A Case for a Shift From Demographics in Targeting to the Empirical Correlation of TV Viewing with Product Purchasing

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The topic of my talk is the empirical measurement of correlations between TV viewing and product purchasing. My objective is to illustrate that the use of demographics alone in media planning can be quite inefficient, and the prospects for improving upon targeting efficiency through demographically-based techniques are dim. After covering some examples which support this contention, I'll then propose an alternative system for measuring audience characteristics based on purchase data rather than demographic data and made possible through new electronic technology, and will show you some actual results taken from a recent study. I will close with a discussion of what is needed in order for such an evolution in audience measurement methodology to take place.

First, I would like to briefly review the details of the data collection system that we at Information Resources have asssembled. In each of 8 markets across the country, we have installed UPC scanners in stores accounting for an average of 95% of grocery ACV. A sample of 3,000 households per market has been selected to participate in a special panel. Each shopping member of each panel household carries a special ID Card which they present to the cashiers upon check out. The identification number is entered by the cashier, and all of the panelist's purchases in all categories are recorded with a degree of precision and detail not available through any other data collection technique.

For a subset of these panelists, currently a total of 6000 across the 8 markets, special metering devices which record set tuning by 5 second intervals have been attached to their television sets. This provides continuous data on set status which can be translated into daypart and program information.

Importantly, the same households are used for the collection of purchasing and viewing, and both types of data are collected via electronic means. What we offer here is not an alternative to some of the syndicated data bases that currently exist, but a significant advancement in the inherent data quality and, as a consequence, the introduction of exciting new applications.

Specifically, purchasing information collected via syndicated surveys can be proven to have error ranges on the order of 300-500%. And, these error ranges are not consistent across categories. Therefore, if a category with a reporting error of 200% is compared to a category with a reporting error of 300%, the results will show differences which do not necessarily reflect differences in purchasing patterns, but simply differences in consumer recall error for the two categories. Similarly, the use of meters rather than diaries provides more accurate viewing information, although it is currently limited to the household level. However, this limitation can be overcome through techniques that I will describe later. Finally when we shift to the use of people-meters the inconvenience of household-level data will disappear completely.

The continuity of the data is also important, since we track information 365 days a year, rather than report on only an annual or semi-annual basis. And, data are available with a turnaround time of only a few weeks, providing information in a timely fashion. Having hopefully given you enough background on the system, I would like to now get into the topic of audience measurement.

There are two basic types of TV audience measurements that one must obtain. First, it is important to measure the <u>size</u> of the audience, or the number or proportion of households or individuals watching a given program or a given daypart. This is done through rating and share measures. Second, it is important to measure the <u>type</u> of audience, which is currently expressed in terms of demographics. A program with a high rating is not necessarily a good program to advertise on unless it also delivers the appropirate type of viewer. But for the most part, demographics are really a surrogate. Of ultimate importance is the propensity of the viewer to be likely to purchase the advertised brand. As an extreme example, if you are advertising cat food you would like your ads to reach households which have cats, regardless of their demos. But currently, one attempts to characterize households that are most likely to own cats, and individuals who are most likely to purchase cat foods, in terms of demographics. Then, by choosing programs which reach those demographic audiences, it is hoped that you will be doing a more efficient job of advertising cat food than if you simply advertised it randomly.

It is this second element of audience measurement, the type of audience, that I will be concentrating on. It is much simpler to measure the size of an audience, and there are several companies that have been doing this for some time as well as some new entries on the horizon. While improvements will certainly continue to evolvein measuring audience size, we feel the biggest opportunity for advertisers is in how the type of audience is measured.

We believe that there will be an important measurement shift from the use of demographics as a surrogate to the direct measurement of purchase behavior in classifying audience types. While this will not happen overnight, I hope to illustrate to you that this is certainly a desirable goal, and given time, this shift will come about.

Annually, advertisers spend over 12 billion to advertise package goods, creating over 5 trillion household impressions. Some 2,000 brands in 500 categories advertise on television in a given year. Yet, if one looks at how this advertising is targeted, for the most part each of these 2,000 brands advertises to one of three demographic segments. And 70% of that advertising is directed simply toward adult women. Sometimes it is women 18-49, sometime 25-54, and sometimes total adult women, but essentially we have 2,000 brands each advertising to basically the same segment of adult women. (Actually, there is relatively little difference in an 18-49 vs. a 25-54 target, as will be shown later). It simply is not logical to expect 3 or 4 highly correlated alternative demographic definitions within the adult women segment to be adequate for optimizing the targeting for each of these 2,000 brands.

Rather, for a given brand in a given category, there is a particular mix of programming which will be most appropriate for that brand, while the best mix of programming will be different for some other brand, either in the same or different category. And these are differences in programming which cannot be identified by demographics. It is easy to illustrate that in any demographic segment, significant differences in purchase propensity exists.

Ex 1

What typically is found to be illustrated here. Among all women 18-49, if two categories are examined 4 segments will emerge. There will be asegment that purchases neither of the two categories, two segments that each buy one category but not the other, and a segment that buys both. Numerous examples may be obvious such as health and nutritional foods versus junk and snack foods, or frozen meals versus baking mixes, cat food vs. dog food, and so forth.

ex2

This next chart shows actual data taken from a recent analysis conducted for one of our major clients. Two categories were examined, and are denoted here and in the subsequent exhibits simply as category 1 and category 2. The company's brands in both categories have defined women 25-54 as the primary target segments for media purposes. And importantly, even though these categories have virtually the same demo target, they are somewhat supplementary products in that heavy users of one tend to not be heavy users of the other. (Butter and margerine ar examples of two such categories.) This exhibit shows 4 columns with each column representing households classified on the basis of age of female head. For each category, the chart shows the percent of households within each age segment who purchase that category in six months. Note for both categories, although purchase incidence is slightly higher within the under-55 segment, the difference is not that great. The separation of female heads into a 55+ vs. an under-55 grouping simply does not do a very good job of separating households on the basis of their propensity to purchase each of these categories. There is a significant proportion of buyers within the non-target age group, and a significant proportion of non-buyers within the target age groups. This general result can be shown for most categories and brands. One way to try to improve upon this is by using several demographics in describing the target audience. For Category 1 in this example, there is a more specific target description used in strategic planning which is households with female heads age 25-64, 3 or more members, and incomes of $20,000+.

8 x 3

Here we are comparing that particular segment to all households who do not fit that description. As you can see, the purchase incidence is 23% higher within the target segment. The next measure here is pints purchased per buyer in a six month period, which can be seen to be 26% higher. The product of percent buying times pints per buyer provides a measure of per capita sales, from which a sales index versus total households can be computed within each segment. Within the target segment, the sales index is 1.27, compared to .83 among non-target households. Thus, overall per capita sales of this category are 53% higher within the target audience. So far, this is a step in the right direction because the per capita consumption index is much higher within the target audience. However, by adding additional variables one ends up carving out a segment which represents a smaller proportion of the total U.S. As this next line shows, this target segment actually represents only about 40% of all households. If one computes the actual percentage of category sales obtained from househoulds within each segment, it turns out that about half of category sales are obtained from households who are not within the target segment definition. Therefore, even though the relative purchasing is much higher within the target audience, the fact that it is a relatively small proportion of the population means that half of the category sales potential is missed by concentrating on that target description. Well, what can be done about this?

Suppose we are trying to classify buyers vs. non-buyers of this or any other product. You will usually find that both buyers and non-buyers include women of all ages. Thus, age and sex alone do little good. If we were to go out and conduct extensive research to learn everything we could about buyers vs. non-buyers of any product, and look at a wide variety of demographics as well as attitudes and lifestyles, we would certainly find differences. Differences have to exist, because if the two groups were identical, then they would not differ in purchase behavior. There must be some factors which distinguish these groups. It is just that the factors are not not always known. Therefore, two such groups are different in terms of buying patterns, and these are presumably a function of differences in demographics, attitudes, lifestyles, etc., then why would one expect them to have the same TV viewing patterns? Given that two such groups can be shown to differ with respect to buying patterns as well as other characteristics it is not unreasonable to expect that there probably are also differences in preferences for certain television programs.

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The result is simply illustrated in this next exhibit. If you look at a given category that tends to be purchased by, say, 60% of all women 18-49, and identify all programs that deliver strong audiences of women 18-49, this is what you will find. Out of all programs that deliver women 18-49, they do not always deliver them in the same proportion of buyers vs. non-buyers of that category. Certain shows, as in this example Show B, will deliver higher concentrations of category buyers than will other shows, even though their audience demographics are the same. It is literally impossible for every program to result in the result the same proportion of buyers vs. non-buyers. And, there is no reason to believe that such differences should not be consistent. After all, only age and sex are used to define program audiences.

If one were to take Show A and Show B and compare all available demographic, attitudinal, and lifestyle information about their audiences, differences between the two would certainly emerge. Therefore, why not expect to see differences in purchasing between the audiences? The problem both here and in the previous examples is that we simply do not use enough descriptors to distinguish between buyers vs. non-buyers of a given product, or viewers of one show vs. viewers of another show. And in many ways it is a non-solvable problem because even if one could determine all of the variables needed to accurately predict such differences, the process would be incredibly complex.

Fortunately, all of the intermediate variables can be circumvented by simply taking an empirical measurement of how viewing correlates with purchasing. The measure we use to do this is called a leverage index. The leverage index is simply a ratio of purchasing within a specific audience, such as the audience of a particular program, vs. purchasing for all households. A leverage index of 125 means that per capita consumption within that particular audience is 25% higher than average. An index of 80 means that per capita consumption within the audience is 20% less than the average. Back to our previous exhibit, Show A had a low leverage index, while Show B had a high index. Yet, they had the same demographics.

A few important comments about the leverage index is first, it is a per-rating-point measure. That is, the leverage index is does not relate to program rating. It is a relative measure which needs to be applied to the program's rating. It is also an <u>additional</u> piece of information, not a substitute for information currently used in evaluating programs. This is a very important point to stress since we must still consider audience demographics, ratings, GRP's, cost and other factors in evaluating any program. The leverage index is simply an additional piece of information that can enable us to make more efficient media decisions. Finally, the leverage index currently is a household measure, since we do not yet distinguish either viewing or purchasing on an individual basis. However, that is not a severe limitation. If one has a target audience definition of women 24-54, the inherent assumption is that the likely purchasers are women 25-54. Therefore, one would expect households with women 25-54 to exhibit a higher purchasing level for that item than other households. In other words, purchases made by individuals will show up in purchase data measured at the household level, and that is the key element of information we will be using.

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The next chart is scatter plot of the correlation that exists between the incidence of women 25-54 within a program's audience and the leverage index for category #1. Each dot represents a network TV program, and these results are based on the first quarter of 1984. The figures on the left scale are simply women 25-54 per hundred TV viewing households, and represent each programs average audience as taken directly from the national rating sample. The leverage index on the bottom scale is the leverage index that we have computed from identifying households who regularly tune into these programs, and indexing their previous six month's consumption for category 1 vs. the average level of consumption across all households. If brands in this category are targeted towards women 25-54, presumably the expectation is that women 24-54 are more apt to be category buyers. If that is the case, the purchases of these women will show up in their household's data. We should then see a positive correlation. For this type of analysis it is not necessary to have individual purchasing data. As you can see from the exhibit, there is only a slight positive correlation between the incidence of women 25-54 and the leverage index. The correlation coefficient is .38 yielding an R^2 of 14%, meaning that the incidence of women 25-54 explains only 14% of the variation in the leverage index. Looking at these results in a different manner, if one selects a given incidence range of women 25-54, perhaps 40-45, with that demo profile there are programs with a high leverage index and programs with a low leverage index. In fact, for any given audience composition there exists a significant variation in purchase propensity for a given category. Therefore, once a demographic criterion is established, by concentrating on the programs which in addition deliver higher leverage indices, one is better off.

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This next exhibit provides the same information for Category #2. In this case, we have actually a negative correlation yet a similar R^2. The negative correlation does not mean that the client should choose shows with a low incidence of women 25-54, it just means that there are many other factors determining the purchasing patterns of this category. Again, if one looks at a given incidence of women 25-54, say 40-45, there is a variation of a low of 72 to a high of almost 130 in the index. Clearly, once the demographic criteria are established, the use of programs with high indices is going to be more efficient than the use of programs with average or low indices.

7-13

We have looked at this sort of correlation across nemerous categories, correlating each category's leverage index with the corresponding target audience incidence and have consistently found little or no correlation. But I don't think this is surprising, since for the most part every advertised brand and category has pretty much the same desired demographic target audience. You are either targeting towards women 18-49 and women 25-54, which correlate to each other with a .97 coefficient as can be seen here. If, those demographics always offered good correlations with the propensity to purchase each category, it would suggest that all product categories are positively correlated with each other, a result which obviously is not the case.

Therefore, given these results which show a failure of demographics to significantly discreminate consumption patterns, plus the preceding data which show the inability of demographics to do a very good job of identifying which programs deliver buyers vs. non-buyers of any category, it seems that the desireability of using purchase data directly in the selection of programs for specific brands or categories is obvious. But his does not mean that viewer demographics are unimportant. Only that purchase data should be included in the analysis.

However, even though these results would replicate themselves over and over again for numerous brands and categories, and are supported by data other than our own, there is some basic resistance in the industry to aggressively try to shift to the increased use of purchase data in making media decisions.

Back in January, the EMRC held a Needs Definition Conference with the objective of defining short-term and long-term key needs in TV audience measurement. One of the needs that came out of that conference classified as "most pressing" was extended measurement of individuals. This is a need that is note restricted either to demographics or product usage but is just a need to have individual rather than household data. This is a need that we certainly agree with, and our future plans call for a shift from households to persons measurement. Therefore, no more discussion is required on that point.

However, the availability of more demographics recieved a rating of "important". And, the result which really surprised me, the ability to monitor product usage was classified as "least important". Thus, in the face of very strong evidence that the use of demographics alone in media planning has limited value in terms of efficiency, and that theoretically the use of product data would offer significant improvements, a collective group of industry experts still ended up with a consensus that said the objective both short and long-term should be to strive for more and better demographics, putting product usage on the sideline. This is particularly ironic since most of the major packaged goods advertisers are currently working with us in funding research with the objective of developing a system of media planning and execution that is based on product usage. But, when representatives of some of those same advertisers were assembled with a group also representing agencies and networks, the collective emphasis still came out on demographics.

Now, even though a larger sample size and more responses to demographic questions willoffer more detailed demograhics, there is little to gain from it. There will still be purchase differences within demographic segments, regardless of how demographic segments are defined. And, the use of more demos in defining a target segments will result in segments that represent smaller sources of actual sales volume, and additionally will complicate the whole planning buying and execution process. So why is there such an attachment to demographics?

It seems that for one thing, demographics have 20 or 30 years of momentum and tradition behind them, and the industry is comfortable working with them. All of the current systems used in planning, buying and executing media are demographically based, and any system which would minimize emphasis on demographics and increase emphasis on purchase data would require literally a complete restructuring of the whole system. Thus, even conceptually it is not at all an easy shift to make. Finally, we are finding that when we introduce this concept, it immediately creates an expectation of a perfect product, or a perfect alternative to demographics which is available now and that simply is not the case.

Instead, a gradual evolution is going to be required. It is not going to be an overnight development, but we have to have a start somewher. An evolution is required, and as we see it it might go as follows.

First, there is no doubt that we need to continually improve current methods by coming up with systems for developing better data of the same type. This includes the continued use of demographics, the shift towards electronics in measurement, and the shift towards persons measurement rather than household measurement. A major advancement here is hoped to be the people meter, which many companies including ourselves currently have in test. The progress in these areas should certainly continue, but simultaneously we should start investigating new methods which used new types of data even though they are only beginnings. While we are still improving the current methods, we can at the same time concieve and begin to develop entirely new systems which may ultimately look nothing like the systems that are currently used today.

One particular evolution scenario might be as follows. The ultimate objective would be to obtain electronic data on viewer purchasing. This would be accurate, electronic data from a completely representative sample which correlated individual viewing behavior to the same individual's purchase behavior. If that could be achieved, one could argue that there would be little if any use for demographics. One could directly correlate invidual viewing with individual purchasing and make media decisions on that basis. But that is obviously not going to happen for sometime. So let's go back and look at where we came from, where we are now, and where we might be able to go in striving toward that ultimate objective.

A while back, household demographics were used in defining audience characteristics. This eventually shifted to viewer demographics with the recognition that people not households buy products. Viewer demographics are now being combined with geographic breakdowns, and limited use of certain types of other data as a slight enhancement to what viewer demographics alone can provide. Following this trend, it seems that if we can add household purchasing data to viewer demographics, this would be the most easily achieved next step, although certainly not the ultimate solution. Note that nothing is being removed from the previous phase, which is the current state of the art. We are simply adding household purchasing to what is currently available.

Finally, we hope to eventually shift from viewer demos combined with household purchasing to a system where we can collect person viewing directly, from people meters, and purchase data for the same individuals through ID cards that are coded by individual rather than household. But this ultimate objective is not going to be achieved overnight. An evolution is required, and we believe now is the time to begin shifting in that direction through the use of household purchasing in conjunction with everything else we already know about TV audiences. This does not mean that we or anybody else can yet offer flawless household purchase data with which to do this. Within each step there must be a beginning and a continuous transition through that particular step with respect to data quality and sample projectability.

Let us now talk about exactly how we can go about beginning to incorporate household purchasing with viewer demos and illustrate the power of this approach. Demos are first viewed as a necessary but not a sufficient target description. That is, it may well be that if an individual is going to make a purchase of your brand, there is a high probability that that individual is going to be a woman 18-49, or 25-54. However, not every woman 18-49 or every women 25-54 is going to be a potential purchaser. Thus, we can begin with demos as a necessary criteria but then differentiate one step further with information on household purchasing patterns. Thus, if you are advertising spaghetti sauce and your target audience is women 18-49, you are better off reaching a woman 18-49 who lives in household that purchases spaghetti sauce than you are reaching a woman 18-49 who lives in a household that does not consume spaghetti sauce. Under this approach, household-level purchase data is quite adequate.

Now let us talk for a minute about the types of classifications that are available based on purchase behavior. I have generally been talking in terms of category buyers vs. non-buyers which is the most obvious initial classification, but it is certainly not always the correct classification for every brand. It may be that you are specifically targeting ads against current category non-buyers with the objective of expanding the category. However, in most brands the target would be a known category user, so I think that this objectiveis fine to illustrate the technique. However, it is important to realize that with the scanning data that are available classifications can be based on brand buyers vs. non-buyers, brand loyal buyers vs. deal/price sensitive buyers, buyers defined by certain types of grocery shopping patterns, or any combinations of the above. The important fact is that however you define your target in terms of buying behavior, a household can be classified as either fitting that behavior or not. Furthermore, they can be classified as exhibiting that behavior on average, above average, or below average. Once the behavior objective is defined, a leverage index for each household can be computed which expresses the extent to which that household exhibits that purchase behavior. That leverage, when combined with viewer demographics, will then help sort out program alternatives.

The next few charts illustrate the effect of leverage on audience composition. 14

In this example we have a program which delivers an 8 rating against women

24-54, which is for this example the target audience. Let us assume that the target segment we are trying to reach represents 50% of all households with female heads aged 25-54. For instance, perhaps half of all such households purchase the category. The fact is, even though this program delivers an 8 rating against women 25-54, only half of those women live in households who purchase the category. Advertising to the other half is essentially wasted,or best of minimal value. Thus, this program delivers 4 rating against women 25-54 who are also within the target buying segment. This next exhibit shows 15
the effect of leverage. Leverage, again, is simply the relative incidence of the desired buying behavior within the demographic audience. Thus, with a leverage of 1.25, a program with an 8 rating against women 25-54 actually delivers a 5 rating against women 25-54 who live in households that purchase the category of interest. In contrast, with leverage of .75 a program can have a similar 8 rating but deliver only a 3 rating against women 25-54 who live in households that purchase that category. Thus, these three programs look identical as far as demographics are concernd and would cost you the same, but program B will be much better than program C in this particular category since it delivers less waste. Similarly, differences in leverage can compensate 16
for differences in total rating. Here you can see that a program with only a 7 rating but a leverage of 1.25 will deliver the same relevant audience as a program with an 11 rating and a leverage of .75. The use of leverage clearly has a significant impact on show selection. Next, I would like to show you some actual results for the analysis we did on Category I. Here you see the highest and lowest 3 programs for this category in terms of leverage index. 17
These programs were six of the dots you saw earlier on the scatter plot. We have an average index of about 115 for the high shows and about 75 for the low

shows. The high shows in this example on average provide a 50% higher index than the low shows. This is a very significant difference.

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Next, lets look at the Category 2 indices vs. Category 1. Here we have the 3 highest and 3 lowest programs for Category 2 in the first column, and alongside have listed the corresponding indices for Category 1. Both of these categories have the same women 25-54 target audience for network television. Yet, the three shows that delivered the highest index for Category 2 deliver a very low index for Category 1, and the 3 programs that exhibit the lowest index for Category 2 deliver high indices for Category 1. Also shown here is the demographic incidence of women 25-54 in each show, which on average does not differ that much between the two groups. And, if one compares "Days of our Lives" on top to "Loving" at the bottom we see an almost identical demographic profile but a total reversal in the efficiency of each program in reaching households with consumption patterns for Category 1 vs. Category 2. Clearly, this information would have important implications for this client regarding which programs are allocated from network inventory to which brands.

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We also took a look at the average index actually achieved in the brand's ad schedule. This exhibit shows brand X, which is the client's Category 2 brand, listing its prime time advertising schedule for January, 1984. For each program in which an ad appeared, the corresponding index for Category 2 is shown. On average, the brand's January prime time schedule achieved an index of 102.

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Here are the same results for brand X during daytime in January during which it achieved an average index of 100. As you can see, without taking purchase data directly into account, this brand achieves an average leverage. We have examined dozens of brands in this manner and have found that in most instances, brands currently average a leverage index of between 95 and 105. This is not at all surprising since purchase data are not used directly in developing media schedules. Only demographics are used, and you saw earlier how ineffective they are in discriminating the purchasing of program audiences. Note also that this chart shows the corresponding incidence of women 25-54 for each of the programs used in this brand's ad schedule, and the average is 40.

To illustrate how leverage could be used, we then took this schedule, looked at other programs in this company's network inventory, and rearranged the January schedule in such a way that we excluded a few of the shows with low indices and replaced them with programs with high indices, but did not change 21
the demographics. The resulting hypothetical schedule is shown here. Notice that we have increased the average leverage from 100 to 112 while the average incidence of women 25-54 remains essentially the same. In fact, it actually decreased slightly to 39. The important factor is that simply by making a few rearrangements in which particular programs were utilized, we have achieved a 12% effective increase in advertising delivery to category buyers. This is the same result that would have been achieved by a 12% increase in the ad budget. For example, if this brand spends $10 million annually, this rearrangement of programs to increase leverage would have the same effect as a $1.2 million increase in the brand's ad budget in terms of how

many gross impressions are actually delivered to category buyers. In rearranging the schedule, it is important that other constraints such as cost, demographics, GRP's, etc., are still maintained. However, we have been able to do this without very much difficulty.

Finally, let's take a look at some of the cost implications. Here we see the average network cost per point against women 25-54, which is $2400. 22
However, since the target audience is buyers of category I, and not all households purchase category I, we can divide the total cost per point by the incidence of category purchasing to compute a cost per point against women 24-54 who buy Category I and find that it is $4,000. Similarly, Category 2 has a lower purchase incidence so the cost per point against women 25-54 who buy Category 2 is $5700. Therefore, although we do not want to give up our actual budget constraints, we can now work to maximize efficiencies in terms of buyer-adjusted cost. This next example shows how dramatic a difference between two shows can be.

"Days of Our Lives" and "Ryan's Hope" each exhibit a fairly similar incidence 23
of women 25-54 per thousand viewing households. Therefore, as far as the demographics are concerned these two programs look relatively similar. Furthermore, the cost per point against the target demographic audience is also fairly similar for these two programs, and so for ease of illustration I am using the same number. Now, suppose that the advertisedbrand is a Category 2 brand. If we assume that each program has average leverage, we can add to this chart the cost per point against women 25-54 who purchase Category 2, which is $5700 from the previous exhibit. But these programs do not each

exhibit the same leverage.

As you can see, "Days of Our Lives" delivers a leverage of 1.27 against Category 2, while "Ryan's Hope" delivers a leverage of .71. If these indices are divided into the cost per point per category buyer, you find that the <u>actual</u> cost per point against women 25-54 who are category buyers for "Days of Our Lives" is about $4500, yet it is $8000 for "Ryan's Hope". Even though these two programs look almost identical with respect to demographics and total cost per point, the cost per point against women 25-54 who buy Category 2 is almost twice as high within "Ryan's Hope" vs. "Days of Our Lives". It is not difficult to see how, at least conceptually, the use of these kind of data in planning and allocating program inventory can dramatically increase efficiencies and minimize the cost of reaching the desired type of buyer.

Obviously, if this type of approach is to work there must be enough variation in the leverage of various programs such that it is not always the same programs that are desired for all brands. But, that would not be expected anyway because if so, it would imply that all categories are correlated with each other. This next exhibit shows the leverage indices for 5 categories for 6 24
selected daytime programs. The target audience for each of these categories is women 25-54, but you can see the variation that exists in the leverage index. The first two categories are somewhat complementary since the programs that are good for one are not good for the other, and vice versa. For Category 3 we have a mixture. For Category 4, note that although there is a variation across the shows, all of the shows index high. This reveals that daytime programming in general offers high leverage for this category. In

contrast, in Category 5 most of the programs index low, indicating that daytime programming generally offers low leverage for category 5. Although I have not discussed it here, we have found that the concept of leverage applies also to choice of dayparts, network vs. independent stations, and other alternatives.

The reason I have concentrated primarily on individual programs is because given the way the industry is currently structured, the most immediate application of these data is in allocation of network inventory. This is an area where advertisers and their agencies have the greatest flexibility, compared to the actual buying of network time. To help accomplish this, early next year we will be offering a computerized system for optimal allocation of network inventory. This will be a client-accessed system where one would input data on available program inventory including information on anticipated ratings and demographics. However, leverage indices will also be input for each program. Each brand's objectives would be input in terms of target audience, GRP's, budget, daypart and other constraints. Thus, the first two steps would be pretty much in line with the procedures used today in allocating inventory. However, the system would assign programs to each brand in such a way as to not only satisfy their conventional constraints, but do so in such a way as to maximize leverage. Thus, whereas currently each brand would recieve a package of programs that would deliver a certain level of GRP's to the specified target audience within a budget constraint, rather than do so with a package of shows that delivers an average leverage of about 100, we feel that we can increase that average leverage to anywhere from 110 to 130, the net result of which would be equivalent to an increase of 10 to 30% in advertising spending against the buyer segment of interest.

As far as future plans and where we see this all going, one of the first steps will be sample expansion on a geographic basis. Although we believe, and have evidence that support the fact that, our current 8 market system is quite projectible in many applications, we have plans to expand to a fully nationally-projectable sample over the course of the next year, including the addition of major market areas. We also plan a shift to person data, which refers to the use of electronic devices to monitor individual person viewing rather than household set status. Eventually we plan to identify individual purchasers rather than use the household as the purchasing unit as well.

However, this will not be achieved overnight, and as we move ahead in developing these capabilities a corresponding requirement must be a willing shift in industry attitudes and procedures. Specifically, an increase in the reliance and acceptance of purchase data as tool for evaluating TV audiences and using that data in the planning, buying and allocation process. Of course, this will require the joint cooperation of all sides including advertisers, agencies and ultimately the networks. As I mentioned earlier, this will clearly be a gradual evolution, as neither us or anyone else moving this direction will be able to offer overnight perfection.

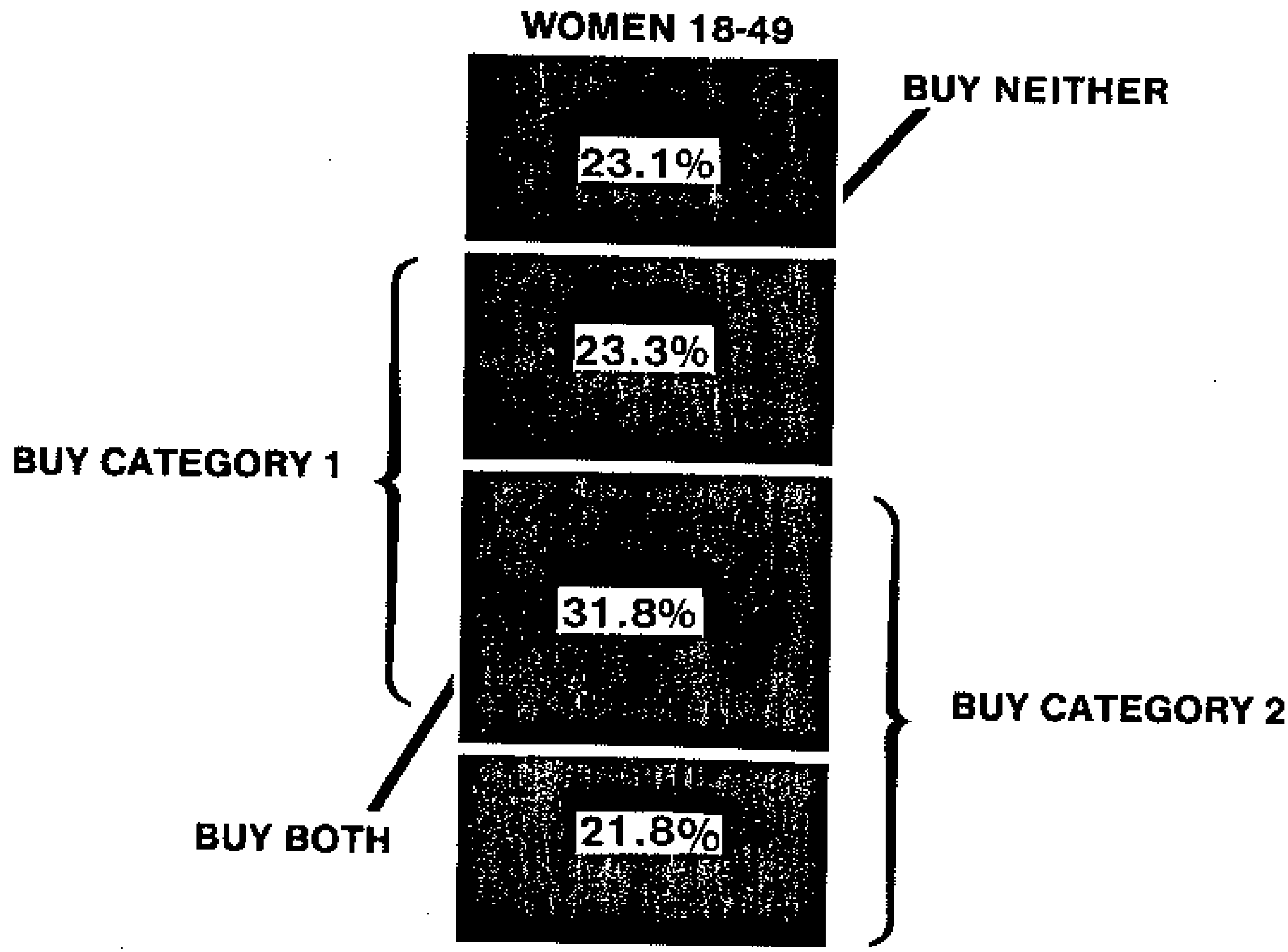
Yet, there must be a starting point and someone must take the initiative with the objective that the end result will greatly benefit all parties involved. And all involved parties must take an open minded approach and exhibit a willingness to try entirely new approaches rather than be constrained by habit to conventional methods. As more and more evidence is compiled in support of our claims on the value of purchase data, it will become even more obvious that the potential savings from the shift in methodology we are proposing are enormous.

Assuming that an average of 15% increase in efficiency can be achieved, where efficiency is defined as the extent to which ads are reaching viewers in households with a high propensity to purchase the products, this translates to anywhere from a $5 to $25 million savings for a single brand. For a major advertiser this savings can easily translate to anywhere from $15 to $50 million. Finally, for the industry as a whole a 15% increase in efficiency would mean an equivalent of savings of relatively $2 billion in terms of the amount of advertising waste that is cut back.

In closing, I would like to stress that in everything I have said I am not trying to find fault in any specific system or procedure that currently exists, and I don't think that anything that I am saying suggests that there has been inadequate use of traditionally available data. The problem has been that until now, and until the advent of electonically based systems for collecting and integrating data that before were unavailable, it was simply not possible to use anything but demographics in defining audiences, and you can do only so much with demographics. The introduction of scanning data and the proliferation of meters, both on a household basis and shortly on a person's basis, are going to offer us an entirely new set of tools, and correspondingly an entirely now set of data with which to work. There is no reason to expect that that being the case, the techniques that we have used for the last 10 or 20 years may not be the same techniques that we will use in the future. It is important that we recognize this, since undoubtedly it is not going to be an easy shift to make. But all the evidence suggests that this is the direction things are going, and when you take a look at the dollar implications of what can be achieved, it is a trend that is simply cannot be ignored.

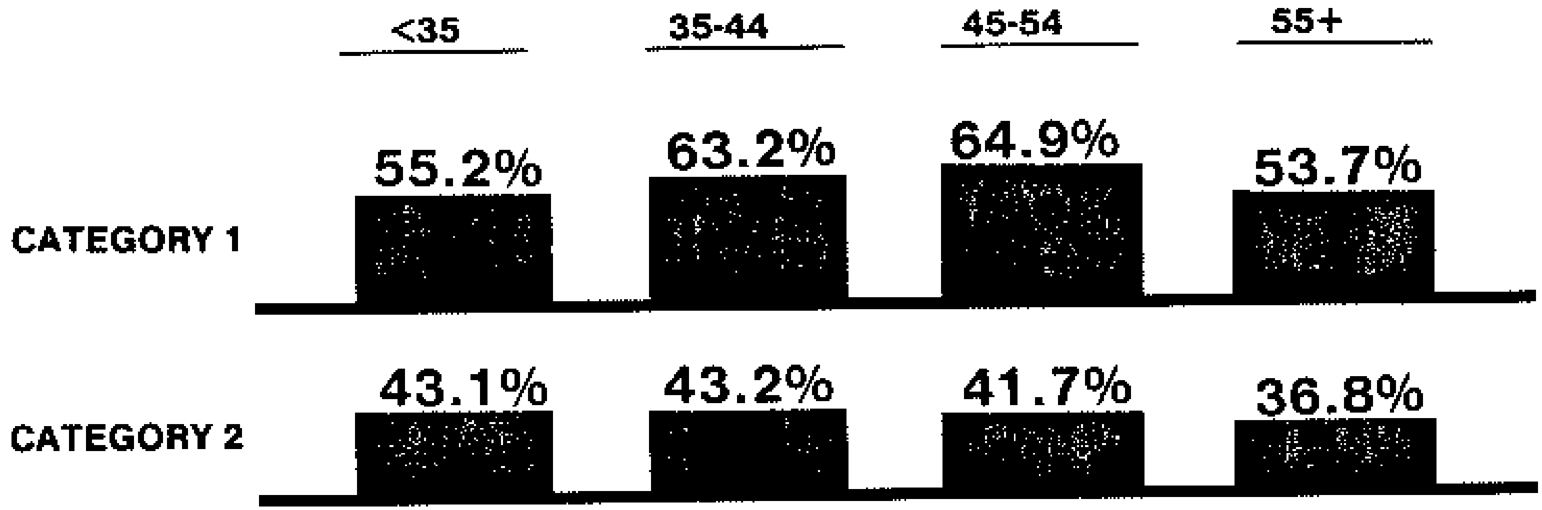
Thank you all very much for your attention, and for the opportunity to speak here today. Especially, I would like to thank the advertisers who have stepped out on the wire a little bit in working with us to help develop our capabilities in this area and produce some of the results I have shared with you here today.

DIFFERENCES IN PURCHASE PROPENSITY EXIST WITHIN ANY DEMO SEGMENT



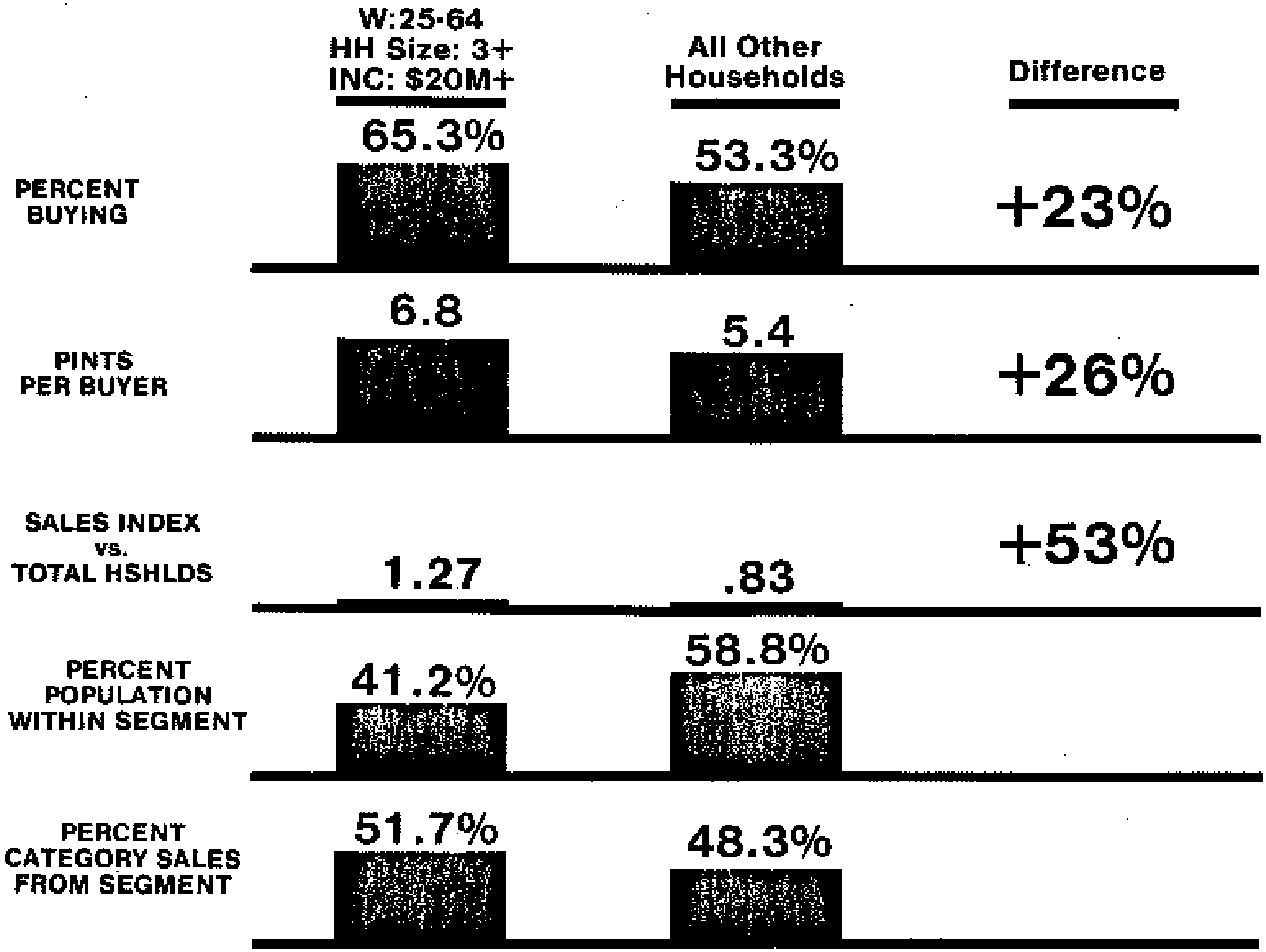
2

CATEGORY PURCHASE INCIDENCE BY AGE OF FEMALE HEAD



3

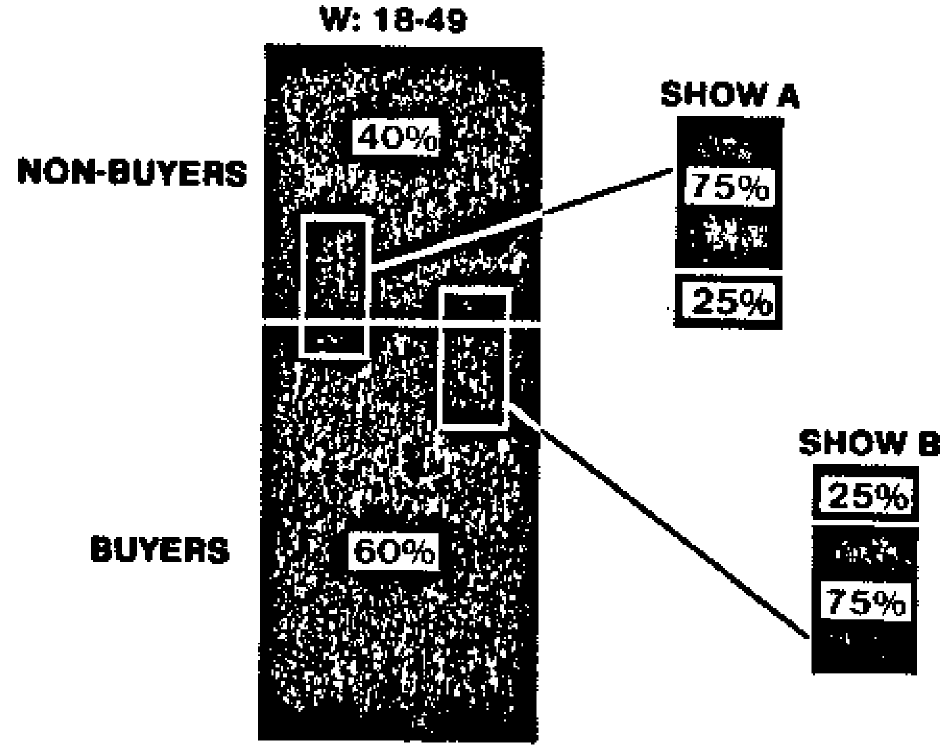
CATEGORY 1 PURCHASING BY TARGET VS. NON-TARGET HOUSEHOLDS



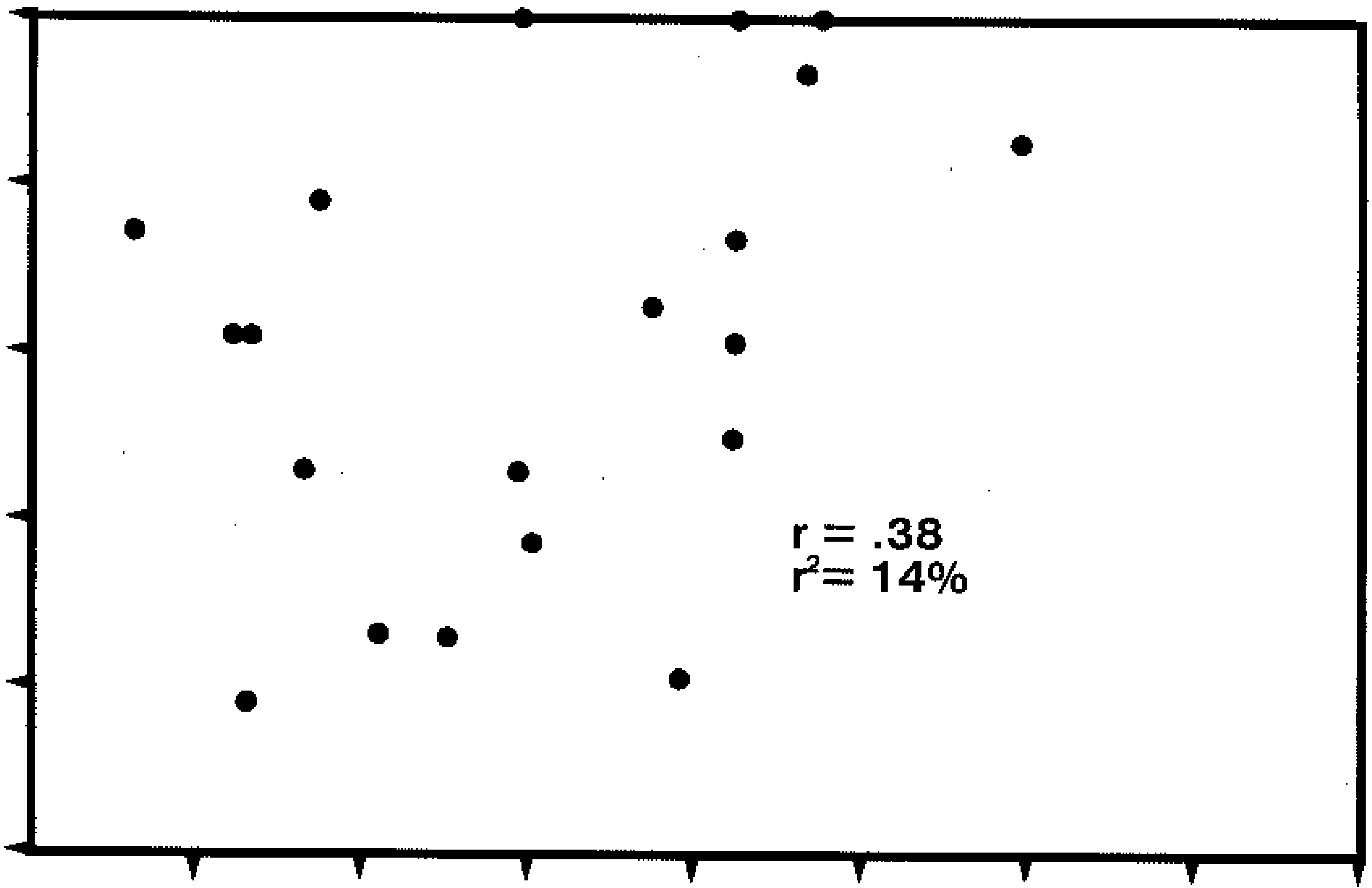
4

Exhibit 4

PROGRAMS EXHIBIT SKEWS NOT EXPLAINED BY DEMOGRAPHICS

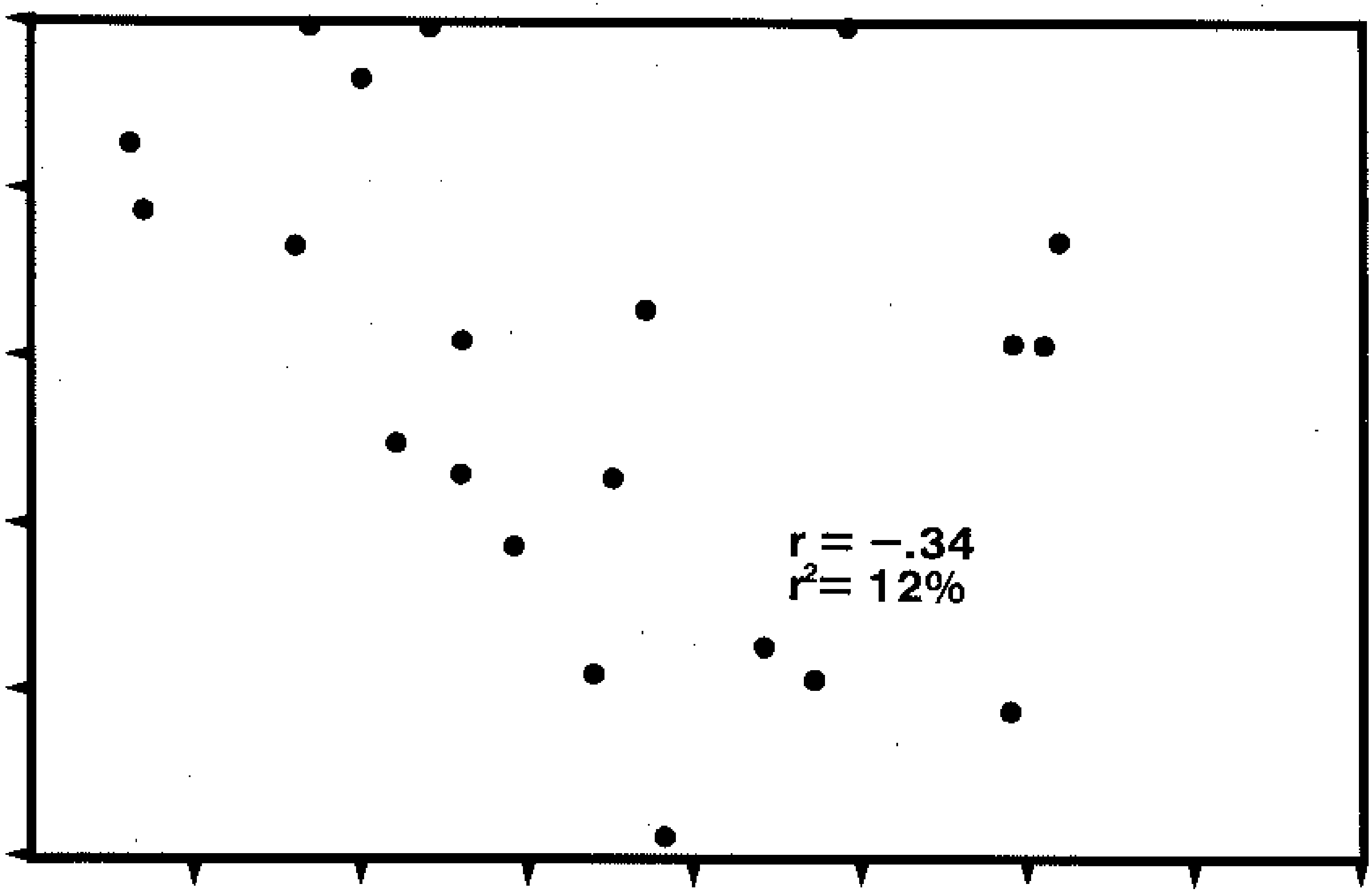


CATEGORY 1
W: 25-54 INCIDENCE VS. PRODUCT LEVERAGE
DAYTIME NETWORK TV



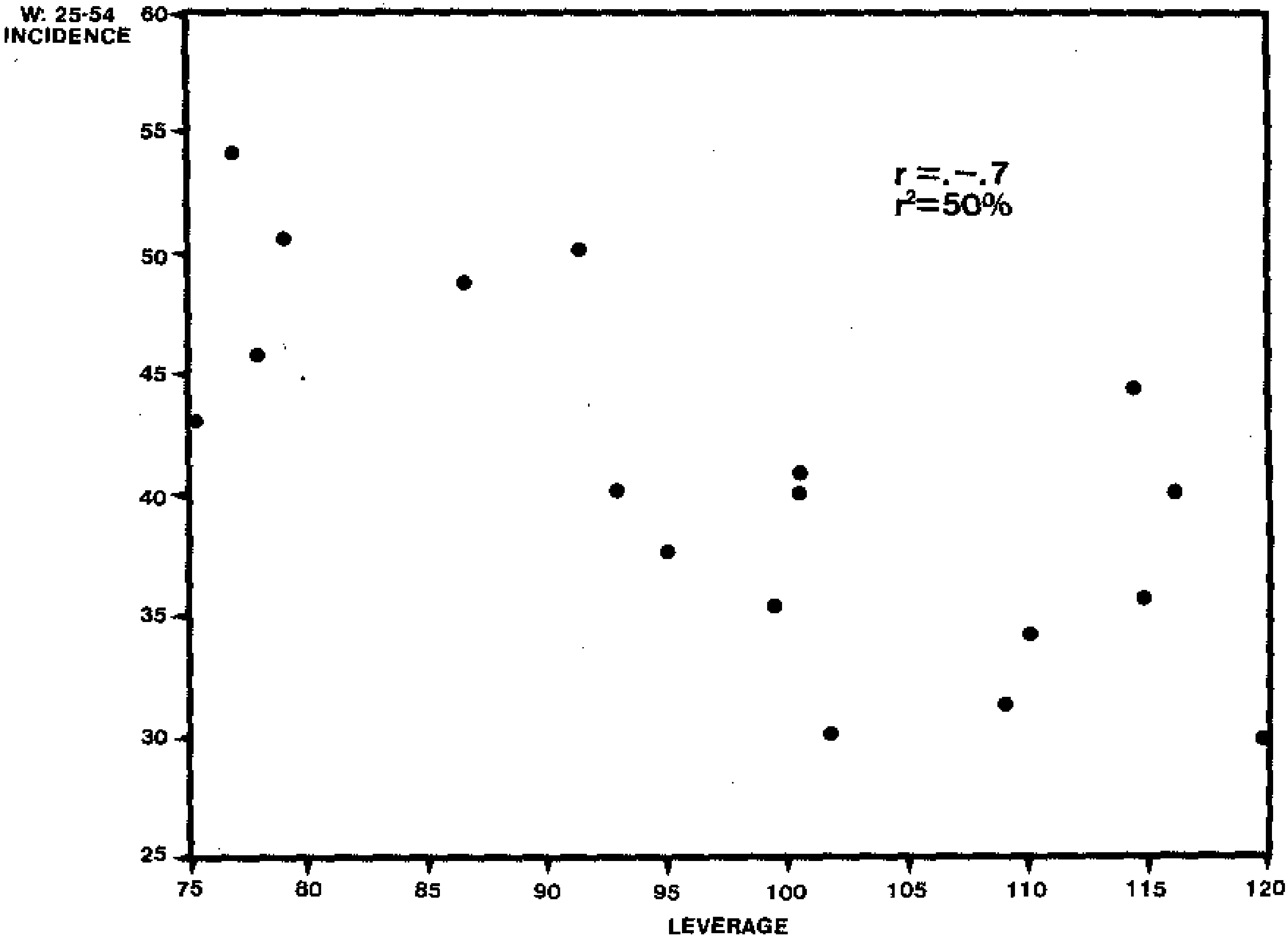
6

CATEGORY 2
W: 25-54 INCIDENCE VS. PRODUCT LEVERAGE
DAYTIME NETWORK TV

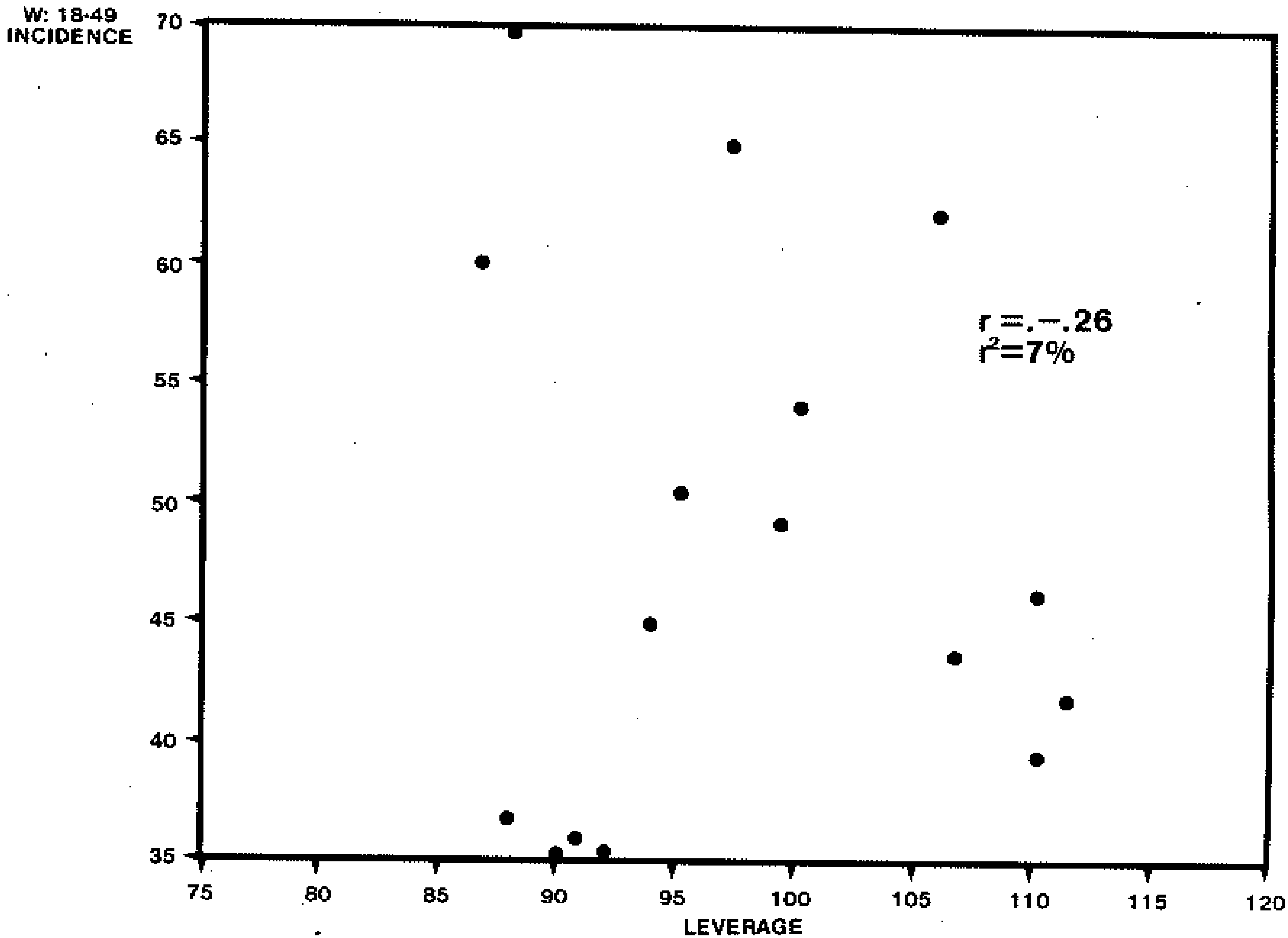


7

REGULAR GROUND COFFEE
W: 25-54 INCIDENCE VS. PRODUCT LEVERAGE
DAYTIME NETWORK TV

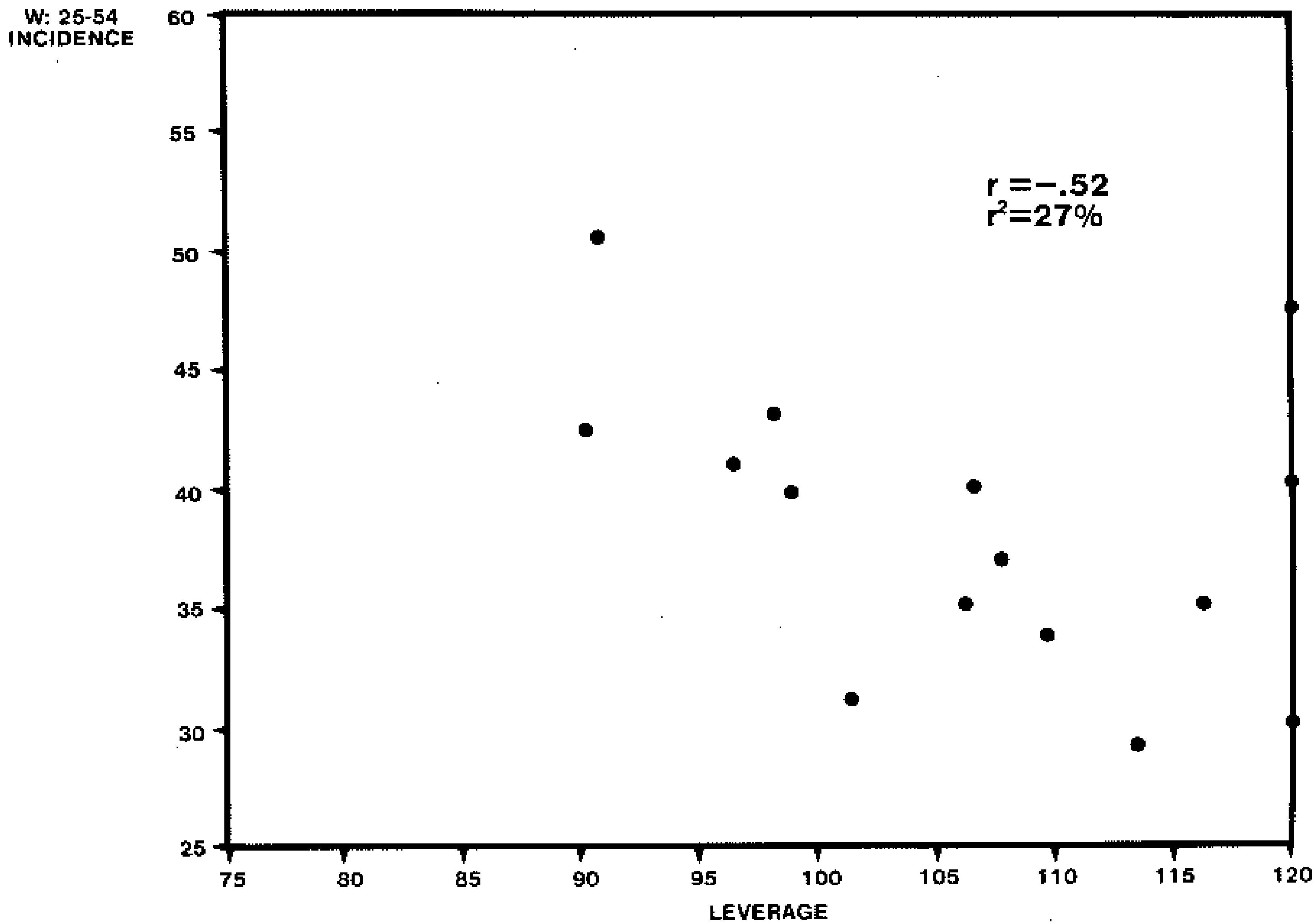


SNACK CRACKERS
W: 18-49 INCIDENCE VS. PRODUCT LEVERAGE
DAYTIME NETWORK TV



9

INSTANT COFFEE
W: 25-54 INCIDENCE VS. PRODUCT LEVERAGE
DAYTIME NETWORK TV



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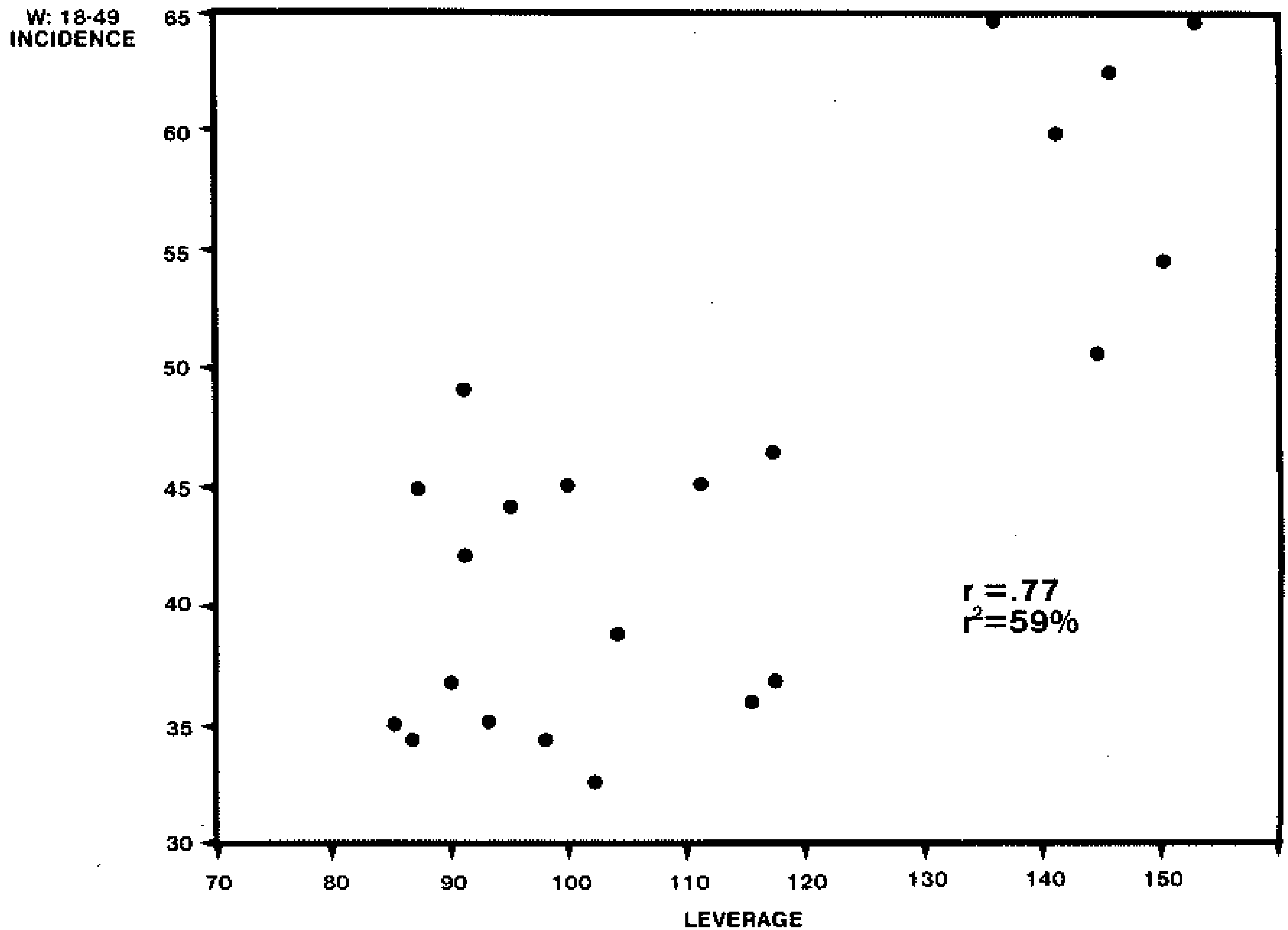
CORN CHIPS
W: 18-49 INCIDENCE VS. PRODUCT LEVERAGE
DAYTIME NETWORK TV



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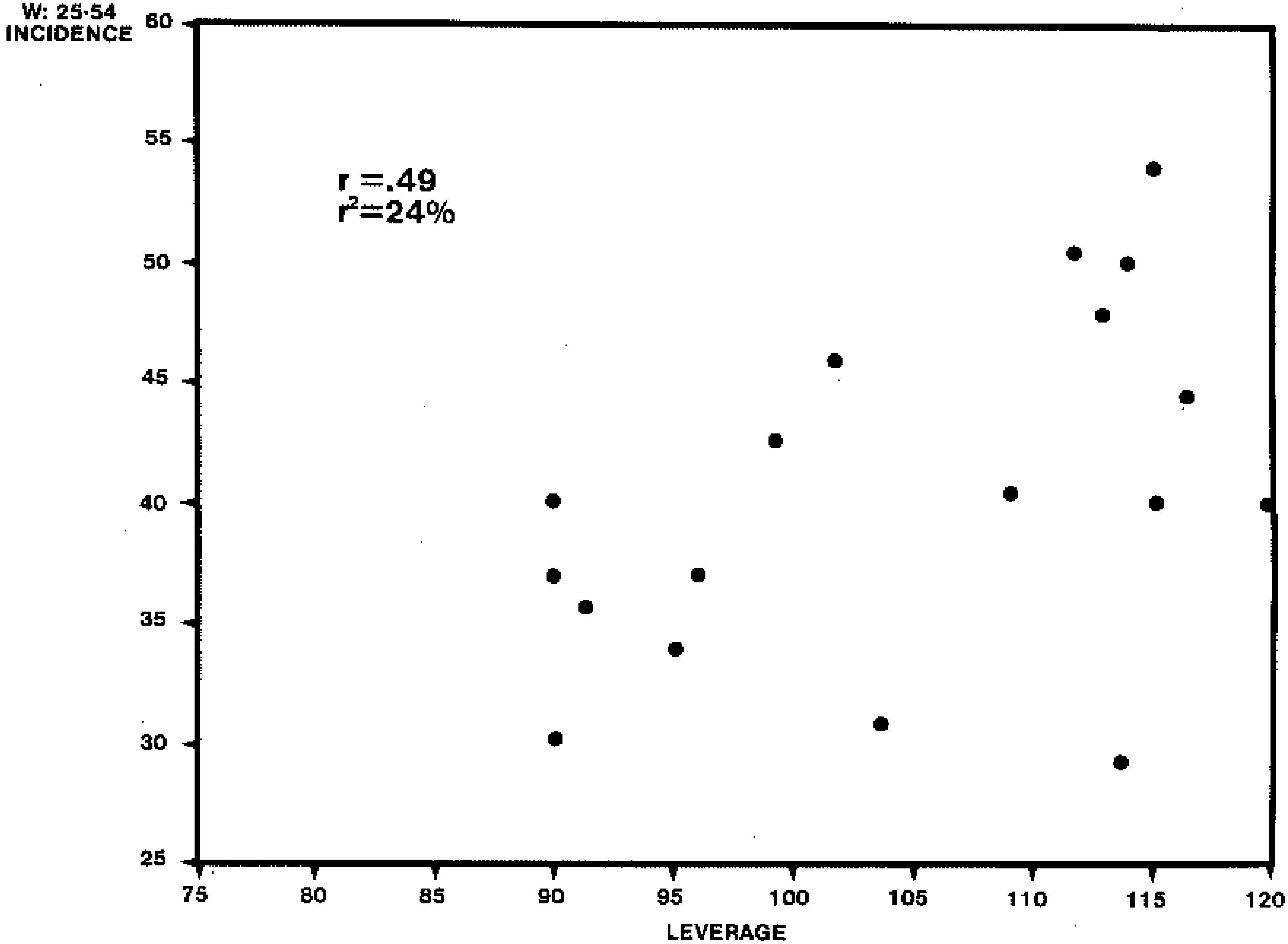
DRY PACKAGED DINNERS
W: 25-54 INCIDENCE VS. PRODUCT LEVERAGE
DAYTIME NETWORK TV



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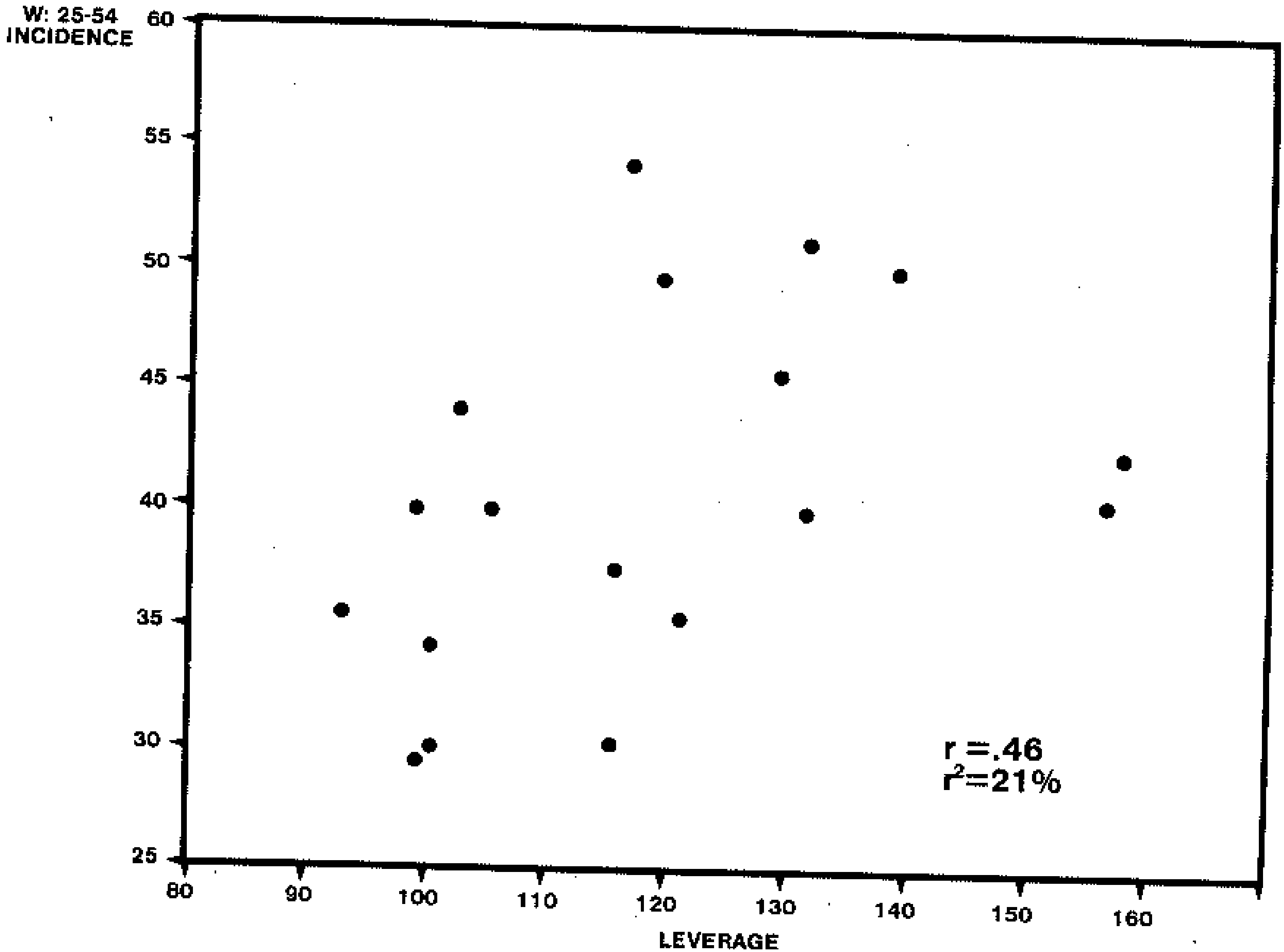
BBQ SAUCE
W: 25-54 INCIDENCE VS. PRODUCT LEVERAGE
DAYTIME NETWORK TV



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SUMMARY OF RESULTS
TARGET DEMO VS. ACTUAL LEVERAGE

CATEGORY	CORRELATION	r^2
#1	+.4	14%
#2	–.3	12%
Reg. Grnd. Coffee	+.7	50%
Instant Coffee	–.5	27%
BBQ Sauce	+.5	21%
Packaged Dinners	+.5	24%
Corn Chips	+.8	59%
Fabric Softeners	–.0	0
Snack Crackers	–.3	7%
Average	+.04	24%

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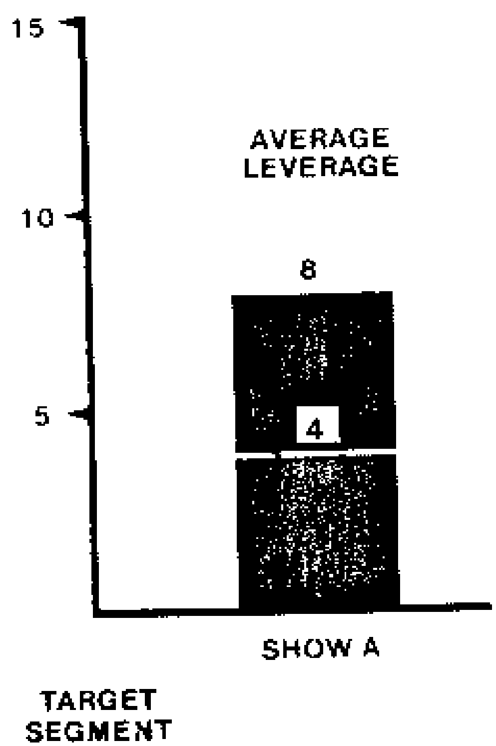
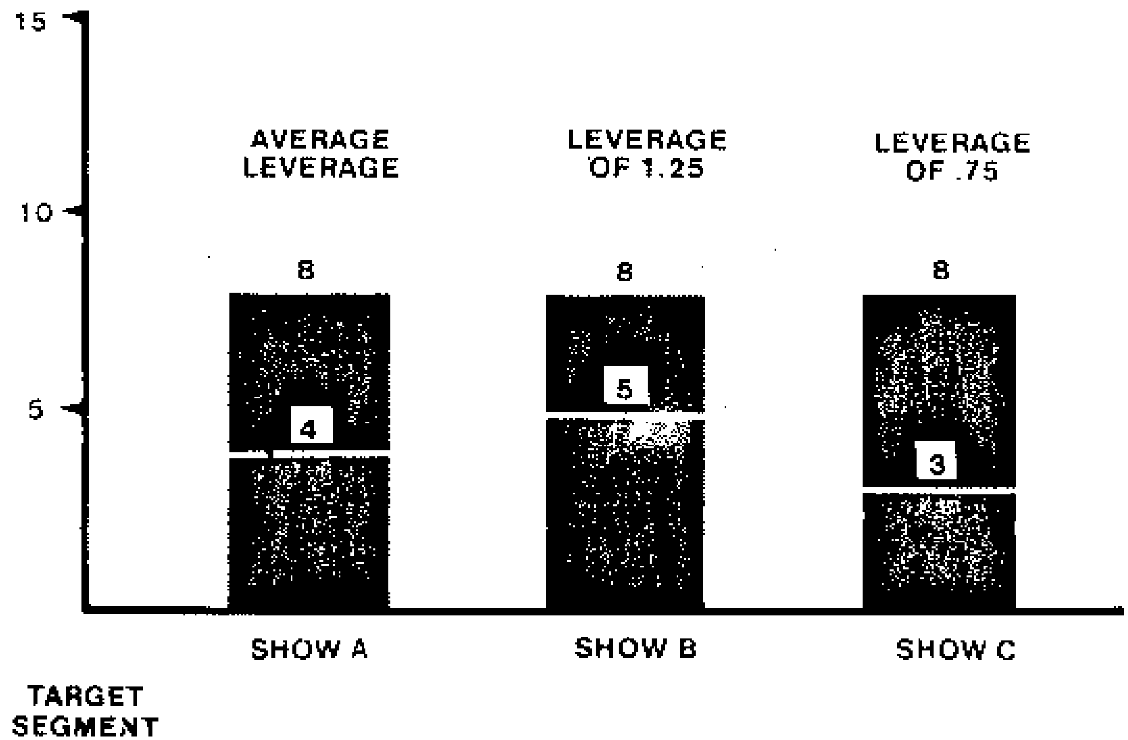
EFFECT OF LEVERAGE ON AUDIENCE COMP



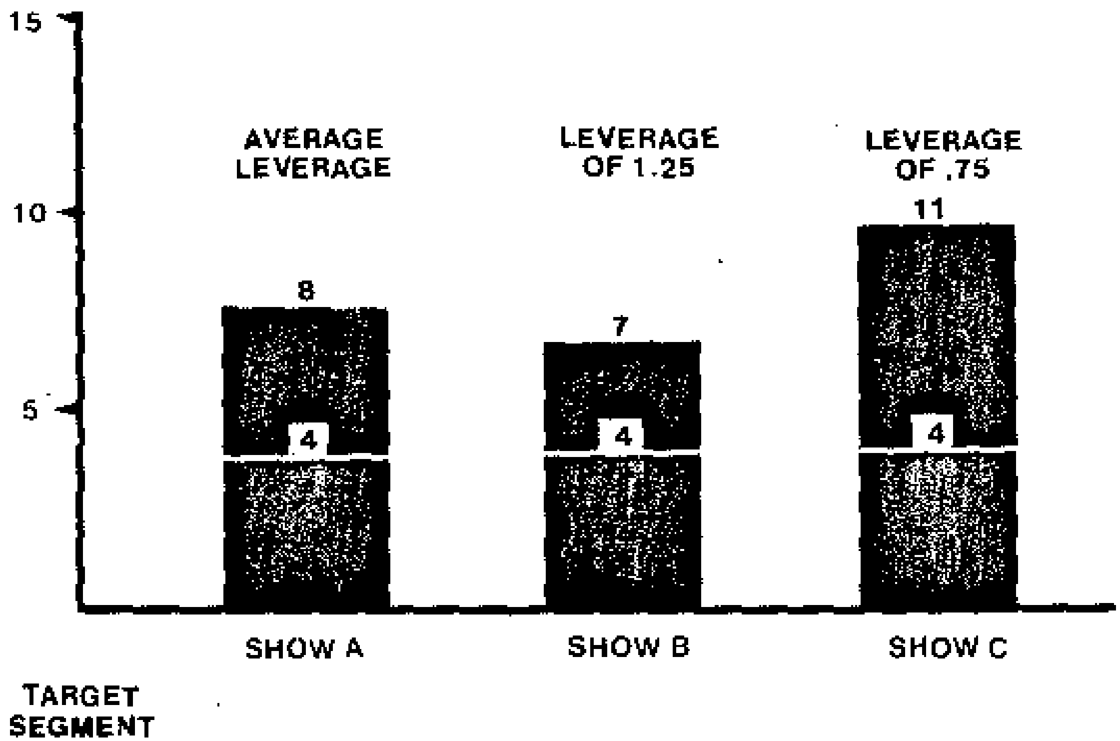
15

EFFECT OF LEVERAGE ON AUDIENCE COMP



16

EFFECT OF LEVERAGE ON AUDIENCE COMP



CATEGORY 1
DAYTIME PROGRAMS

HIGHEST	NORMALIZED INDEX
Ryan's Hope	124
One Life To Live	112
General Hospital	111
LOWEST	
Another World	78
Young & Restless	77
Days Of Our Lives	70

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CATEGORY 2 VS. CATEGORY 1
DAYTIME PROGRAMS

HIGHEST	CAT. 2 INDEX	CAT. 1 INDEX	W: 25-54 INCIDENCE
Days Of Our Lives	127	70	44
Another World	126	78	40
Young & Restless	124	77	40
	126	75	41
LOWEST			
One Life To Live	82	112	51
Loving	81	107	43
Ryan's Hope	71	124	46
	78	114	47

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BRAND X
JAN 84 NETWORK ADS - ACTUAL

PRIME

SHOW (REG. ONLY)	CAT. 2 INDEX
NBC Movie	113
Ripley's	106
ABC Movie	100
After Mash (2)	103
That's Incredible	99
Hart To Hart	100
CBS Movie	88
Wtd. Ave.	102

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BRAND X
JAN 84 NETWORK ADS - ACTUAL

DAYTIME

SHOW	CAT. 2 INDEX	W: 25-54
Days Of Our Lives	127	44
Young & Restless	124	40
General Hospital	85	48
All My Children	89	54
Guiding Light	91	50
One Life To Live	82	51
Capitol (2)	87	37
Price Is Right (3)	112	31
Dream House	94	34
Wtd. Ave.	100	40

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BRAND X
JAN 84 NETWORK ADS - HYPOTHETICAL

SHOW	CAT. 2 INDEX	W: 25-54
Days Of Our Lives	127	44
Young & Restless	124	40
Another World (2)	126	40
New Newlywed Game	114	50
Price Is Right (3)	112	31
Benson	102	41
Wheel Of Fortune	100	36
Search For Tomorrow	99	30
All My Children	89	54
Wtd. Ave.	112	39

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COST PER POINT
BASED ON DEMOS
+ PURCHASE BEHAVIOR

DAYTIME CPP

W: 25-54/Total	$2,400
W: 25-54/Cat. 1 Buyers	$4,000
W: 25-54/Cat. 2 Buyers	$5,700

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EFFECT OF LEVERAGE ON COST PER POINT

	DAYS OF OUR LIVES	RYAN'S HOPE
W: 25-54/1000 Hshlds	437	460
CPP W: 25-54/Total	$2,400	$2,400
CPP W:25-54/Cat. 2 Buyers		
Average Leverage	$5,700	$5,700
Actual Leverage		
- Index	1.27	.71
- Cost	$4,488	$8,028

CATEGORY INDICES FOR SELECTED DAYTIME PROGRAMS

	CATEGORY				
	1	2	3	4	5
Days Of Our Lives	87	127	116	104	85
Another World	97	126	121	106	86
Match Game/H. Squares	96	124	113	109	89
Capitol	133	87	90	114	82
General Hospital	138	85	113	120	103
Ryan's Hope	154	71	102	128	101