ABSTRACT
        Analysis indicates that the appropriate time lag
between cause and effect--between presentation of a press agenda and
learning of issue saliences--is from two to six months, with a
four-month lag being generally acceptable for newspaper
agenda-setting. A shorter lag appears more appropriate for television
agenda-setting. Within the framework of agenda-setting research, this
paper demonstrates the need for more precise theorizing,
methodologies, and identifying of causal relationships in
nonexperimental settings. Cross-lagged correlation is illustrated as
one technique for empirically identifying the appropriate time lag
and aiding in the development of agenda-setting theory. It is
concluded that further research should focus on specifying the causal
process suggested in the agenda-setting theory of media effects, as
well as on developing new methods for measuring and relating media
and public issue agendas. (RB)

Measuring the Cumulative Agenda-Setting

Influence of the Mass Media

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Influence of the Mass Media

Communication researchers have joined their colleagues
in sociology and social psychology in the development of
new approaches to testing causal relationships in non-
experimental situations. This panel is an indicant of
this interest; similar panels have become almost common-
place at communication conventions.

Despite this interest, however, the implications of
these new techniques for theory development in communica-
tion have not been given much attention. Yet the statis-
tical and logical assumptions inherent in the techniques
both make demands on theorists and place limitations on
the kinds of statements they can make.

Recent advancements in development of a theory of
communication effects under the general rubric of agenda-
setting provide a framework for examination of the impact
of one of these new techniques -- cross-lagged correlation
-- on theory. Data available allow us to make some
important decisions about what a theory of these effects
should look like in terms of the required time-span for
observation of the effects and the cumulative nature of
the effect itself.

Background

Campbell and Stanley (1963) discuss correlational analysis in terms of its power for disconfirmation of posited hypotheses. Correlation does not imply causation, they note, but if a high correlation between two variables occurs, the credibility of the hypothesis is strengthened in that it has survived a chance of disconfirmation. If a zero correlation is obtained, the credibility of the hypothesis is greatly diminished.

In communication research two types of correlational data predominate. In the first and most common case, measures of some set of variables are obtained for a given group of analysis units, usually individual respondents to a field interview schedule, and correlations between the variables calculated. This, of course, is the simple cross-sectional design. In the second case, a single unit of analysis, usually a country or other political entity, is assigned values on two or more variables at a set interval, for a given number of intervals, and the correlation calculated between these measures across the time period. This is a time series analysis design, so common in economics.

Introducing the cross-sectional design measurement of the same unit of analysis at more than one time point

allows for a new set of correlations between data from
time one and data from time two. This new data, coupled
with the key assumption that an effect should correlate
higher with a prior cause than with a subsequent cause,
is the central element of the cross-lagged technique.
In terms of Figure I, this means that rX_1Y_2 should be
greater than rX_2Y_1. The Campbell and Stanley logic,
spelled out here, parallels that used by Lazarsfeld around
1948 in a mimeographed report on the relationship between
two dichotomous variables over a time.* Campbell and
Stanley appear to have pinned the title "time lagged
correlation" on the technique.

Traditionally, the single-unit, repeated measure
correlational data from time series studies has been
analyzed in a manner ignoring the temporal strengths
of the data. Campbell (1963), however, suggested that
the simple correlational analysis of this type parallels
the time series, quasi-experiment. Central to both the
correlational and experimental techniques is the observa-
tion of change in the dependent variable co-occuring with
change in the independent variable. In the time series
case, this finding is plagued by the questions of the
direction of causality and the existence of a third
variable causing both the presumed independent and
dependent variables.

*The unpublished Lazarsfeld paper is discussed at length
in Campbell and Stanley (1963).

Campbell argues, however, that "...through an absence of plausible rival hypotheses, in some cases, a temporal correlation is unambiguously interpretable..." (p. 230). To illustrate what Campbell is arguing, we would have little difficulty in choosing the hypothesis that rainfall caused a rise in wheat prices rather than the hypothesis that wheat prices caused rain if we observed a consistent correlation between the two variables, simply because one hypothesis a priori is very unlikely. Such clear-cut relationships, however, are infrequent in communication research.

Campbell (1963) has suggested that a lagged technique also can be employed to gain information about causal ordering of variables from time series data. Relying on the above stated reasoning that a cause at time one should correlate higher with an effect at time two than an effect at time one correlates with a cause at time two, he suggests lagging the series correlations and comparing the supposed time one cause and time two effect relationship with the time one effect and time two cause relationship. In other words, the magnitude of two cross-lags are compared.

Statistical Assumptions for the Use of Correlations

In both the time lagged and the simple time series
analyses, basic assumptions must be made in order to
employ the standard measure of covariation, the Pearson
Product Moment Correlation Coefficient. (However Pelz
and Andrews, 1964, used a nonparametric statistic; and
some of the data presented in this paper are based on
nonparametric statistics.)

For use of Pearson r, in addition to the requirement
that the data be measured on a scale with equal intervals,
the relationship between these two variables is assumed
to be linear, each variable must be normally distributed,
and the relationship between the variables must be homo-
scedastic. The latter requirement is that the spread
of variance about the best fitting straight line through
the distribution is approximately the same at all levels
of the two variables. When these assumptions are met,
the relationship is said to be bivariate-normal. Nunnally
(1967) and McNemar (1969) argue, however, the correlation
statistic is robust and these assumptions need not be
met provided the violation is not extreme.

A simple scatter plot of the data can be helpful
in itself in estimation of linearity, normality, and
homoscedasticity.

An additional assumption of the mathematical model

used to fit a line through the distribution of the rela-
tionship between two variables is particularly important
for time series data. Wonnacott and Wonnacott (1969)
note that the model, specified by the equation

$$Y = \alpha + \beta X + u$$

where u is the error or disturbance term, requires that
each value of the specific variable entered into the
analysis must be independent of the other values of that
variable around it. In other words, Y_1 is not affected
by Y_2 and Y_2 is not affected by either Y_1 or Y_3. Only
when this is true will u have a normal distribution, as
is required for maximum likelihood estimation of elements
of the model. But in time series data this assumption
will rarely be completely satisfied since the same unit
of analysis is used across time measurements. In other
words, the design is a repeated measures one, with all
the observations taken on the same "individual." It is
therefore unlikely that the disturbance term (u) in the
equation specifying the relationship between X and Y
will be random. This occurrence is referred to as auto-
correlation. The autocorrelation would be expected to
distort the correlation (probably exaggerating it) be-
tween the two variables.

Recent Developments in Cross-Lagged Techniques

Recent developments in cross-lagged analysis have
both increased the sophistication of the technique and
the understanding of its limitations. Pelz and Andrews
(1964), working primarily from the Campbell discussions,
have isolated five elementary assumptions necessary for
the analysis.

First, it must be assumed that the variable X_1 (the
presumed cause) in Figure I does not become constant, but
rather continues to change over time. If this were not
the case, the comparison specified by Campbell (between
rX_1Y_2 and rX_2Y_1) becomes less meaningful. (Essentially,
this leaves only the comparison between rY_1Y_2 and rX_1Y_2.
Since an item will almost certainly correlate better
with itself over time than with the cause, there is little
valuable information available.) This assumption, then,
requires that relationships studied be ongoing ones,
which is the usual case in social research. (It is im-
portant to realize that while the computational assumption
is merely that variable X changes, the logical assumption
is that such change is real and not due to measurement
unreliability. That this is so will become clearer as
the discussion proceeds.) Since the expectation is that
variable X is under the control of other outside variables

at time 1 (otherwise it would not be expected to change
between time 1 and time 2), the nature of that relation-
ship becomes important. If variable Z is the sole cause
of changes in variable X, and a saturation effect occurs
such that at some point Z no longer changes X, use of
cross-lags would be inappropriate.

There is an additional circumstance for which the
X_1 to X_2 correlation will be prohibitively large, causing
problems in interpretation of time-lagged panel data.
If mean changes in the panel from time 1 to time 2 do
occur, but the amount of change is constant across all
units of the panel, perfect correlation between X_1 and X_2
will result, making cross-lagged comparisons meaningless.

A second assumption discussed by Pelz and Andrews
has to do with the interval chosen for time lags. Since
the expectation is that rX_1Y_1 is less than rX_1Y_2 (if
X_1 is caused by some Z and Y_1 is caused by a prior X
but Y_2 is caused by X_1), then some measure of Y prior to
the impact of X_1 on Y must be obtainable. This require-
ment that the causal impact not be instantaneous probably
is not too limiting for communication research, where
most effects are cumulative rather than immediate. Yet
it is part of the larger problem of determination of the
proper time lag which serves as a major thrust of this
paper. The problem will be discussed in more detail later.

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The third Pelz and Andrews assumption is a check on
the first, requiring that while X should be inconsistent
over time, it should not be too inconsistent. No problem
will arise due to inconsistency if the causal sequencing
is correct, i.e., if the lag corresponds to the true one
required for X to effect Y. But if the lag is incorrect,
the calculation of the cross correlations (rX_1Y_2 and
rX_2Y_1) will be incorrect due to improper exclusion of
the second wave variables. In other words, the correla-
tions would be weakened by exclusion of an intermediary
step. To the extent, however, that the true lag for X
and Y is the same, this overestimation of that lag would
not disturb the relative comparisons of the cross-lagged
correlations.

The fourth assumption listed by Pelz and Andrews
is really an extension of the third. If the simultaneous
correlations between X and Y do not hold relatively con-
stant over the time ($rX_1Y_1 \neq rX_2Y_2$), the predicted in-
equalities between the cross-lagged correlations (rX_1Y_2
and rX_2Y_1) might not hold. In other words, there cannot
be qualtiative differences in the relationship between
the two variables across the time lag. It must be
assumed that the researcher has entered the ongoing
relationship at a point during which no major change
in the nature of that relationship is taking place.

The final Pelz and Andrews assumption is that of lin-
earity. Not only is this necessary, as they note, for

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computation of the product moment correlation coefficient,
but it will also be necessary to meet the first, third
and fourth assumptions.

Rozelle and Campbell (1969), in commenting on the
Pelz and Andrews work, note that the test for differential
impact of X and Y on each other makes an elementary assump-
tion that may not be easily met. Essentially the test of
rX_1Y_2 vs. rY_1X_2 assumes that, if one r is greater than
the other, the smaller coefficient is mostly spurious.
But, Rozelle and Campbell note, rX_1Y_2 will be greater
than rY_1X_2 if the positive effect of X_1 on Y_2 plus the
negative effect of Y_1 on X_2 is greater than the positive
effect of Y_1 on X_2 plus the negative effect of X_1 on Y_2.
In other words, the simple test of the relative size of
the cross-lag correlations is not as straight-forward
as first thought, and the findings may be confounded
beyond interpretation if only the cross-lag comparisons
are made.

Rozelle and Campbell argue, however, that knowledge
of rX_1X_2 and rY_1Y_2 and of rX_1Y_1 and rX_2Y_2 allow for com-
putation of a cross-lag baseline which helps clarify the
confound problem. Via the baseline the researcher is
given a no-cause minimum correlation against which to
check both for X_1 causes Y_2 and Y_1 causes X_2. It remains
possible, however, that both the rX_1Y_2 and rY_1X_2 correla-

tion will be greater than the baseline, indicating the effects of X and Y on each other. Interpretation of these baseline comparisons is confounded, however, by the lack of a criterion against which to test deviation from the baseline. No statistical test is presently available. Bohrnstedt (1969), arguing that the best predictor of either X or Y at time two will be the respective time one measures, also offers a complicated partial formula that allows the researcher to pull out the effect of the time one measures. This partial is like the Rozelle and Campbell baseline in that it allows for fuller interpretation of the cross-lagged correlations.

The Bohrnstedt emphasis on partialling out the time one measures, as well as the earlier simple partialling by Pelz and Andrews (1964) and the inherent partialling in the Rozelle and Campbell baseline, are important additions to the cross-lagged technique. The intent of these techniques is to eliminate all possible exogenous variables (Z) that might create spurious X_1Y_2 or Y_1X_2 correlations.

If X_1 and Y_1 were spuriously correlated only because of some common cause (Z), then partialling out Y_1 from the X_1Y_2 correlation should reduce it to near zero. What remains when this correlation does not go to zero is the

effect of X. No Z variable occurring <u>after</u> <u>time</u> <u>one</u> can
spuriously create a X_1Y_2 correlation since that Z cannot
effect X_1. This partialling can be successful, however,
only to the extent that the lag for the effect of Z on X
and Y is the same. When this assumption is not met, the
partialling may not be successful in eliminating the
spurious Z effects.

Duncan (1969), Heise (1970), and Pelz and Lew (1970)
have extended work on path analysis to time lagged data
in a more formal statement of the partialling technique.
Heise (1970) argues that the correlation between X_1 and Y_2
as well as the correlation between Y_1 and X_2 are not merely
functions of the underlying parameters, path Y_2X_1 and path
X_2Y_1 respectively. Specifically, this comparison of raw
correlations could be upset if the stabilities of X and
Y were moderately different. Essentially, this is the
same partialling argument used by Pelz and Andrews (1964),
Rozelle and Campbell (1969) and Bohrnstedt (1969). Heise,
however, prefers the path coefficients over partials

> "...since these are estimates of parameters in
> a specific model of change, whereas the partial cor-
> relations estimate no such parameters in any model
> yet proposed for panel data." (p. 10)

Out of the 12 logically possible paths in a four
variable system, four can be eliminated immediately be-
cause of the time dimension since later states cannot

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determine earlier states.* The assumption of the existence
of something other than an instantaneous causal link be-
tween X and Y allows for the elimination of still four
more paths.** While it is assumed that X_1 and Y_1 are not
causally related, they can be correlated. In fact, Heise
notes, such a relationship would be expected because of
the past effect of X on Y. In addition, two new variables
are introduced into the system, each indicating the outside
disturbances on X_2 and Y_2 during the time lag. The
inclusion of these hypothetical variables indicates
that while part of the variance in X_2 and Y_2 is inter-
pretable in terms of the X_1 and Y_1 paths, other variables
have been acting upon both X_2 and Y_2. The path model,
adapted from Heise's, is shown in Figure II.

Acceptance of the path framework requires the fol-
lowing additional assumptions listed by Heise: (1) Non-
colinearity -- that correlations among the variables are
not so close to 1.00 that it is difficult to separate the
effects of one variable from another; (2) Constancy --
that the causal relations in the system operate continu-
ously and that the structure of the relationship does
not change with time; (3) Equivalence -- that all units
of the sample are subject to the same causal laws; (4) Equal
Causal Lags -- that the time lag period for all relationships

*Eliminated, in Figure II, are: pX_1X_2; pY_1Y_2; pX_1Y_2; pY_1X_2.
**Eliminated are: pX_1Y_1; pY_1X_1; pX_2Y_2; pY_2X_2.

is about the same; (5) Measurement Error -- that it is
absent, and (6) Disturbances -- that the variables out-
side the system in time two are unrelated to time one
variables.

While the last two assumptions seem unlikely to
ever be met, Heise, using siumlation data, goes on to
demonstrate that violation of these two assumptions
does not affect inferences about the existence of the
relationship between X and Y, but it can have adverse
effects on parameter estimation.

The Time Lag

The assumptions discussed to this point are listed
in Figure III. In both cross-lag and time series data,
the most important decision concerns selection of the proper
time lag. While cross-lag and time series techniques are
appropriate methodologies in general for generating evidence
about causal processes, the likelihood of obtaining inter-
pretable or unequivocal answers about the nature and
direction of the causal effects is dependent upon the
methodology being applied to the appropriate time intervals.
Where the theoretical conceptualization of the process
does not state in specific terms, at least tentatively,
the nature of the time lag between cause and effect, the
researcher simply must guess where to plug in his
empirical observations and collect the data needed for

cross-lag or time series analysis. In short, application of any methodology designed to yield causal evidence is constrained by the state of the theory about the process being studied.

Too often discussions of the theory and methodology of mass communication research proceed in isolated, water-tight compartments. In those all too rare instances where they are brought into parallel, the focus is on the constraining effects of method on theory testing and development. For example, the greatly increased attention to cross-lag and time series data among communication scientists in recent years stems from a growing awareness that cross-sectional data and the usual techniques of analysis applied to it are too static to support the causal assertions of our hypotheses about the process and effects of mass communication.

But just as methodology can constrain our theoretical efforts, it is equally the case that the state of theory can limit our successful applications of even the most sophisticated methodologies. In the past this clearly has been the case in research on the agenda-setting function of mass communication. The central idea of agenda-setting is that the mass media through their day-to-day selection and display of news influence our perceptions of what are the important problems and issues of the day.

Agenda-setting asserts that audiences learn these saliences from the news media, incorporating a similar set of weights into their personal agendas. While the production of these saliences is largely a by-product of journalism practice and tradition, they nevertheless are attributes of the messages transmitted to the audience. And, asserts the idea of agenda-setting, they are among the most important message attributes transmitted to the audience.

This concept of the agenda-setting function of the mass media is a relational concept specifying a strong positive relationship between the emphases of mass communication and the salience of these topics to the individuals in the audience. This concept is stated in causal terms: increased salience of a topic or issue in the mass media influences (causes) the salience of that topic or issue among the public.

While a great deal of correlational evidence supporting the idea of an agenda-setting function has accumulated in the literature (McCombs and Shaw, 1972, 1974; Becker, McCombs and McLeod, in press), direct causal testing of the agenda-setting hypothesis has been difficult. Tipton, Haney and Basehart (1975) applied cross-lagged correlational analysis to panel data from the 1971 Kentucky gubernatorial election in an effort to test the causal assertions of agenda-setting. However, the equivocal outcome of much of their analysis results in large

part from the particular time interval selected. In the absence of any theoretical guidance regarding the appropriate time lag to use, they had to use the convenient logic of the calendar, and so collected data during October and again in November.

Most of the writers who have dealt with cross-lagged correlations and/or time series data have expressed concern about the problem of determination of the proper lag. Pelz and Andrews (1964) discuss the difficulty in determining causal ordering when one variable changes over a regular cycle, returning to exactly the same value after a given number of units. Blalock (1964) notes that reciprocal causality may cause improper inferences, particularly if the lag is chosen so that only one step of the causation has taken place. If reciprocal causality occurs within the chosen time lag, however, improper inferences are unlikely to occur since X_1Y_2 and Y_1X_2 should both be large and above the Rozelle and Campbell baseline.

Another case in which improper selection of the time lag could lead to faulty inferences results from the impact of the possible Z variables. If some Z variable has a differential lag for its impact on X and Y, such that its effect on X was felt at time one but its effect on Y was not felt until time two, the X_1Y_2 correlation would be spurious. None of the partialling techniques could eliminate such a possibility, which would produce a large X_1Y_2 correlation due merely to the common cause.

Selection of what may be too short a time lag also
severely restricts the power of the cross-lagged
technique, leaving the researcher unable to show any
effect for the independent variable.

In the case of agenda-setting, designation of the
time lag between the media's promulgation of an agenda
of issues and the public's acceptance of these issues as
the salient topics of the day is a key substantive question
which the theory must address. Once the idea of an agenda-
setting influence of the press is even tentatively accepted,
an obvious next question is: How long does it take the
public to learn the press' agenda? Over what period of
time does the learning of salience take place?

Answers to these questions are also important methodo-
logically. What represents appropriate data for cross-
lagged or time series analysis? Across what time interval
can we best capture the agenda-setting process in our
statistical analyses?

Cumulative Effect of Mass Communication

Knowledge of the time required for the mass media
to bring a topic to the public's attention, to place an
item on the agenda, is important to agenda-setting theory
both from a substantive and methodological standpoint.
There are two key questions: What is the time lag between

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appearance of an item on the media's agenda and its appear-
ance on the public agenda? Over what length of time does
the cumulative impact of mass communication build up? Both
questions are important, both for the descriptive precision
of the theory and for methodological decisions about what
time span the researcher should content analyse.

Some preliminary answers to these two questions are
already in hand. Using the personal agenda topics from
the 1973 Syracuse Sophomore Study and from the 1972 Char-
lotte Voter Study - both designed as agenda-setting projects*
- coders worked with issues of Time and Newsweek magazines
to determine the media agendas for six months before and
three months after the dates of the fieldwork.

When the media content is combined in systematic
monthly increments with the Syracuse sophomore's public
agenda, a striking pattern of stability results in the
Pearson correlations between media and public agendas.
In Figure IV the correlations increase monotonically as
the time span cumulates backward in time from the interview
period. There is a rapid rise in the correlation coefficients

*The Syracuse Sophomore Study, conducted in the fall of
1973, is one of the few non-election campaign studies of agenda-
setting. That study interviewed a random sample of 302 male
sophomores on the Syracuse University campus. Beyond the convenience
of this sample design, it yielded good controls on sex, age, and
level of education. The analysis presented here has been reported
in greater detail by Stone (1975). In contrast, the Charlotte
Voter Study interviewed a panel of 227 randomly selected registered
voters in Charlotte, North Carolina in June, October and November
of 1972. Obviously, these respondents are quite varied demo-
graphically.

from the interview period to a time two months prior to
the interviews. After that, the correlations continue
to increase but at a much diminished rate.

In all, the maximum time frame during which the
media agenda best matches the public agenda is a four-
month period extending from six months to two months
prior to the interview period.

The pattern of correlations also demonstrates that
more than the cumulative impact of mass communication is
involved. There definitely is a time lag in the movement
of issue saliences from the media agenda to the public
agenda.

In Figure IV, the cumulative three-month impact of
media yields an r of +.67. The correlation based on the
media content for only two months prior -- no cumulation --
is +.72, essentially the same. Going back three months,
the cumulative r is +.85 and the isolated r, +.77, again
highly similar.

However, given a two to three month lag, other patterns
in Figure IV demonstrate the cumulative effects of mass
communication across time.

Had the proof of the hypothesis rested on the sopho-
more data alone, we could accept a period from six months
to two months before the interview period as the optimal
agenda-setting period. But the Charlotte data modify this
finding.

Data based on the June wave of the Charlotte study
presented in Figure V show patterns moderately similar
to those of the Syracuse study. In fact, the correlation
of +.42 for the period from five months to two months
before the interviews is the single highest correlation.
But the smooth, monotonic pattern of the Syracuse study
is absent.

Data based on the October wave, presented in Figure VI,
also show some inconsistencies, especially in the data
including the October media content. This first set of
agenda-setting correlations shows no cumulative time trend
at all. But there is a cumulative, monotonic trend in
the other three sets in Figure VI. The strength of the
correlations is similar to the Charlotte June wave,
but much weaker than for the Syracuse Sophomore Study.

Most likely, the key to the differences in these
patterns, especially the differences in the strengths of
the correlations, lies in the social context. The Char-
lotte data is taken from a Presidential campaign, a time
when politics is terribly salient to the media if not
to all the electorate. In contrast, the Syracuse survey
was taken among students during a period when no election
was on the horizon. The political issues of the day,
salient to both media and students alike, were the Middle
East War -- the kind of event that moves rapidly onto
everyone's agenda -- and Watergate -- an issue with
which the media had labored for over a year to place on
the national agenda.

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In short, we are comparing a period when the political field was largely left to the media with an election period both when numerous other forces are at work on voters' agendas and when the high salience of politics for the media generally outweighs its salience among the electorate.

The overall result was to attenuate the correlations in the campaign period, but not to remove the cumulative pattern of mass communication impact on personal agendas except at the height of the political campaign. This initial effort documents the cumulative impact of the press on public opinion over a two to six month period. Future replications should probe more into these situational factors, including the types of issues on the public agenda, which shape the cumulative impact of mass communication on public agendas.

Cross-lag Data

Stone (1975) provides empirical support for the time lag originally selected for the 1972 Charlotte voter study. In the absence of any theoretical specification of what the appropriate time lag should be, that study also used a combination of intuition and the convenience of the calendar in deciding upon interviews with a panel of voters in June and October. Fortunately, as the Stone data now leads us to believe, that four-month lag is a reasonably appropriate one for cross-lagged correlational

analysis. And as we shall see, some rather striking answers about the agenda-setting process are emerging from the analysis.

The array of information generated in each cross-lagged analysis is again illustrated in Figure VII, which uses the agendas of the Charlotte Observer for June and October and the agendas for those same months of those Charlotte voters who indicated that the Observer was the only newspaper they read. In this initial analysis the evidence is quite clear. The agenda-setting relationship (Newspaper at Time One correlated with Voters at Time Two) is substantially stronger than the alternative hypothesis (Voters at Time One correlated with the Newspaper at Time Two). The rank-order correlations (Spearman's rho) based on the seven key issues in 1972 are +.51 versus +.19, a difference of .32 between the two.*

Furthermore, this across-time correlation between the newspaper agenda and the voters' agenda is stronger than either of the synchronous (same-time) correlations between newspaper and voter agendas. That is, the newspaper agenda of political issues in June is a better predictor of the voters' agenda in October than it is of the voters' agenda in June.

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*While the "n" used to calculate the rank-order correlations is only 7, the number of major issues on the agenda, the correlation coefficients are far more stable than this n suggests because the issue rankings are based on the responses of 178 voters and over 200 newspaper items in each month analyzed. In short, the 7 issues are observation points at which data on large numbers of cases (voters or news stories) is aggregated.

Similarly, the June newspaper agenda is a better predictor than the October newspaper agenda of how the voters rank the issues in October. These comparisons of the across-time agenda-setting correlation with the static June and October agenda-setting correlations are further evidence of the causal influence of the media on voters' perceptions of the key issues over time.

These two comparisons with the agenda-setting cross-lagged correlation taken from Figure VII are summarized in the first line of Table I. There we see that the agenda-setting cross-lag correlation coefficient does exceed the alternative cross-lag relationship (by +.32) and that the agenda-setting cross-lag coefficient also exceeds both of the synchronous agenda-setting co-efficients, being .05 points more than the larger of the two static, synchronous correlations. Table I also summarizes the results of two additional cross-lagged analyses which examine the agenda-setting role of television. In one, the cross-lagged analysis matched the CBS agenda in June and October against the agenda of voters who reported using CBS as their regular source of news. In the other, the same cross-lagged analysis was repeated for NBC and NBC viewers.

Unlike the analysis of newspaper influence across time, the television data does not yield any patterns of agenda-setting across time. In both cases the correlation of TV at Time One with Voters at Time Two is weaker than the obverse, Voters at Time One with TV at Time Two. Furthermore, the cross-lagged agenda-setting correlation is weaker than either of the synchronous correlations between the voters' agenda and the TV agenda. For example, CBS in June correlates only +.30 with Voters in October. But in June the CBS/Voters correlation is +.32 and in October the match is +.77.

In short, once an appropriate time lag has been identified for analysis, some unequivocal evidence about the agenda-setting role of the press begins to emerge. As we see here in the cross-lagged analysis, there is striking evidence of a long-term effect of the newspaper on voters' agendas. In line with a scattering of other evidence in the agenda-setting literature, this effect seems to be absent for television news. Additional evidence presented elsewhere (Shaw and McCombs, in preparation) demonstrates that the newspaper and TV patterns in Table I hold when a variety of controls are applied and also demonstrates a short-term agenda-setting role for television.

Conclusions

Within the framework of agenda-setting research, this
paper has demonstrated the need for more precise theorizing,
as well as more precise methodology, for detecting and
specifying causal relationships in nonexperimental settings.

As illustrated here, specification of an appropriate
time lag is especially important when using a longitudinal
study design and cross-lagged correlation. Our paper has
illustrated one technique for empirically identifying the
appropriate time lag and aiding in the development of
agenda-setting theory by specifying the lag. The emphasis
here is on the theoretical and empirical steps that must
precede fruitful use of cross-lagged correlation as much
as, or even more than, on the application of the cross-
lagged correlation technique itself.

To further refine the agenda-setting theory of media
effects, evidence has been presented which tentatively
indicates that the appropriate time lag between cause
and effect (between presentation of a press agenda and
learning of issue saliences) is from two to six months,
with a four-month lag being generally acceptable for
newspaper agenda-setting. A shorter lag appears more
appropriate for television agenda-setting.

Although evidence has been provided bearing on the
assumptions of non-instantaneous effects and the interval

for effects, there are still unanswered questions about the constancy of the relationships and about the situational factors affecting the process, including the types of issues on the public agenda and the other forces (such as interpersonal communication) at work on voters' agendas.

Further research should focus on specifying the causal process suggested in the agenda-setting theory of media effects, as well as on developing new methods for measuring and relating media and public issue agendas.

In building communication theory, agenda-setting or otherwise, we need to keep in mind the requirements of our methods as well as the needs of our field.

Figure I

Time 1.   Time 2.

$$X_1 \overline{\hspace{5cm}} X_2$$
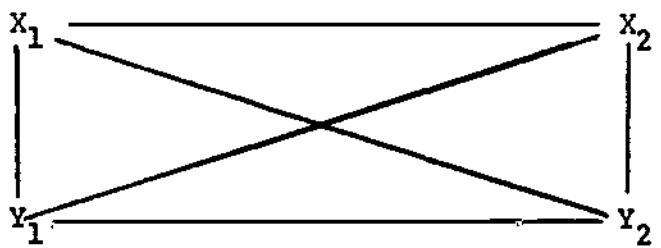
The correlations between X_1 and Y_1 and between X_2 and Y_2 are called simultaneous or synchronous. The correlations between X_1 and X_2 and between Y_1 and Y_2 are called simple lagged correlations or test-retest correlations. The correlations between X_1 and Y_2 and between Y_1 and X_2 are cross-lagged correlations.

Figure II

$$pX_2X_1$$

$$X_1 \longrightarrow X_2$$

$$pY_2X_1$$

$$rX_1Y_1$$

$$pX_2Y_1$$

$$Y_1 \longrightarrow Y_2$$

$$pY_2Y_1$$

$$Z_b$$

$$pX_2Z_b$$

$$rZ_aZ_b$$

$$pY_2Z_a$$

$$Z_a$$
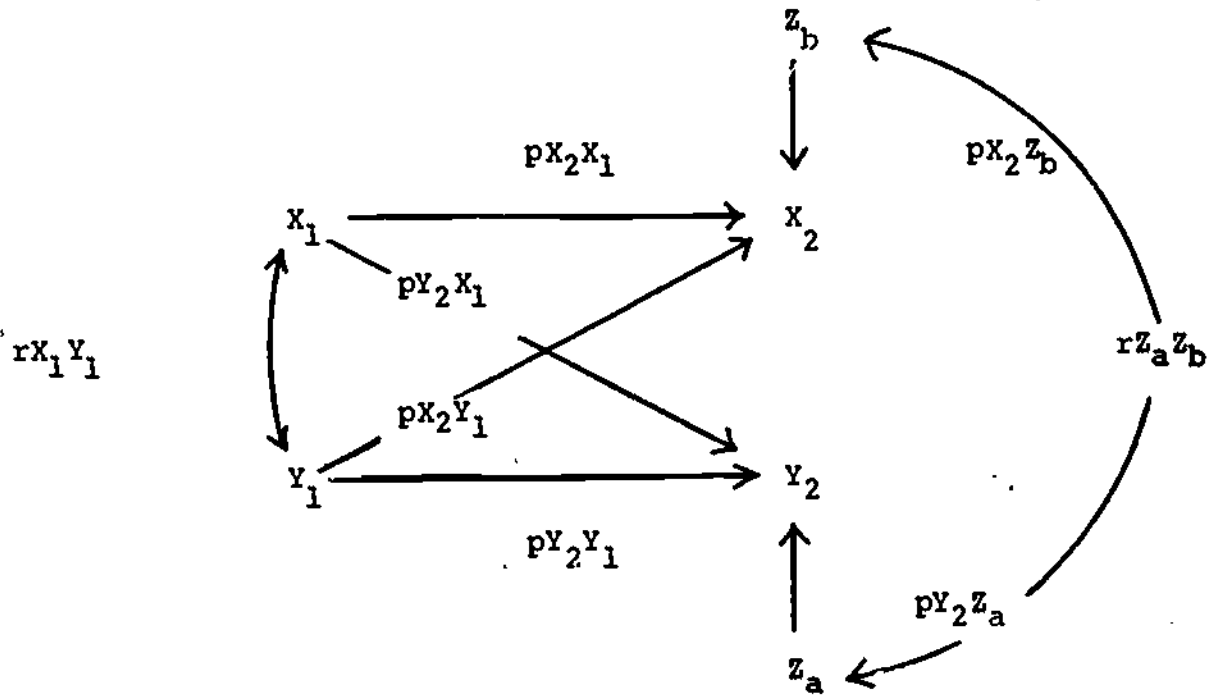
Figure III

Assumptions Needed for Cross-Lagged Correlation
and Path Analysis Over Time

I. Statistical Assumptions

    A. Equal interval measurement
    B. Linearity
    C. Normal distribution
    D. Homoscedasticity
    E. Lack of autocorrelation

II. Inherent Logic of Cross-Lagged Comparisons

    A. Ongoing relationships
    B. Non-instantaneous effects
    C. Approximately equal intervals for effects of variables
    D. Nature of the relationships must be static
    E. Linearity of relationships (redundant with I B)

III. Additional Assumptions Required for Path Analysis Over Time

    A. Non colinearity
    B. Constancy of relationships (redundant with II A and II D)
    C. Equivalence of causal relationships
    D. Equal time lags (redundant with II C)
    E. Absence of measurement error
    F. Independence of disturbance terms

FIGURE IV: Sophomore Data

Correlations with agenda by monthly periods before and after interview period.

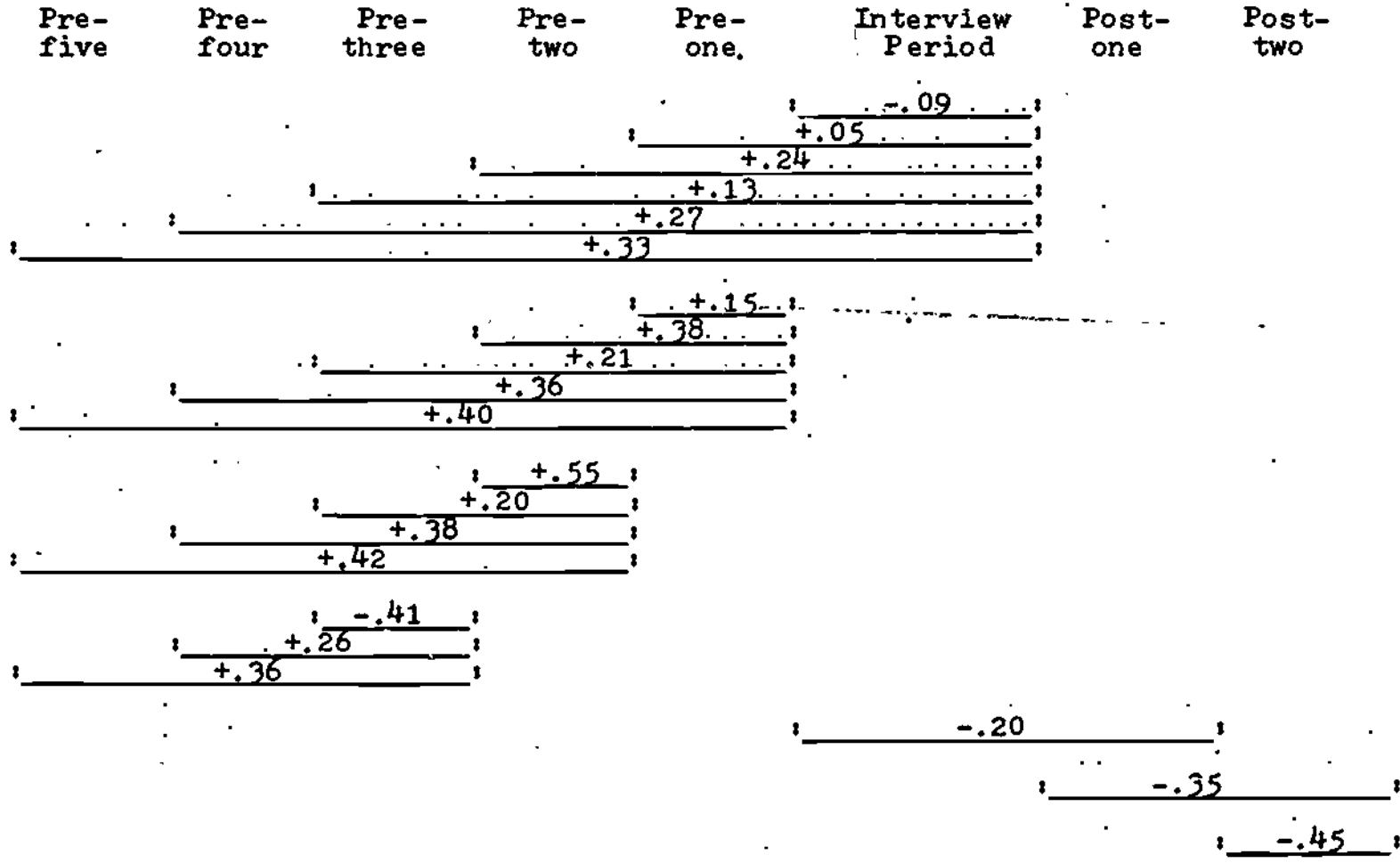| Pre-seven	Pre-six	Pre-five	Pre-four	Pre-three	Pre-two	Pre-one	Interview Period	Post-one	Post-two

```
                                                    :  +.44  :
                                              :    +.45      :
                                        :      +.67          :
                                  :       +.85               :
                            :          +.88      . . .   .   :
                      :            +.87                      :
                :             +.86        . . . . .          :
          :               +.88                               :


                                              :  +.24 :
                                        :    +.67     :
                                  :      +.78         :
                            :        +.79            :
                      :          +.80.               :
                :     . .      +.86   . . .          :
          :           +.88                           :


                                        :+ .72 :
                                  :     +.78   :
                            :       +.78       :
                      :          +.80          :
                :     . . . .   +.82 . . .      :
          :           +.84                      :


                                  : +.77 :            :        +.6?        :
                            :     +.77   :
                      :       +.80       :                  :      +.47      :
                :     . . .   +.82 . . .  :
          :           +.84        .       :                        : +.05 :
```

FIGURE V: Charlotte Data--June

Correlations with agenda by monthly periods before and after interviews.

Pre- five	Pre- four	Pre- three	Pre- two	Pre- one.	Interview Period	Post- one	Post- two

-.09

+.05

+.24

+.13

+.27

+.33

+.15

+.38

+.21

+.36

+.40

+.55

+.20

+.38

+.42

-.41

+.26

+.36

-.20

-.35

-.45
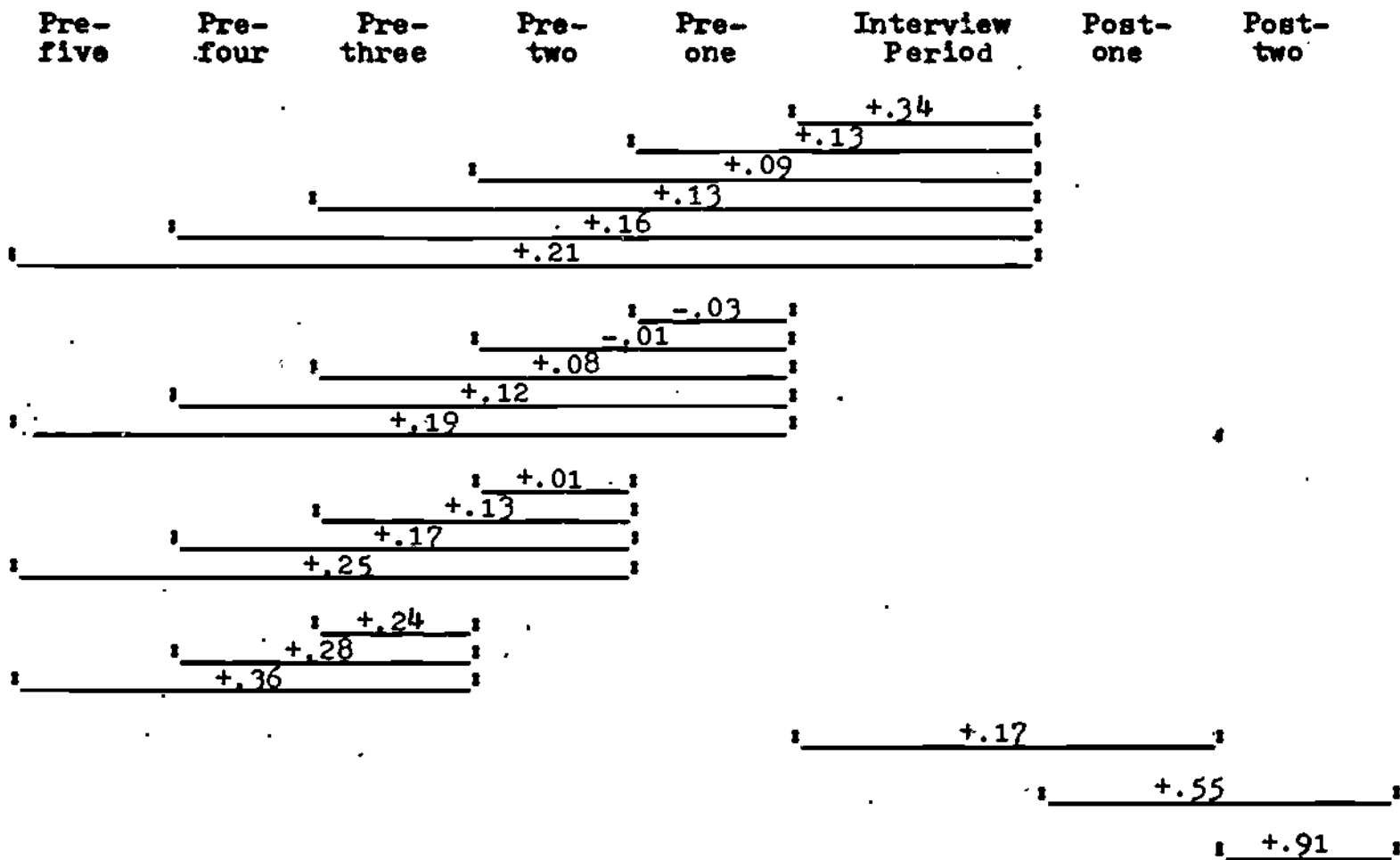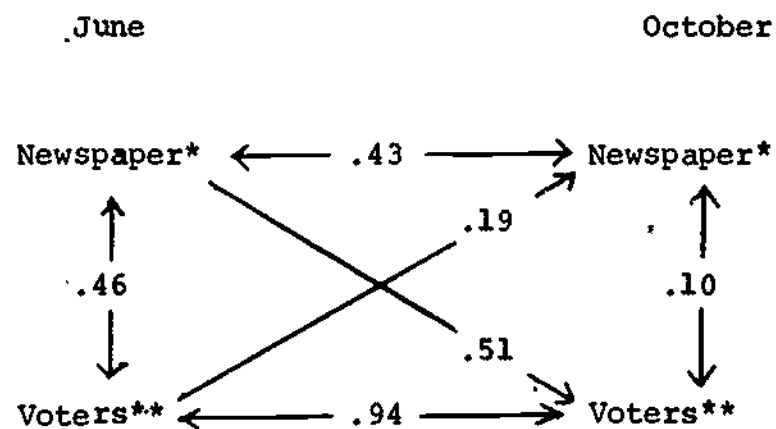
34

32

FIGURE VI: Charlotte Data-- October

Correlations with agenda by monthly periods before and after interviews.

Pre-five	Pre-four	Pre-three	Pre-two	Pre-one	Interview Period	Post-one	Post-two

$+.34$

$+.13$

$+.09$

$+.13$

$+.16$

$+.21$

$-.03$

$-.01$

$+.08$

$+.12$

$+.19$

$+.01$

$+.13$

$+.17$

$+.25$

$+.24$

$+.28$

$+.36$

$+.17$

$+.55$

$+.91$

35

33

Figure VII: Cross-lagged correlation comparison of
Charlotte Voters and the Charlotte Observer
in June and October 1972.

June   October

Newspaper* ←——— .43 ———→ Newspaper*

        ↑   ↑
                    .19
     .46   .10
                    .51
        ↓   ↓

Voters** ←——— .94 ———→ Voters**

*The newspaper agenda used here is based on a
content analysis of all content except advertising
for the month shown.

**Analysis based on only those panel members who
read only the Charlotte Observer (N=178).

Table I. Cross-lagged correlation comparisons of Charlotte voter agendas and various mass media agendas in June and October 1972.

Voter Group	Is Media → Voters > Voters → Media		Cross-lag > Synchronous	
A. Charlotte Observer readers	Yes	+.32*	Yes	+.05
B. CBS viewers	No	-.31**	No	-.02
C. NBC viewers	No	-.52**	No	-.20

* The Media ──→ Voters cross-lag exceeds the baseline correlation, while the Voter ──→ Media cross-lag does not. For details' on computing the baseline (value expected by chance) see Leonard Tipton et al., "Media Agenda-Setting in City and State Election Campaigns," Journalism Quarterly, 52 (1975): 15-22.

** The Voter ──→ Media cross-lag exceeds the baseline correlation, while the Media──→Voter (agenda-setting) cross-lag does not.

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