a reduction in the number of subscribers and a reduction in consumer welfare.

In Section IV of this report, we explained why Sidak's first two assumptions are unreasonable in light of the facts. In this Appendix, we show that Sidak's assumption of a constant subscription price is *inconsistent* with profit-maximizing behaviour. More precisely, we show that a profit-maximizing firm would reduce the subscription price following an increase in the number of commercials. As a result of the lower profit-maximizing price, we find that the quantity of subscriptions would rise, not fall. We also find that consumer welfare would rise, not fall, due to the lower price and increased quantity of subscriptions.

Sidak's assumption that the subscription price would remain constant is analytically incorrect. As we explained in our initial report, an increase in per subscriber advertising revenue would lead a profit-maximizing firm to reduce the subscription price in order to attract more subscribers.[1] Sidak ignores this very important implication of his own model. In addition, in Sidak's model, an increase in the number of commercials would make demand for satellite radio more elastic, which would give the firm an additional profit incentive to reduce the subscription price. In Sidak's model a profit-maximizing firm would reduce the price sufficiently to increase the number of subscribers. These changes in turn would lead to an increase in consumer welfare.

This Appendix has three sections. First, it describes the model set out in Sidak's submissions.[2] Second, it demonstrates that an increase in the number of commercials would lead a profit-maximizing firm to reduce its subscription price and increase the number of subscribers. Third, it shows that the reduction in the profit-maximizing subscription price and increase in the number of subscribers are sufficiently large to lead to an increase in consumer welfare, despite the increase in the number of commercials.

2. SIDAK'S FORMAL MODEL

Sidak assumes that the demand for satellite radio has the following form:

$$P = (u - bQ)(1 - vt/T) \tag{1}$$

Intuitively, if there are no commercials (i.e., $t = 0$), then the relationship between the subscription price (P) and the number of subscribers (Q) reduces to $P = u - bQ$, where u denotes the "choke price" (i.e., the price at which demand would fall to zero) and u/b is the "saturation point" (i.e., the number of consumers who would subscribe if the service was free). If instead the number of commercials was the same as on terrestrial radio (i.e., $t = T$), then Equation (1) would imply $P = (u - bQ)(1 - v)$, and thus the subscription price (P) would have to fall by a fraction v for the same number (Q) of consumers to continue to subscribe. In other words, the parameter v can be interpreted as the share of the value of satellite radio that consumers attribute to the commercial-free nature of satellite radio.

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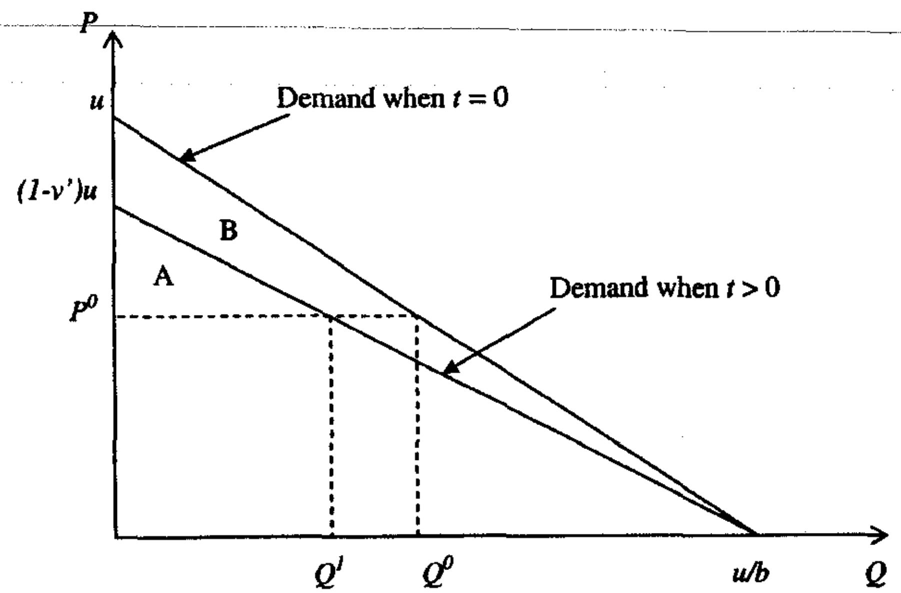
[1] This is a standard result in two-sided markets where there are two revenue streams. The increase in ancillary advertising revenues has exactly the same effect as a reduction in variable costs. Of course, here the demand curve also shifts down. *See* CRA FCC Report at ¶150.

[2] Sidak refers to a formal model in at least three submissions: Sidak Supplemental at ¶¶43-46; Sidak 3rd Supplemental at ¶¶70-76, and Sidak-Singer 10-8-2007 Ex Parte Letter. Although Sidak does not fully describe his model, those references and the results reported in Figure 2 of Sidak 3rd Supplemental are consistent with the formal model described in this Appendix.

Sidak assumes that the saturation point of satellite radio does not depend on the number of commercials. Therefore, an increase in the number of commercials reduces demand by pivoting it around the horizontal intercept, as illustrated in Figure B1.

Figure B1: Sidak's model



Sidak assumes that satellite radio faces zero marginal costs and considers a benchmark case with no commercials (i.e., $t = 0$), a subscription price of $12.99 (i.e., $P^0 = 12.99$) and 17 million subscribers (i.e., $Q^0 = 17$).[3] He assumes that terrestrial radio listeners must "endure" 9.42 minutes of commercials per hour of listening (i.e., $T = 9.42$) and considers three different scenarios with respect to the amount of advertising that satellite radio listeners would have to endure post-merger (i.e., $t = 1$, $t = 3$, and $t = 5$).[4] For each of these three scenarios, demand pivots around the horizontal intercept as illustrated in Figure B1.[5] Thus, the horizontal intercept

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[3] See Sidak Supplemental at ¶44 and Sidak 3rd Supplemental at ¶71-73. Under those assumptions, profit maximization implies $P^0 = u/2$ and $Q^0 = u/2b$. This allows us to determine the values of the parameters u and b. That is, $u = 25.98$ and $b = 12.99/17 \cong 0.76$.

[4] See Sidak Supplemental at ¶43 and Figure 2 in Sidak 3rd Supplemental.

[5] A larger amount of advertising implies that the new demand curve is lower.

does not change but the vertical intercept is lower when the amount of advertising is higher. Specifically, the vertical intercept equals $(1-v')u$, where $v' = vt/T$.[6] As explained above, v is the fraction of the value of satellite radio that consumers attribute to the fact that satellite radio is commercial-free. Thus, if satellite radio were to air the same amount of commercials as terrestrial radio (i.e., if $t = T$), then the value of satellite radio would decrease by a fraction v. If instead satellite radio were to air one-half of the amount of commercials aired by terrestrial radio (i.e., $t = T/2$), then the value of satellite radio would decrease by a fraction $v/2$ (i.e., $v' = v/2$). Thus, v' is the percentage reduction in value caused by an increase in the amount of advertising; the magnitude of v' depends on the amount t of additional commercials and on the magnitude of the preference parameter v. Sidak considers three different scenarios for the magnitude of v (i.e., $v = 10\%$, $v = 30\%$, and $v = 50\%$).[7]

Sidak analyzes the effects of increasing advertising under the unrealistic assumption that the subscription price would remain constant at $P = P^0$. As shown in Figure B1, under this unrealistic assumption, the number of subscribers would decrease from Q^0 to Q^1. This in turn would cause a reduction in consumer welfare equal to Area B in Figure B1.[8]

In the next section, we will show that Sidak's model implies that a profit-maximizing firm would reduce the subscription price following an increase in the amount of commercials. As a result, and in sharp contrast with Sidak's results, the number of subscribers would increase. In addition, consumer welfare would increase in the scenarios where the firm would find it profitable to increase the amount of commercials.[9]

3. THE INCENTIVE TO REDUCE THE SUBSCRIPTION PRICE AND INCREASE THE NUMBER OF SUBSCRIBERS

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6 The actual form of v' is not reported explicitly in Sidak's declarations, but it is consistent with Sidak's results as reported in Sidak Supplemental at ¶44 and in Sidak 3rd Supplemental at ¶72 and Figure 2.

7 A larger value of v implies a larger reduction in demand following an increase in advertising.

8 Initially, consumer welfare corresponds to the sum of Area A and Area B. After the increase in the number of commercials (and holding the subscription price constant), consumer welfare corresponds to Area A. Thus, in Sidak's model, the reduction in consumer welfare due to an increase in advertising is equal to Area B. (Sidak estimates the reduction in consumer welfare using an approximation of Area B. His approximation leads to an overstatement of the actual area.)

9 Some of Sidak's scenarios assume a number of commercials that would lead to lower profits than having no commercials. Such unprofitable scenarios are irrelevant.