Demographics of Newspaper Readership: Predictors and Patterns of U.S. Consumption

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ABSTRACT This study of 101 newspapers and markets finds that the strongest predictors of readership are length of residence and age in most markets, although the effect sizes vary across newspapers and markets. Income also has a highly significant positive overall effect. The effect of education is small, but varies considerably across newspapers/markets. The fraction of variation in readership accounted for by demographics is small, indicating that newspapers have a broad reach across demographic groups.

KEY WORDS: Audiences, newspapers, demographics, readership

Who reads the newspaper? This question is of interest to businesses, journalists, and society at large, prompted by professional, marketing, and civic concerns. The answer is often sought in demographics. Studies have found that income has a positive correlation with readership. Age is also related to readership, although there is some evidence that this relationship may be curvilinear in that both younger and older people are more likely to be nonreaders (Burgoon and Burgoon 1980). Education is consistently found to have a positive correlation with readership (Burgoon and Burgoon 1980). Length of residence is sometimes found to have a positive relationship with readership, but other studies have not found it significant (Burgoon and Burgoon 1980). Gender is unrelated to readership in several studies (Burgoon and Burgoon 1980; Schoenbach, et al. 1999; Loges and Ball-Rokeach 1993; Lain 1986). Overall, readers have been characterized as established. "Reading in the US can be described to some extent as determined by one's lifestyle: a higher income, a good education, being male and of an age indicating a state in life that may be called `established' (Schoenbach, et al. 1999, p. 237)." At the societal level, research seems consistent with Bourdieu's observation that newspapers in the United States serve to separate some social groups from others, particularly from the lower strata of society.

While this picture of who reads seems clear, four important issues need to be addressed. Three of these are methodological and have to do with the way readership is measured, how the relationship with readership is statistically modeled, and whether the relationship between readership and demographics is different across markets. This study addresses these issues to obtain a more complete picture of readership. The fourth issue is empirical. Demographics seem to be important in explaining readership. But just how important they are is unclear. This study seeks to determine whether demographics, taken as a whole, are a major determinant of readership or only a small part of the story.

FOUR ISSUES

Readership as a Latent Variable

In the past, industry has relied on measures of readership such as paid circulation or the number who read the newspaper yesterday. Previous academic research studies have considered readership in terms of a single aspect of reading the newspaper and measured this, most often, with a single question. Usually this question has been about the frequency of reading the newspaper, for example the number of times read during the previous week. The limitations of using a single aspect of readership have recently been pointed-up by Calder and Malthouse (2003).

Calder and Malthouse (2003) argue that readership should be measured as a latent variable. What we observe (ask questions about) are manifestations of readership. No single manifestation is adequate to characterize a person's level of readership. Reading the paper twice in one week is one manifestation. Reading it for ten minutes each time, versus twenty, is another. Both should be taken into account to measure readership. Single manifestations will have poorer validity and lower reliability than a composite measure. The Calder and Malthouse (2003) analysis indicated that it is necessary to consider at least six manifestations of readership. These are the frequency of reading, the time spent reading, and the completeness of reading the paper for weekdays and, separately, for Sundays. These variables can be combined into a single score on a unidimensional scale of readership.[1]

This score can be computed with respect to readership for a single target newspaper. In this case it is called RBS (the Reader Behavior Score) and is appropriate for studying the readership of individual newspapers. The score can also be computed over all of the newspapers a person reads. We refer to this as TRBS, the Total Reader Behavior Score. For the details of computing RBS and TRBS, and information about the reliability and validity of these measures, see Calder and Malthouse (2003).

Both RBS and TRBS are used in this study. By relating demographics to these measures of readership we can obtain a better picture of the role of demographics. It is well known that using any single measure can have a smaller correlation with other variables than a more reliable composite variable; this is often called attenuation and is due to measurement error in the individual measure (Everitt 1984, pp. 6-8). Moreover, we are likely to avoid limited and even spurious results by using a measure such as RBS or TRBS that has greater validity. The newspaper and advertising industries are also considering more comprehensive definitions of readership (Fitzgerald 2000; Wilson 1999).

Nonlinear relationships

The second methodological issue involves how the relationship between a demographic variable and readership, either RBS or TRBS, is specified in the statistical model. All studies of such questions necessarily entail the use of a model. Linear regression models are generally preferred, but we need a more flexible model to capture potentially important features of the relationship. One such feature is nonlinearity. There is no reason to expect, and several studies have noted, that demographic variables will always relate to readership in a linear way. Other researchers have approached this by introducing transformations of predictor variables into their linear models. We use additive models with smoothing splines. The details are provided later.

Modeling Heterogeneity across Markets

The third methodological issue is that the relationship between a demographic variable and readership may be different for different newspapers. It is well known that statistical relationships can be dependent on the units in which the relationship occurs. For example, education could be a strong predictor of readership in one market, but not in another. A previous study has found evidence of differences across newspapers: "Correlates of readership do differ from one market to the next. However, there are factors common to two or more markets. …

[1] Also see http://www.medill.nwu.edu/faculty/malthouse/ftp/rbsdemo.html for computational details.

Income and age appear in all four models, but the patterns of the relationships are not always the same (Burgoon and Burgoon 1980, p. 595)." Education enters some of their models, but not others. Their study is limited in that it based on a convenience sample of four Gannett newspapers and the methodology they use, separate stepwise regressions for each newspaper, does not allow for a systematic quantification of the heterogeneity across markets.

Another example of heterogeneity across units is children's homework (Kreft and de Leeuw 1998). What is the relationship between the time spent on homework and test results? If one simply correlates the two variables across a national sample, a picture of the relationship emerges. But if one takes into account that any student is a member of a unit, some school, a different picture may emerge. Specifically different relationships may exist for different schools. Newspapers are analogous to schools in this way, as units, and should be explicitly considered in the analysis.

It is necessary to do two things to incorporate newspapers, as a higher unit of analysis, as well as readers, as a lower unit of analysis, into our study. The first is to examine a random sample of newspapers, and a random sample of potential readers of the different newspapers. In this study we use a stratified sample of 101 newspapers drawn from the universe of U.S. daily newspapers. A random sample of potential readers is drawn from each of the 101 newspaper markets. This necessitates a very large sample of potential readers. The second is to use a statistical analysis that can explicitly model heterogeneity across newspapers such as a random coefficient model.

So in addition to using the additive models mentioned above to modeling nonlinearities, we also use random coefficient models to handle differences in the relationship between demographic variables and readership due to differences among newspapers. In the case of RBS, which considers an individual newspaper, these differences are due to specific individual newspapers. In the case of TRBS, which considers all of the newspapers a person reads, they are due to different newspaper markets. Note that the stimuli to which people are exposed, the available newspapers, vary across market.

We should point out that in our view these three issues are not methodological niceties. Each represents a potentially vital issue if the demographics of readership are to be fully understood.

Fraction of Variation in Readership Explained by Demographics

The fourth question we address is to what extent is readership accounted for by demographics? If demographics account for a large percentage of readership, then certain demographic groups must read newspapers heavily while others do not. This suggests that newspapers are a targeted medium. If demographics do *not* account for a large percentage of readership, then newspapers have a broad reach across demographic groups.

METHOD

Sampling

We use data from a multi-stage probability sample of the general U.S. population. The data were collected as part of the IMPACT study conducted by the Readership Institute at Northwestern University. The sample was designed to be representative of both the population and of newspapers. Technical details of the sampling procedures are given below.

The first step of the sampling process was to select a representative sample of daily newspapers in the United States. We compiled a sampling frame using lists of newspapers from the Newspaper Association of America, the Audit Bureau of Circulation (ABC), and *Editor and Publisher*. We dropped newspapers with the following characteristics: (1) average daily circulation under 10,000; (2) non-English language; (3) specialty newspapers such as *Investor's Business Daily*; (4) national newspapers (i.e., *New York Times*, *Wall Street Journal*, or *USA Today*). In total, the sampling frame consisted of 846 newspapers. We first drew a stratified random sample of 101 U.S. daily newspapers, stratifying on market and newspaper characteristics such as circulation, urbanicity, competition, market penetration, and the geographical extent of distribution. We stratified the sampling frame into six strata by applying K-means clustering to circulation data from ABC, household counts from the US Postal Service, and demographic data from Claritas and the US Census. In defining the strata we needed to identify the "market" for each newspaper. We defined *home counties* as those counties that make up 80% of total circulation. The strata were defined using the average daily circulation, number of households in the home counties, number of zip codes in the home counties, number of home counties, Claritas' measure of urbanicity averaged over the home counties, number of competitive daily newspapers in the DMA, and a measure of market penetration in the home counties. Characteristics of six strata are summarized in Table 1.

We drew simple random samples without replacement from each stratum so that we would have approximately the same number of newspapers from each stratum. In total, 101 out of 104 newspapers agreed to participate in the study, giving a response rate of 97%. The final list of participating newspapers included 18 from small town, 20 from small town/city+, 14 from small city local, 17 from city local, 15 from city regional, and 17 from big city.

Table 1: Summary Statistics of Strata

Stratum	*N*	Circ.	HH	Zip Codes	Counties	Urbanicity	Pene.	Comp.
Small Town	278	15,464	36,529	11.9	1.3	2.0	1.3	6.2
Small Town / city+	162	36,500	68,897	30.6	3.6	1.6	1.3	3.7
Small City Local	81	29763	131,281	21.8	1.3	2.9	0.8	12.0
City Local	81	96,864	212,684	34.4	1.5	3.0	1.2	9.2
City Regional	64	111,397	219,378	59.2	6.1	2.0	1.2	3.4
Big City	77	366,887	969,606	112.7	3.3	3.6	0.9	10.2

Notes: total number of newspapers in stratum (*N*), average circulation, average number of households in home market, average number of zip codes in home market, average number of counties in home market, average urbanicity, average penetration in home market, and average number of competitive newspapers in the market. For urbanicity, 1=Rural, 2=Town, 3=City, 4=Suburb, and 5=Urban. For penetration, larger values indicate higher penetration; an average of 1.3 should be regarded as high penetration and an average of 0.9 moderate penetration.

The second step of the sampling procedure was to draw a random sample of consumers from each of the 101 newspaper markets. We drew names randomly from the zip codes accounting for 80% of circulation within each newspaper's home market. The sampling frame was lists of names compiled by a direct marketing list provider. We mailed 115,890 surveys between June 1, 2000 and July 15, 2000. The number of surveys mailed to each market was selected to produce approximately the same number of respondents. Surveys were allocated to zip codes within a market in proportion to the number of people living in the zip code. The individual in the household 18 years or older with the most recent birthday was asked to complete the survey. An incentive of $3 was attached to each survey, and responders were entered into drawings for 15 cash prizes. In total, 37,036 responded, giving a response rate of 37%. The distribution of the number of responses in each market was normal shaped with a mean of 337, standard deviation of 46, minimum of 271, and maximum of 472. Response rates in individual markets varied between 25% and 50% with a standard deviation of 6%.

The last step in the sampling procedure was to do a telephone survey of non-responders. This was done to determine if non-responders were systematically different from responders. Over the phone, we administered an abridged version of the mail survey to a random sample of 2000 non-responders to the mail survey, approximately 20 from each market. We found that non-responders were more likely to be nonreaders. The results of the phone survey were accordingly used to compute sampling weights to correct for this in the main survey. It turned out that 74% of non-responders were “readers,” meaning they look into a newspaper during a typical 7-day week, while 93% of responders were readers.

Respondents to the mail survey were also weighted based on age and sex to make the sample more representative. Weights were computed to reflect a random sample from the United States using data from phone survey, Claritas, and the 1990 Census.

The Questionnaire

RBS (reader behavior scores) and TRBS (total RBS) are the dependent variables of our analyses. RBS measures an individual's readership of a particular newspaper and TRBS measures readership of all daily newspaper. Respondents were also asked their sex, birth date (recoded to age as of 2000), education, household income, and years of residence in their town or community. Details on question wording are available at the Readership Institute's web site.[2]

RESULTS

The analysis is divided into two sections. The first uses additive models to examine nonlinear relationships and establish an upper bound for the fraction of variation in readership that can be "explained" by five demographic variables. The second uses random coefficient models to examine differences due to newspapers and markets.

The analysis examines effects on two dependent variables, RBS and TRBS. RBS is a measure of the readership of a specific paper and the results of regressions involving RBS should be thought of as a study of what affects readership of the "local paper." Recall that only people living in the primary market of the newspaper were included in the sample. TRBS is a measure of readership of any newspaper.

Let $(x_{ij1},\dots,x_{ij5})'$ denote the values of income (variable 1), education (2), age (3), residence (4), and female (5), respectively, for respondent *i* of newspaper *j*=1, …, 101. The variable female takes the value 1 if the respondent is female and 0 otherwise; thus, a positive slope coefficient for female would indicate that females read more than males. Hereafter, the variable *i* indexes respondents, *j* newspapers, and *k* variables.

We first provide pair-wise correlations in Table 2 among variables to assess the extent of multicollinearity. None of the correlations are alarmingly large, with the largest being between age and length of residence and between education and income; all other correlations are small. The condition number is 3.5, indicating no serious problem with multicollinearity (Montgomery and Peck 1982, p.301). The table also gives correlations with the two dependent variables. Age and length of

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2 See http://www.readership.org/consumers/survey/data/consumer_survey.pdf for the complete questionnaire. See http://www.medill.nwu.edu/faculty/malthouse/ftp/rbsdemo.html for details of this analysis.

residence have the largest correlations with both measures of readership. The correlations with income are substantially smaller and those with education are even smaller. The correlations with sex are very small. All correlations with the dependent variables are very highly significant (P<0.01, two-sided), but the sample size is large so even tiny correlations will be "significantly" different from 0. The computations of these P-values ignore the clustering in the data. The clustering is modeled correctly later with the random coefficient models. For this reason, we will not report P-values for the additive models. Also, within-market correlations can be larger or smaller than these national estimates.

Table 2: Pearson Correlations among Demographic Predictor Variables

	Education	*Income*	*Female*	*Residence*	*Age*
Education		0.40	-0.14	-0.22	-0.16
Income			-0.11	-0.16	-0.16
Female				0.02	0.00
Residence					0.46
RBS	0.03	0.07	-0.02	0.19	0.19
TRBS	0.07	0.11	-0.03	0.18	0.23

Additive Model with Smoothing Splines

We first examine the relationship between readership and demographics across newspapers and later study the relationship for individual newspapers. Across newspapers (ignoring individual market effects), a linear regression model of readership on the demographics involves estimating

$$y_{ij} = \alpha + \sum_{k=1}^{4} x_{ijk}\beta_k + x_{ij5}\beta_5 + e_{ij}, \tag{1}$$

where α is the intercept, e_{ij} are normal with mean 0 and variance σ^2, and β_k is the slope for variable k. The dependent variable, y_{ij} is "readership;" we estimate the model separately for RBS and TRBS. Parameters α, $\beta_1, \ldots, \beta_5$, and σ^2 are estimated by the regression. An additive model (Hastie and Tibshirani 1990) generalizes the linear regression model by allowing for nonlinear main effects:

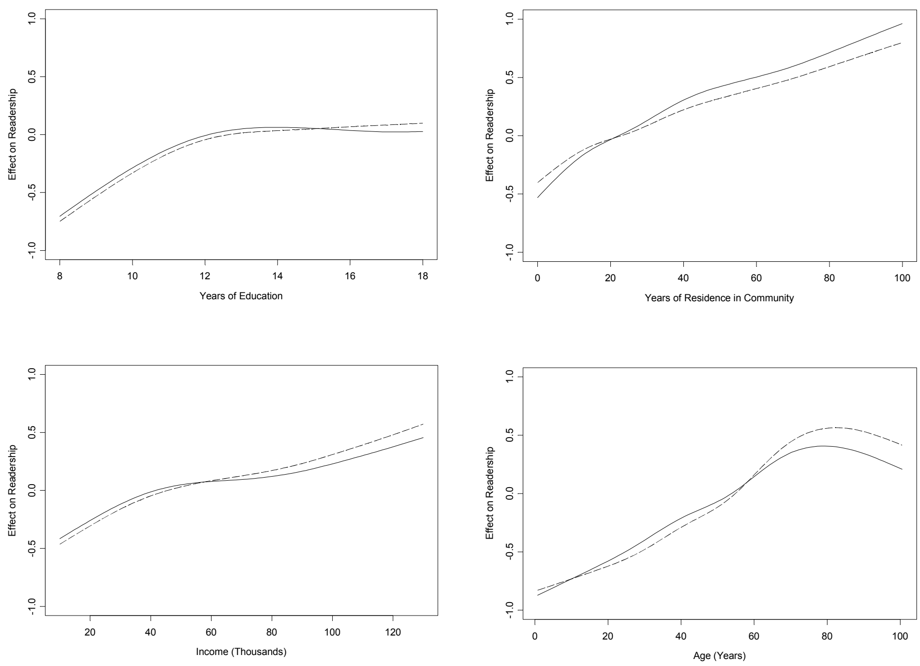
$$y_{ij} = \alpha + \sum_{k=1}^{4} f_k(x_{ijk}) + x_{ij5}\beta_5 + e_{ij} \tag{2}$$

where the assumptions on α and e_{ij} are identical to those for the linear model, and $f_1, \ldots, f_4$ are continuous functions, which we model with a cubic smoothing spline having 3 degrees of freedom. Functions f_k are generalizations of β_k, k=1, 2, 3, 4. "Parameters" α, f_1, f_2, f_3, f_4, β_5, and σ^2 are estimated to minimize the same least-squares objective function as linear regression,

$$\sum_{i} \sum_{j} (y_{ij} - \alpha - \sum_{k=1}^{4} f_k(x_{ijk}) - x_{ij5}\beta_5)^2 . \tag{3}$$

We estimated the models specified in equations (1) and (2) using the S-plus software package after dropping cases where any of the variables used in this regression were missing (25,007 observations). Estimates of functions f_k for both RBS and TRBS are shown in Figure 1. The graphs of function f_k show the effect of a particular predictor variable on readership; if one wished to create such a graph for a linear regression model, the graph would be a straight line having a slope of the estimated coefficient. Education has a positive effect on RBS and TRBS until about 13 years of education; those with 13 years of education do not read more, on average, than those with more than 13 years. Income and residency have nearly linear effects. Age has a strong positive relationship with readership until the age of 80, when readership begins to decline. Note that these estimates are national averages, which do not account for market heterogeneity.

Figure 1: Effects of Demographic Variables (f_k) on Readership for All Markets Combined



Notes: The solid lines show effects on RBS and the dashed lines show effect on TRBS. The parameter estimates for female are 0.0198 and -0.0347 for RBS and TRBS, respectively.

We can examine how much readership is explained by the various demographics by noting the difference in R^2 with a variable in and without it. Table 3 compares the values of R^2 for several models. Note the following:

1. The demographics considered here are weak predictors of readership. Even after modeling for nonlinear main effects with an additive model, these demographics only account for 10% of the variation in readership. Readership must be determined by other factors.
2. The relationships between readership and these demographics is somewhat nonlinear. For RBS, R^2 improves from 6.63% to 7.85%, or 18% = (0.0785-0.0663)/0.0663 by adding the nonlinear terms; for TRBS, R^2 improves by 15%. With the large sample size, this improvement is highly significant.
3. Length of residence and age are the most important predictors of readership. When both of these variables are dropped from the RBS and TRBS models, R^2 decreases to 1.13% and 2.05% respectively. Income, education, and sex only explain 1-2% of the variation in readership. When age or residence is dropped from the model, R^2 decreases by a substantial amount; age and residence are moderately correlated (0.46) and thus can serve as surrogates for each other to some extent.
4. Age seems to be a more important predictor of TRBS than of RBS. When age is dropped from the RBS model, R^2 decreases from 7.85% to 5.89%, a 25% decrease. When age is dropped from the TRBS model, R^2 decreased from 10.02% to 6.65%, a 34% decrease. The difference between the RBS and TRBS models is not as great for length of residence.
5. Income and education explain some variation in readership, but not as much as years of residence or age.
6. Sex has very little effect on readership. The coefficient is not significantly different from 0 (P=0.1345, two-sided) even with the very large sample size. R^2, when rounded to four decimal places, does not change when sex is dropped from the model.
7. We also quantified the amount of non-linearity by replacing the smoothing terms with linear terms. If the model with the linear term has essentially the same R^2 value as the model with the smoother, we conclude that the relationship is essentially linear. R^2 decreases the most for age.

Table 3: Values of R^2 for Various Models

Model	*RBS R^2*	*TRBS R^2*
Linear Regression	0.0663	0.0875
Additive Model	0.0785	0.1002
Additive Model w/o Residence	0.0587	0.0870
Additive Model w/o Age	0.0589	0.0655
Additive Model w/o Income	0.0666	0.0800
Additive Model w/o Education	0.0750	0.0952
Additive Model w/o Female	0.0785	0.1002
Add Model w/o Residence, Age	0.0113	0.0205
Add Model w/o Education, Income	0.0587	0.0656
Linear Age	0.0744	0.0938
Linear Education	0.0755	0.0975
Linear Residence	0.0764	0.0988
Linear Income	0.0763	0.0984
SST	95,260	81,057

Next, we studied the relationship between demographics and RBS for specific newspapers to answer the following two questions. First, do demographics "explain" readership in some markets better than in others? Second, does the non-linearity, both extent and shape, of the relationship vary across market? We estimated the following two models in every newspaper market j = 1, ..., 101:

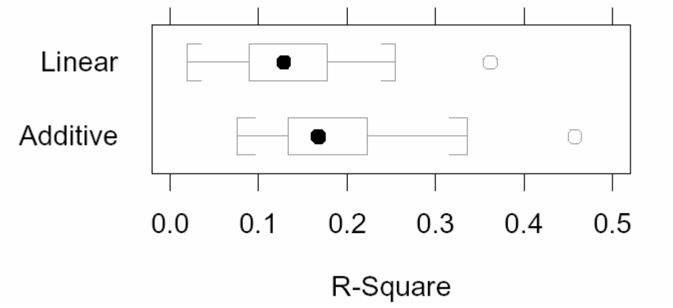
$$y_{ij} = \alpha_j + \sum_{k=1}^{4} x_{ijk}\beta_{jk} + e_{ij} \tag{4}$$

$$y_{ij} = \alpha_j + \sum_{k=1}^{4} f_{jk}(x_{ijk}) + e_{ij} \tag{5}$$

Note that the only differences between (1) and (4) are that there is a separate set of slopes and intercepts for each market and female is dropped from the model, since it does not explain much in any market as we show in the next section; likewise for equations (2) and (5). We fitted a total of 101 linear regression models and 101 additive models with splines.

We computed values of R^2 for each of the 202 models. The distributions of these values are summarized with boxplots in Figure 2. These values should be regarded as upper bounds for R^2. The sample sizes for individual markets varied from 271 to 472, with an average of 337. Each model for an individual market had 13 degrees of freedom (4 variables × 3 degrees of freedom + 1 intercept).

Figure 2: Distributions of R^2 Values Resulting from Linear Regression Models and Additive Models



Note. RBS on age, education, income, length of residence, and sex) with smoothing splines across 101 newspaper markets

The average value of R^2 for the additive models is 18%, indicating that in the typical market demographics "explain" only a small portion of readership. In all but one market, the values of R^2 are between 7.5% and 33.6%; there is one outlier, where R^2=45.8%. Thus, the reach of newspapers is not captured so well by demographics.

To understand how the nature of the nonlinearities varies across market, Figure 3 shows the functions f_{jk} for a random sample of 20 markets. The main point of these graphs is that there is considerable heterogeneity in the nature of the nonlinearities across markets. In some markets effects are flat; in some cases we see inverted "U" relationships; in some cases we see positive, but diminishing marginal increases. The implication for advertising researchers is that individual markets must be studied separately.

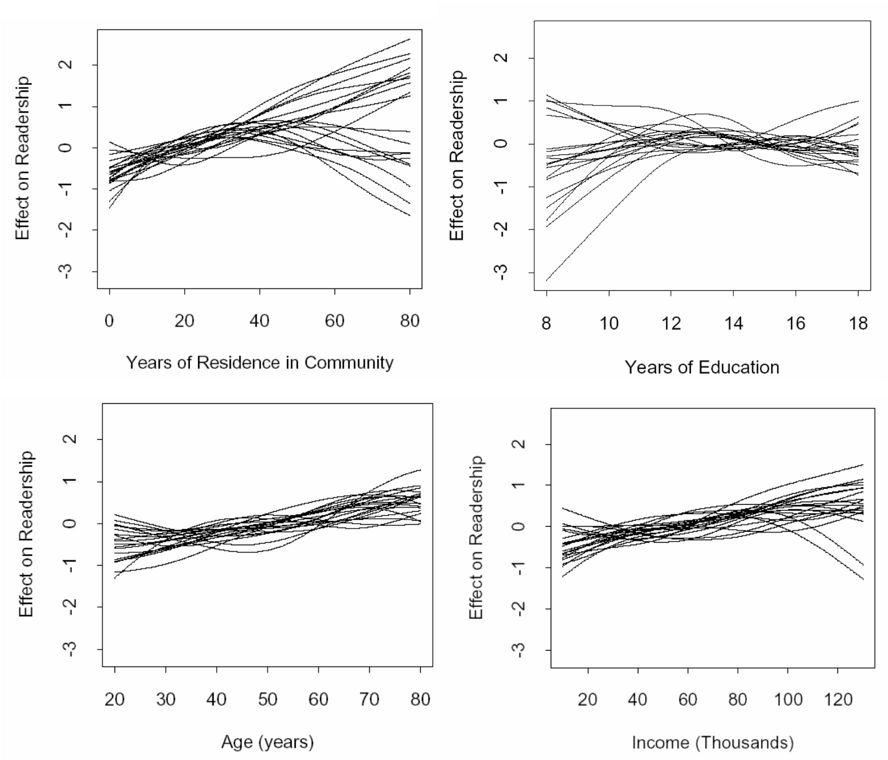
Random Coefficient Model

A more parsimonious way of modeling heterogeneity across markets is with random coefficient models (Kreft and de Leeuw 1998). Assume that the variables x_{ij1}, ..., x_{ij5} have been standardized to have mean 0 and variance 1 within each market. We estimate the following model:

$$y_{ij} = \sum_{k=1}^{5} x_{ijk} b_{jk} + e_{ij}, \tag{6}$$

where e_{ij} are normal random variables with mean 0 and variance σ^2, and coefficient b_{jk} is a normal random variable with mean β_k. We estimate this model in SAS with an *unstructured covariance* model. The interpretation of b_{j1} is the slope for income (variable 1) in market *j*. The interpretation of β_1 is mean slope of income for the entire the industry. The model also estimates $V(b_{jk})$. For example, the interpretation of $V(b_{j2})$ is the variance of the slopes for education across markets. If $V(b_{j2}) \approx 0$ we would conclude that the effect of education on readership is the same in

Figure 3: Effects of Demographic Variables (f_{jk}) on Readership as Measured by RBS in 20 Markets



every market; conversely, if $V(b_{j2})$ is large, we would conclude that the effect of education on readership varies greatly by market. The unstructured covariance option also estimates the covariances between slopes. For example, the interpretation of $C(b_{j1}, b_{j2})$ is the covariance between the slopes of education and income; if this covariance is negative then markets having a large effect of education on readership also tend to have a small effect of income on readership.

Note how more parsimonious this model is than equation (4). In the previous model the number of parameters estimated increased linearly with the number of newspapers; for each newspaper we estimate 5 slopes, an intercept, and the error variance σ^2, giving a total of 707 parameters for 101 newspapers. With random coefficient models, the number of parameters does not increase with more newspapers; we estimate five slopes (β_k), the 15 unique entries in the covariance matrix of the slopes, and the common error variance (σ^2). We do not make any attempt to model nonlinearities. While it is possible to transform predictor variables before estimating the model, the transformation required varies considerably across market.

We estimated the model using proc mixed in SAS with the default estimation method, restricted maximum likelihood (REML). Estimates of slopes for individual newspapers were made using empirical best linear unbiased predictors (EBLUPs). Estimates of β_k and the covariances of the slopes are given in Tables 4, 5, and 6. The marginal distributions of b_k are shown in Figure 4. The residual variance (σ^2) is estimated as 0.9135 (standard error 0.0082) for RBS and 0.9051 (0.0081) for TRBS. Note the following:

1. *Length of residence* has the largest effect (β_k=0.188) for both RBS and TRBS, confirming the conclusion from the additive model that this is an important variable. The variance of the residence slopes across newspapers $V(b_{j4})$ is also by far the largest (.01319 for RBS and .01231 for TRBS), suggesting that it is not equally important in all markets. The boxplots reveal that the slope estimates are close 0 or negative for up to a quarter of the markets.
2. *Education* is not significantly different from 0 for RBS, and has a small, but highly significant, effect for TRBS. We also estimated this model without income. When income is dropped from the RBS model, the effect for education is 0.065 and has a P-value less than 00001. Recall that education and income have a positive correlation and thus can serve as surrogates for one another to some extent. The variance of the slopes across newspaper $V(b_{j2})$, however, is large. The boxplots show clearly that in some markets education has a positive effect on readership while in others the effect is negative. Negative effects are particularly common when RBS is the dependent variable. Thus, for some newspapers, the more educated a person is, the less likely the person reads the particular paper.
3. *Age* and *Income* have similar effects on readership. Both have substantial *positive* effect sizes that vary across markets.
4. *Sex* has little effect on readership in any market. With TRBS as the dependent variable, the slope for sex, β_k = –0.005, is not significantly different from 0; the overall slope for when RBS is the dependent variable is also small. The variances are the smallest of the predictor variables, which is reflected by the short box plots. This indicates that sex has little effect on readership in any market.
5. *Covariances*. There are several significant covariances, which are likely related to the correlations among predictor variables. For example, the covariance between the slopes of age and residence with RBS as the dependent variable is –5.57, but these two variables have a positive correlation (0.46) and both have positive overall correlations with readership.

Table 4: Estimated Effects (β_k) and *P*-values for Random Coefficient Model

	RBS			***TRBS***		
Variable	Estimate	Std Err	*P*-Value	Estimate	Std Err	*P*-Value
Income	0.127	0.0107	<0.0001	0.150	0.0100	<0.0001
Education	0.012	0.0111	0.2870	0.052	0.0113	<0.0001
Age	0.140	0.0103	<0.0001	0.177	0.0110	<0.0001
Residence	0.188	0.0135	<0.0001	0.157	0.0131	<0.0001
Female	0.016	0.0069	0.0195	-0.004	0.0074	0.6071

Table 5: Estimated Covariance Matrix C(b_{jk}, $b_{jk'}$) and Correlations ($C(b_{jk}, b_{jk'}) / \sqrt{V(b_{jk})V(b_{jk'})}$) for the Model of RBS, with Computed Correlations Above the Diagonal

	Income	***Education***	***Age***	***Residence***	***Female***
Income	7.34**	-0.121	0.256	-0.180	-0.119
Education	-0.92	7.88**	0.344	-0.355	0.081
Age	1.68	2.34*	5.88**	-0.632	-0.007
Residence	-1.77	-3.62*	-5.57**	13.19**	-0.002
Female	0.35	0.25	-0.02	-0.01	1.22*

Notes: All (co)variances have been multiplied by 10^3. Stars give results from testing H_0: C(b_{jk}, $b_{jk'}$)=0 against a two-sided alternative; a single star indicates a P-value less than .05 and a double star less than .01.

Table 6: Estimated Covariance Matrix C(b_{jk}, $b_{jk'}$) and Correlations ($C(b_{jk}, b_{jk'}) / \sqrt{V(b_{jk})V(b_{jk'})}$) for the Model of TRBS, with Computed Correlations above the Diagonal

	Income	**Education**	**Age**	**Residence**	**Female**
Income	5.77**	-0.537	-0.116	0.038	0.083
Education	-3.73**	8.35**	0.414	-0.193	0.294
Age	-0.75	3.23*	7.28**	-0.641	0.175
Residence	0.32	-1.96	-6.07**	12.31**	-0.027
Female	0.28	1.19	0.66	-0.13	1.95**

Note: All (co)variances have been multiplied by 10^3.

The boxplots and variances suggest that the demographic correlates of readership vary across markets, e.g., in some markets education has a positive effect on readership while in others it has a negative effect. This raises the question of whether there are distinct types of newspapers. We investigate this question by applying k-means clustering to the estimated regression coefficients b_{jk} from the RBS model, i.e., we have 101 observations (newspapers) and five variables (the estimated slopes). We use the RBS coefficients because we want to find types of newspapers; clustering TRBS coefficients would produce a typology of newspaper markets, which seems less interesting.

We selected the 4-cluster solution, which has a cubic clustering criterion of 1.434, indicating that it is a reasonable cluster solution. Table 7 summarizes the distributions of slopes by cluster.

- Cluster 1 (19/101 newspapers). Age has the strongest effect; the older a person, the higher readership is on average. Income also has a strong effect. Length of residence has little effect.
- Cluster 2 (14/101 newspapers). Large residence and income effects, negative education effects.
- Cluster 3 (40/101 newspapers). Average newspaper: moderate residence, age, and income effects.
- Cluster 4 (28/101 newspapers). Large residence effects, small negative education effects, small positive income effects.

A newspaper could determine which cluster it is in by estimating the regression model described above to arrive at slopes. It would then compute the Euclidean distance between the slope estimates and each of the four cluster centroid given in Table 7. The newspaper is assigned to the cluster with the closest centroid, just as the *K*-mean algorithm operates.

Table 7: Cluster Means Grouping Newspapers by the Estimated Effect of Five Demographic Variables on RBS

Variable	*Cluster 1*	*Cluster 2*	*Cluster 3*	*Cluster 4*
Income	0.15	0.18	0.14	0.07
Education	0.08	-0.06	0.03	-0.02
Age	0.20	0.10	0.16	0.08
Residence	0.04	0.30	0.16	0.27
Female	0.01	0.01	0.02	0.01

CONCLUSIONS

The main contribution of this article is to examine how readership depends on demographic variables across different newspapers and markets. We find that there is considerable heterogeneity across both newspapers and markets for length of residence, education, income, and age, e.g., in some markets the effect of education on readership is positive while in others it is negative. The non-linearity of the relationship also varies considerably across markets. We suggest four types of newspapers based on which demographics drives readership of the newspaper.

Of these five demographics, length of residence and age have the strongest effects, which are positive overall and for most individual newspapers/markets. Income also has a positive effect on readership. The effect of education is very small overall, but varies considerably across newspapers/markets. Sex has little effect anywhere. The overall effect of age is somewhat nonlinear, with readership declining after the age of 75-

80. The overall effect of education is also nonlinear; it is positive for less than 12 years of and flat thereafter.

Our analysis also provides estimates of national effects of demographics, averaging over newspaper/markets. The fraction of readership variation explained by these demographic variables is small, suggesting that readership is better determined by factors other than these five demographics. This also indicates that newspapers can be used to reach all ages. If the fraction of variation in readership explained by demographics had been large, we would have concluded that newspapers were finely targeted towards a particular demographic segment, but this is not the case. Researchers and practitioners must look beyond demographics to explain newspaper readership.

Future research should propose variables that can better explain readership. We hypothesize that the consumer experience – what consumers think and feel when they read a newspaper – will be more predictive of readership and more actionable to the practitioner than demographics. Our research has identified such experiences (Calder and Malthouse 2004) and related experiences to usage.

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