Audience Flow Past and Present: Television Inheritance Effects Reconsidered

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Television inheritance effects, inordinately high levels of audience duplication between programs scheduled back-to-back, have helped broadcasters manage audience flow for decades. This study uses 2004 national peoplemeter data collected by Nielsen to replicate a study of inheritance effects done 20 years earlier. It finds the same predictors explain either 96% or 58% of variance in the duplicated audience, depending upon the measure of duplication that is used. The research resolves discrepancies in the literature on inheritance effects and casts serious doubt on the common practice of inferring audience duplication from the strength of correlations between lead-in and lead-out program ratings.

Inheritance effects are one of the most important, and robust, of all television audience behaviors. Also known as lead-in effects, or simply audience flow, they have been routinely reported in the academic literature for over 40 years. Essentially, they describe the tendency of people who watch one program on a given network to stay tuned to the next, resulting in disproportionately large "duplicated audiences." If the lead-in program has a big rating, it confers an advantage on the following program. Conversely, if the first show has a small audience, it handicaps its successor. Neither the growth of alternative delivery systems nor the universal penetration of remotes seems to have diminished the phenomenon. Inheritance effects are, to this day, the foundation of programming strategies that have been in use for several decades (Adams, 1997; Eastman & Ferguson, 2006; Webster, Phalen, & Lichty, 2006).

Yet, many studies that claim to document inheritance effects are hampered by their inability to directly observe the duplicated audience. Further, there is a lack of conceptual clarity on how to measure inheritance effects that leads to widely divergent, even contradictory, results. This study addresses those problems by using Nielsen

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peoplemeter data (a) to replicate a study of inheritance published 20 years ago (Webster, 1985), and (b) to extend the analysis to consider a different dependent measure. This author finds that the relationships identified in 1985 are generally stronger in 2004, resulting in a model that explains 96% of the variance in the duplicated audience. However, an alternative measure of inheritance provides new insights into this central feature of television audience behavior.

The Literature on Inheritance Effects

Audience flow is a topic of enduring interest to broadcasters. As early as 1945, C. E. Hooper, the long defunct ratings company, offered radio stations a service to track audience flow to and from other stations ("Advertising News and Notes," 1945). Beville's (1988) history of audience ratings describes network researchers routinely analyzing audience flow with household-by-household data from Nielsen. Legendary TV programmers like Fred Silverman and Brandon Tartikoff built their reputations, in part, on their ability to manage audience flow (Gitlin, 1983).

These recurring patterns of audience behavior are best understood within a theoretical framework that recognizes audience availability, viewer program preferences, and the many structural factors that constrain those preferences (e.g., Rust & Eechambadi, 1989; Webster & Phalen, 1997). Webster (1985) argued that the general phenomenon of adjacent program audience duplication was, in the first instance, the result of audience availability. That is, programs scheduled back-to-back were likely to enjoy high levels of duplication simply because the same people tended to be available (i.e., watching TV) in adjacent time periods. Within that context, viewer preferences and the structure of program options determined the ebb and flow of audiences. Some have ascribed audience flow to simple audience inertia and passivity. Adams (1997), for example, argued that "flow theory" had little or nothing to do with people acting on their program preferences. In fact, the relevant theories of program choice take a more nuanced approach that attempts to sort out the tensions between people's program preferences and the way in which those programs are scheduled. That is, at any rate, the framework within which inheritance effects are explored here.

Inheritance effects can be thought of as a special, within-channel, case of audience flow. It is, by far, the most important and widely studied form of audience flow. To the best of the author's knowledge, the first publicly reported evidence of this behavior was offered by Kirsch and Banks (1962), who noted inordinately high levels of audience duplication between programs scheduled back-to-back on the same network. Shortly thereafter, media researchers in Great Britain began studying the same phenomenon, which they dubbed the "inheritance effect" (Goodhardt, Ehrenberg, & Collins, 1975). Since then, many studies have, in one way or another, documented and dissected television inheritance effects. Most can be categorized into one of three types. The first takes the "duplication of viewing law" (Goodhardt et al., 1975) as a point of departure and adapts it to studying inheritance. The second, and largest, group of studies looks for circumstantial evidence of inheritance by comparing the correlations between lead-in and lead-out program ratings or shares under various conditions. The third, like the first, uses direct evidence of inheritance but considers a different dependent measure.

The duplication of viewing law, first introduced by Goodhardt (1966), stipulates that the proportion of the total television audience that sees any two programs is a function of the audience ratings of those programs multiplied by some constant. Mathematically, it can be expressed as

$$r_{st} = r_s r_t k,$$

where r_{st} is the proportion of the population seeing both programs *s* and *t* (i.e., the duplicated audience), and r_s and r_t are the ratings of those program, respectively. The constant *k* was determined empirically and varied according to the channels broadcasting the programs in question. Inheritance effects were originally noted as an exception to the law because adjacent programs on the same channel routinely had larger duplicated audiences than the law predicted.

Headen, Klompmaker, and Rust (1979) argued that the duplication of viewing law was analytically limited and that values of *k* varied too much for it to be considered a constant. Their approach was to predict the duplicated audience (i.e., r_{st}) using a multiple regression equation that allowed investigators to enter additional independent variables. The product of program ratings (i.e., $r_s r_t$) was simply entered as another predictor in the equation. For purposes of estimation, Headen et al. (1979) used a logarithmic transformation of the ratio level variables (i.e., r_{st} and $r_s r_t$). A similar transformation was used by Henriksen (1985).

Webster (1985) adapted Headen et al.'s (1979) approach to study television audience inheritance effects. Using respondent-level Arbitron diary data collected during February 1982 in Portland, Maine, Webster identified all back-to-back program pairs broadcast during prime-time on the three network affiliates. Seventy-four program pairs were identified and used as the unit of analysis. Because respondent-level data were available, it was possible to measure the duplicated audience for each pair. Following Headen et al., data were logarithmically transformed, better meeting the assumptions underlying the linear model—a topic that will be addressed later. Unlike Headen et al., who specified the relationship between program ratings a priori by entering $r_s r_t$, Webster allowed r_s and r_t to enter the equation separately. This approach produced a multiple regression equation in which four predictor variables entered in the following order: (a) the rating of the first program in the pair (i.e., the lead-in rating or r_s), (b) the number of network programs beginning at the end of the first program, (c) the rating of the second program (i.e., the lead-out ratings or r_t), and (d) similarity of program type within the pair. Together, these explained 85% of the variance in the duplicated audience (r_{st}). The current study replicates Webster (1985) using a national sample, thus offering a look at the same relationships 22 years later.

The principle advantage of the first approach to studying inheritance effects is that it offers a direct measure of the behavior in question. The investigator knows what portion of the sample saw both programs in any program pair. This dependent variable can, in turn, be precisely related to other predictors. This is a well-established and very pragmatic method for predicting the duplicated audience. However, the use of program ratings as predictors has an unsatisfying tautological quality. Programs with very small audiences will, necessarily, have tiny duplicated audiences. Programs with very large audiences will, just by chance, have large duplicated audiences. As a result, large correlations between program ratings and the dependent variable are almost a foregone conclusion.

A second, much more common, strategy for studying inheritance effects is to compare the strength of correlations between program ratings or shares under various conditions. For example, if those correlations are higher when back-to-back programs are of the same type, then stronger inheritance effects are typically inferred. Tiedge and Ksobiech (1986) conducted the most sweeping such analysis by correlating the audience shares of adjacent prime-time network programs broadcast between 1963 and 1985. Although the overall correlation was .49, correlations were higher when paired programs were of the same type and when viewers had fewer options on competing networks, thus confirming the relationships reported by Webster (1985). More recent studies have noted the increased penetration of cable, VCRs, and remote control devices, and speculated that these might somehow diminish inheritance effects (e.g., Adams, 1997; Davis & Walker, 1990; McDowell & Dick, 2003; Walker, 1988). Despite some year-to-year fluctuations, the trend in correlations has, if anything, been upward. The overall correlation for 2002 prime-time network program pairs was .66, suggesting no diminution of inheritance effects (McDowell & Dick, 2003).

The second group of studies takes advantage of network program ratings and shares that are routinely reported in the trade press. No customized, and therefore difficult to obtain, analyses of audience duplication are used. Investigators can certainly study programming patterns and their associated ratings over many years, but without the ability to aggregate individual behaviors over time, no direct measure of audience duplication is possible. As McDowell and Dick (2003) noted, there is “a certain leap of faith” (p. 290) required to get from correlated ratings to actual audience duplication. Perhaps that is why research of this sort sometimes identifies itself as studying “lead-in” strategies, or “share maintenance.” It certainly leaves no doubt that back-to-back programs have highly correlated ratings. Several other studies, some less directly concerned with audience flow, have produced similar circumstantial evidence (e.g., Boemer, 1987; Cooper, 1993; Webster & Newton, 1988). Nonetheless, the underlying patterns of inheritance are essentially invisible.

The third group of studies is similar to the first, in that they have a direct measure of the audience shared between adjacent programs. Instead of using the proportion of the total audience that sees two programs (r_{st}) as the dependent variable, they use a related measure. Inheritance is readily thought of as the percentage of the lead-in program audience that watches the second show. In the parlance of the duplication of viewing law, this is simply the duplicated audience divided by the rating of the first program (i.e., r_{st}/r_s). Goodhardt et al. (1975) were the first to describe inheritance effects in this way, perhaps because it was a more intuitively appealing number. Nielsen Media Research refers to this number as the "primary duplication," and that label will be used throughout the remainder of the article.

Eastman, Newton, Riggs, and Neal-Lunsford (1997) used primary duplication to assess the impact of several factors on audience inheritance. They found no correlation between that dependent measure and lead-in ratings or shares. Like Webster (1985), however, they found similarities in program type and the number of competing options to be significant predictors of inheritance. These factors explained 56% of the variance in primary duplication. Incorporating information on various programming tactics (e.g., cold starts, packaging credits with live action, etc.) added marginally to the explained variance. Noting the apparent reduction in R^2 from Webster's 1980s research, Eastman et al. (1997) concluded that the potency of inheritance effects seemed to be in decline. However, that conclusion seems unwarranted because Eastman et al. were essentially comparing "apples and oranges." As will be seen, using primary duplication as a dependent measure of inheritance produces rather different results than using the duplicated audience.

McDowell and Sutherland (2000) also used primary duplication to assess inheritance effects. Their hypothesis was that programs with stronger "brand equity" would do a better job of inheriting lead-in audiences. As operationalized, this essentially boiled down to a prediction that a local newscast with high ratings will enjoy higher primary duplication than competing newscasts with lower ratings. That proved to be the case. Further, in a curious twist, the correlation of newscast ratings with their lead-in ratings was lowest (.59) for the station with the highest primary duplication. This would seem to draw into question the entire practice for using correlations between adjacent program ratings or shares as indication of inheritance effects.

The current study does three things. First, it will replicate, as nearly as possible, Webster's (1985) study of inheritance effects using 2004 duplicated audiences as the dependent variable. That will provide better insights into how changes in the media environment have affected the strength of inheritance effects and the factors that predict them. Specifically, it will test four hypotheses:

H_1: The rating of the first program (r_s) is positively related to duplication.
H_2: The rating of the second program (r_s) is positively related to duplication.
H_3: The number of choices is inversely related to duplication.
H_4: Similarity of within-channel program type is positively related to duplication.

Second, it will test the same hypotheses using primary duplication as the dependent measure. That will provide a clearer understanding of the implications of this alternative measure of inheritance, and resolve the apparent discrepancies in that literature. For example, the research of Eastman et. al. (1997) suggests H_1 will not be supported.

Finally, it will explore the intriguing implication of McDowell and Sutherland's (2000) work that the many studies relying on back-to-back program correlations tell less than would be liked about the underlying mechanisms of audience inheritance. Specifically, it asks the following research question:

RQ_1: When there are relatively high levels of duplication between program pairs, do the ratings of those programs have relatively high correlations?

Method

This study is a secondary analysis of data collected by Nielsen Media Research during the second week in March 2004, using its national peoplemeter sample. This week was chosen because viewing levels were high, there were relatively few repeats, and yet programming was unaffected by the "stunts" that often characterize sweep months. The results are based on all adults, aged 18 and older, who provided useful data during that week, a total of 10,500 individuals.

Like Webster (1985), the units of analysis are pairs of programs scheduled back-to-back on the same broadcast network during prime time. Because there are no national broadcast ratings leading into prime time, 8:00 p.m. to 8:30 p.m. EST was the earliest possible pairing. Similarly, 10:00 p.m. to 10:30 p.m. EST was the latest possible pairing. Webster deliberately chose a local market with three network affiliates (ABC, CBS, and NBC) and no independents to study viewing in an "uncomplicated" environment. By 2004, there were seven commercial broadcast networks available nationwide (ABC, CBS, NBC, FOX, PAX, UPN, and WB). With the exception of PAX, the newer networks ended prime time by 10:00 p.m. EST, and/or were "dark" during the weekends. All in all, a total of 88 program pairings were identified for analysis.

Information on program ratings and duplication was generated using Nielsen's NPower software. Viewers had to watch a program for 6 or more minutes to be included in the program's audience. In the first set of analyses (i.e., Tables 1 and 2) the duplicated audience is the dependent variable (i.e., r_{st}). In the remaining analyses, primary duplication is the dependent variable (i.e., r_{st}/r_s).

Along with the ratings of the programs in each pair, four additional dependent variables were added; these either replicate or amplify on Webster's (1985) scheme. If programs in the pair were of the same type, the pair was coded 1. If they were of different types, the pair was coded zero. There are good grounds, both theoretically and empirically, to expect people to have consistent program type preferences (e.g., Adams, 1997; Eastman et al., 1997; Tiedge & Ksobiech, 1986; Webster & Phalen, 1997). Therefore, program pairs of the same type should enjoy higher levels of inheritance. The biggest challenge is picking the most discriminating program typology. This author opted to use Nielsen's categorization scheme, which recognizes 40 different types. Many of these do not appear in prime time, and, as a practical matter, Nielsen's scheme produces the same result as the 10 category scheme used by Tiedge and

Ksobiech. Because Webster found no significant cross-channel program type effects, that factor was not explored.

An important structural determinant of inheritance is the number of options the audience has to "defect" from a channel at the end of any given program. How many competitors are beginning a new show at that time? Next to the rating of the lead-in program, Webster (1985) found that the number of choices across the three networks was the best predictor of inheritance. Today, of course, the average household can receive over 100 channels of programming (Nielsen Media Research, 2004), so there is almost always an opportunity to defect. Still, more recent research finds that the number of options (now across four choices including FOX) is a significant predictor. The impact of choices was further examined here by coding how many programs begin at the conclusion of the first program in the pair, across three networks (i.e., Big 3 choices), four networks (i.e., Big 4 choices), or all seven networks. The general hypothesis is inheritance will be inversely related to the number of such choices. However, the author leaves as an open research question which of the coding schemes is most effective in explaining duplication.

Finally, to be consistent with Webster (1985), the natural log of the duplicated audience (i.e., ln r_{st}) was used as the dependent variable in the first set of results (Tables 1 and 2), along with a similar transformation of r_s and r_t. In their untransformed state, these variables deviate slightly from the assumptions of the linear model. In the 2004 data, there is modest evidence of heteroscedasticity and nonnormality in the distribution of residuals. Using transformed variables results in a slightly higher R^2 and correlation coefficients than would otherwise be the case, although the overall pattern of results is unchanged. To be consistent with previous research using primary duplication as the measure of inheritance, however, transformations were not used. Omitting transformations permits an "apples to apples" comparison with the vast majority of studies that use untransformed data. Here, again, the overall pattern of results is the same either way.

Results

The results are presented in three parts. The first compares patterns of adjacent program audience duplication from data collected in 1982 and 2004 and reports a multiple regression equation explaining 96% of the variance in 2004 data. The second considers primary duplication as the dependent variable, presenting a correlation matrix and regression equation explaining 58% of the variance. The last addresses RQ_1 by comparing the correlations of adjacent program ratings under conditions of high and low audience duplication.

Table 1 is a correlation matrix depicting the relationships among variables in the 2004 data, set alongside the same relationships in the 1982 data. This is not a perfect replication. The older correlations are based on diary data collected in a local market with pairings across three networks, whereas the newer correlations are based on

Table 1
Correlation Matrix Comparing 1982 and 2004 Data on Audience Duplication

	Rating 1		Rating 2		Choices		Program Type	
	1982	2004	1982	2004	1982	2004	1982	2004
1. Duplication	.83	.95**	.38	.92**	–.39	–.34**	.43	.17
2. Rating 1	—	—	.34	.91**	–.03	–.25*	.21	–.02
3. Rating 2			—	—	.14	–.16	–.08	–.02
4. Choices					—	—	–.46	–.19
5. Program type							—	—

Note: Variables are defined as follows:
1. $\ln(r_{st})$, where r_{st} is the percentage of the population seeing two programs in an adjacent pair.
2. $\ln(r_s)$, where r_s is the percentage of the population seeing the earlier program in an adjacent pair.
3. $\ln(r_t)$, where r_t is the percentage of the population seeing the later program in an adjacent pair.
4. The number of programs beginning on ABC, CBS, and NBC when the earlier program ends, ranging from 0 to 3.
5. Within channel program type, coded 1 if both programs were of the same type, 0 if of different types.

$^*p < .05$. $^{**}p < .01$.

peoplemeters in a national sample with pairings across seven networks. Nonetheless, a number of similarities and differences are noteworthy. The rating of the lead-in program (Rating 1) still enjoyed the single highest correlation with the duplicated audience, supporting H_1. In 1982, it was .83; in 2004, it was .95. However, the rating of the lead-out program in the pair (Rating 2) now had a much higher correlation with the duplicated audience (.92), supporting H_2. Not surprisingly, in the 2004 data, the ratings of the two programs were themselves highly correlated (.91). For purposes of predicting duplication, then, these factors should be expected to offer largely redundant information.

To facilitate comparison to the 1982 data, Table 1 reports only the number of choices across the Big 3 networks (ABC, CBS, and NBC). Interestingly, those two correlations were virtually identical (–.39 vs. –.34), supporting H_3. Since 1982, other networks have become available. The correlation between Big 4 choices and audience duplication was –.28 ($p < .01$). The number of choices on all seven broadcast networks combined was not significantly correlated with audience duplication. Because all of these measures of choice contained redundant information, they were themselves highly correlated (see Table 4).

The influence of program type in the 2004 data, although in the right direction, fell short of statistical significance, failing to support H_4. However, appearances can be deceiving. In the 1982 data, program type was confounded with the number of

Table 2
Determinants of Audience Duplication

	Standardized Coefficients			
Independent Variable	Step 1	Step 2	Step 3	Step 4
Rating 1 (ln r_s)	0.948	0.951	0.666	0.599
Program type		0.187	0.188	0.166
Rating 2 (ln r_t)			0.314	0.364
Big 4 choices				–0.119
Adjusted R^2	0.897	0.932	0.949	0.961
Overall F	761.67	597.16	537.53	543.98
df	1, 86	2, 85	3, 84	4, 83

Note: For all coefficients and values of F, $p < .0001$.

choices ($r = –.46$). Then, virtually all one-choice situations were instances in which situation comedies were scheduled back-to-back. In the 2004 data, program type was statistically independent of all other predictors, and so it might yet account for unexplained variation in audience duplication.

Table 2 presents the results of a stepwise multiple regression procedure in which all six potential predictors were allowed to enter the equation. This replicated Webster (1985) and allows comparison of the relative contributions of different predictors over a 22-year time span. Recall that Webster reported an equation with predictors entering in the following order: (a) Rating 1, (b) choices, (c) Rating 2, and (d) program type. That equation explained 85% of the variance in the duplicated audience. The 2004 data produce a similar result, with two interesting twists. As the largest correlate, Rating 1 again enters the equation first. Variance it shares with Rating 2 was thus assigned to the lead-in rating. So Rating 2, despite its high correlation with the dependent variable, once again enters on the third step of the equation, adding only slightly to the R^2. The second and fourth variables, however, enter in reverse order. Similarity in program type now seems to play a greater role in enhancing audience duplication. Conversely, the impact of the number of choices has diminished. Moreover, among the different operationalizations of choice, the number of Big 4 choices adds the most to explained variance.

Table 3 begins the second part of the results. It reports a correlation matrix including primary duplication as an alternative measure of inheritance and six potential predictor variables. The most striking difference between it and Table 1 is that the rating of the lead-in program is now uncorrelated with duplication. This fails to support H_1, but is consistent with the result reported by Eastman et al. (1997). Rating 2, however, is positively correlated with primary duplication, meaning that more highly rated lead-out programs do a better job of holding the audience from the first program than lower rated programs. This result is consistent with McDowell and Sutherland (2000). The impact of the number of choices hovers roughly in the same range as it did in Ta-

Table 3
Correlates of Primary Duplication in Adjacent Pairs

	Rating 1	Rating 2	Big 3	Big 4	All Networks	Program Type
1. Primary duplication	.04	.26*	–.38**	–.41**	–.31**	.57**
2. Rating 1	—	.79**	–.14	–.06	.08	–.10
3. Rating 2		—	–.08	–.01	.21*	–.11
4. Big 3 choices			—	.90**	–.81**	–.19
5. Big 4 choices				—	.90**	–.18
6. All network choices					—	–.19
7. Program type						—

*$p < .05$. **$p < .01$.

ble 1 (i.e., .30 to .40), but program type seems to emerge in a much more pronounced way, supporting H_3 and H_4.

Table 4 reports a regression equation that uses multiple predictors to explain variation in primary duplication. Because there was no a priori justification for specifying the order in which the variables were to enter the equation, a stepwise procedure was again used. As the strongest correlate, program type enters first, followed by Rating 2. Once again, the number of Big 4 choices is the most effective predictor of inheritance among the different operationalizations of choice. Interestingly, Rating 1 enters on the fourth step, adding appreciably to R^2, but is inversely related to primary duplication. This suggests that when a highly rated program is the lead-in, relatively few of its viewers actually stick around for the following program.

The last section addresses the value of using the correlation between first and second program ratings as an indirect measure of inheritance, which has been standard operating procedure in most studies of the phenomenon. There are two potential

Table 4
Determinants of Primary Duplication

	Standardized Coefficients			
Independent Variable	Step 1	Step 2	Step 3	Step 4
Program type	0.573	0.61	0.554	0.545
Rating 2		0.327	0.318	0.683
Big 4 choices			–0.301	–0.327
Rating 1				–0.464
Adjusted R^2	0.32	0.42	0.504	0.583
Overall *F*	41.96	32.54	30.49	31.4
df	1, 86	2, 85	3, 84	4, 83

Note: For all coefficients and values of *F*, $p < .0001$.

Table 5
Correlations of Adjacent Pair Ratings Under High and Low Inheritance

	Correlation Coefficients	
	High Inheritance	Low Inheritance
Duplicated audience (r_{st})	$r_{st} > 1.70\%$ (n = 44) .566	$r_{st} < 1.70\%$ (n = 44) .812
Primary duplication (r_{st}/r_s)	$r_{st}/r_s > 45\%$ (n = 44) .840	$r_{st}/r_s < 45\%$ (n = 44) .802

measures of the inherited audience, the duplicated audience and the primary duplication. The mean duplicated audience across all 88 pairings was 1.87% (*SD* = 1.43). The mean primary duplication was 47.36% (*SD* = 15.25). Table 5 divides each variable into equally sized conditions of high and low inheritance and reports the correlation coefficient between Rating 1 and Rating 2 across the 44 pairings in each group. To facilitate comparison to the existing literature, neither variable was transformed.

Table 5 answers RQ_1 with rather remarkable findings. The correlation between Rating 1 and Rating 2 among the 44 pairs with the highest primary duplication (*M* = 60%) was .840. The like correlation among the 44 pairs with the lowest primary duplication (*M* = 34%) was .802, a statistically insignificant difference ($z = .525$, $p = .60$). When the duplicated audience was used to create conditions of high and low inheritance, the difference between the correlations is statistically significant ($z = 2.20$, $p = .03$), but in the wrong direction. That is, pairings with the largest duplicated audiences had a lower correlation than pairings with smaller duplicated audiences.

Discussion

This study supports several conclusions about the current state of inheritance effects, how they have changed over the years, and the methods used to investigate them. Earlier studies of inheritance consistently found that the number of program choices—that is, the number of opportunities to "jump ship" for a newly beginning program—was a better predictor of inheritance than similarity of program type (Davis & Walker, 1990; Tiedge & Ksobiech, 1986; Walker, 1988; Webster, 1985). That seems to have changed. Constancy in program type is now the superior predictor of both the duplicated audience and primary duplication, a result that is consistent with Eastman et al. (1997).

This makes a good deal of sense. The structural constraints present in the early 1980s have been eroded in the intervening years. In the past, viewers essentially functioned in a three- or four-channel environment. Today, with several dozen channels available in virtually every household, not to mention remote controls, there is always an opportunity to jump ship. What is interesting is that this structural factor explains anything at all. It still adds appreciably to the ability to predict inheritance, particularly as measured in primary duplication. It is now the case, however, that the number of choices across the Big 4 networks, rather than the Big 3, is the more meaningful determinant. FOX is clearly a large enough presence to affect the equation. Beyond that, taking account of the lesser broadcast networks adds no useful information. They and the myriad cable networks have little enough effect that, in combination, they only produce apparent randomness.

Program type, as operationalized here, is rather like a blunt instrument. As is typical of the literature in this field, program categories are so broad that many potentially important nuances of content are lost. Given the emerging power of program content to explain how audiences flow from one network program to the next, it is probably worth looking at this factor with a more refined typology in mind. That might marginally improve the ability to predict inheritance. And when the results on primary duplication are considered, there is certainly much variance left to be explained.

One problem that has needlessly confused the literature on inheritance is the sometimes unthinking substitution of one dependent measure for another. Although the duplicated audience and primary duplication are mathematically related, they are clearly different. The correlation between the two is roughly .40, so each explains very little variance in the other. Nor does dividing r_{st} by r_s, thus creating primary duplication, simply strip out all of the variation attributable to the lead-in rating. Because both are percentages (or proportions), they are scales bounded on both ends. The duplicated audience, however, expresses size relative to the total audience. Thus, it can never be any bigger than the smaller of the two ratings in a program pair. In today's world, that almost always means the low single digits. Primary duplication expresses size relative only to the lead-in audience, so its values range widely between 0 and 100.

Each measure has certain virtues and limitations. The duplicated audience is most appropriate for analysts concerned with absolute audience sizes. For example, it is useful in building models that predict reach and frequency (e.g., Rust, 1986). Because it has a constant denominator, it also provides a stable metric that can span a variety of different programming configurations (e.g., Goodhardt et al., 1975; Headen et al., 1979). Beyond that, it lacks a certain interest because it is so utterly dependent on the ratings of the programs in any given pairing. After all, lead-in ratings alone explain over 90% of the variance in this dependent measure.

For those who want to understand how program content and structures affect the way audiences flow through the evening, or any other day part, primary duplication is a much more satisfying measure. Expressing inheritance as the percentage of the first program's audience that stayed tuned to watch the second program is an easily understood, and intuitively appealing, number. It greatly reduces the "noise" of absolute program size, and so lets more subtle effects come to the fore. The roles of program type and choices are more pronounced in studies of primary duplication. In a curious way, so too is the impact of highly rated programs. In Table 4, for instance, it can be seen that highly rated programs do a better job of inheriting their lead-in audience, which, in retrospect, seems the most obvious source of their ratings strength. These nuances in the ebb and flow of audiences are more apparent in studies of primary duplication.

This research casts serious doubt on the practice of using the correlation between the ratings of adjacent program pairs to assess the underlying mechanism of inheritance. There is simply no evidence that higher correlations are associated with higher levels of duplication. Studies of share maintenance or lead-in effects that feature this approach (e.g., Davis & Walker, 1990; McDowell & Dick, 2003; Tiedge & Ksobiech, 1986) certainly drive home the point that lead-in ratings are a powerful determinant of lead-out ratings. In addition, it appears that relationship is enhanced by factors known to affect inheritance (i.e., number of choices and program type). However, it is now known that the large audience of a highly rated lead-in is typically lost in disproportionate numbers, resulting in low levels of primary duplication. Again, in retrospect, this seems obvious. If you follow a highly rated program, chances are you have nowhere to go but down.

If back-to-back programs with highly correlated ratings or shares do not necessarily enjoy high levels of audience duplication, it draws into question studies that offer correlations as evidence that inheritance effects are stronger now than they have ever been (e.g., Davis & Walker, 1990; McDowell & Dick, 2003; Walker, 1988). What else might explain ever higher correlations between such program pairs? Is there a plausible alternative explanation for those findings?

It has been widely observed that over the past 20 years, the television audience has become fragmented (Webster, 2005). Average prime-time ratings on major networks are now in the single digits, and ratings on lesser networks are lower still. As audience sizes decline, it seems likely there is a commensurate decline in the variability of audience shares. Small average ratings leave little room for below average ratings to vary (i.e., they cannot dip below 0). High program ratings are increasingly rare as networks target narrower demographics, and audiences exclude networks from consideration by virtue of limited channel repertoires or “defacto selectivity” (Webster, 2005). Whatever the cause, variation in network program shares seems to have diminished over the years (McDowell & Dick, 2003). More than ever, on any given night, each network’s audience shares tend to putter along within a relatively narrow range. That phenomenon might well produce higher correlations between adjacent program ratings. The result would, indeed, be more consistent “share maintenance.” But it is a phenomenon that has little or nothing to do with enhanced audience flow.

That said, this author sees no evidence that inheritance effects are fading away. The relationships between audience duplication and the relevant predictor variables are as strong now as they were in 1982, if not stronger. Whether inheritance effects will continue to hold up in the future is an open question. Digital video recorders and video-on-demand are, at this writing, on verge of widespread adoption. If that happens, and if viewers use them to aggressively reconfigure what the networks are programming, then audience flow as it is known today may well become a thing of the past. But those are very big "ifs."

In larger theoretical terms, this research should serve as a reminder that television program choice is the complicated result of many factors. Some of those factors, like audience availability, may be unrelated to people's preferences for what is on television at any given point in time. Others, like program schedules, further constrain those preferences once they do tune in. As yet, no technological innovations have managed to give viewers completely free rein to exercise their preferences. None of that, however, should make one think that viewers, past or present, are a bunch of passive dolts. This author believes that simple active–passive dichotomies are a counterproductive way to think about audiences (Webster, 1998). It is better to recognize that viewers are simultaneously free agents expressing their preferences and captives of the structures within which they operate. It is only by appreciating how agency and structure play off against each other that one can hope to understand audience formation.

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