Intuitive Time-Series Extrapolation of Sales

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ABSTRACT

Experimental research has found that the accuracy of individuals’ intuitive extrapolation of time-series varies with characteristics of those time-series. A limitation of this research, however, is that it has not studied how task-relevant knowledge affects judgment accuracy, either independently or interactively with characteristics of time-series. This paper develops and experimentally test two hypotheses about the interactive effects of time-series characteristics and time-series knowledge on subjects’ accuracy in the intuitive extrapolation of sales time-series. The results provide some support for the hypotheses, but the forms of the ordinal interactions are not exactly as predicted.
The intuitive extrapolation of financial times-series data is a commonly used judgment procedure in forecasting, planning and control activities by individuals in organizations (Dalrymple, 1987; Lawrence, 1983). In spite of its importance, little research has been conducted to understand factors that affect the accuracy of these intuitive extrapolations (Lawrence & Makridakis, 1989). The extant research has focused on the effects of task characteristics (e.g., time-series trends, autoregressive properties) on judgement accuracy and has not explored either the effects of knowledge or the interactive effects between task characteristics and knowledge. In the current study, the focus is on modeling the interactive effects of two task characteristics of a sales time-series (direction and rate of change) and two types of knowledge about sales time-series (trend pattern recognition and discontinuity pattern recognition) on the accuracy of intuitive sales time-series extrapolation for next-period sales.

The experimental results provided some support for the two hypotheses. Judgment accuracy was found to be an ordinal-interactive function of two task characteristics (time-series direction and rate of change) and pattern recognition knowledge of time-series extrapolations (trend and discontinuity). Both types of knowledge separately ordinarily interacted with the two task characteristics to affect judgment accuracy. While the observed forms of these interactions were visually similar to their predicted forms, they were statistically different.
The remainder of this paper is organized as follows. The next section reviews the literature on the effects of task characteristics and task knowledge on the judgment accuracy of intuitive sales time-series extrapolation. This review is used as a basis for developing two hypotheses. The next two sections describe the experimental method and present the results of testing the hypotheses. Finally, the last section has a discussion of the results and presentation of some directions for future research.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Overview

In general, judgment accuracy is a interactive function of task and individual characteristics (Anderson, 1990; Einhorn & Hogarth, 1981; Newell & Simon, 1972). This interaction often results from the use of conditional or adaptive information processing (Anderson, 1990; Payne, Bettman & Johnson, 1993). That is, individuals will select different information processing strategies for the same judgment task based on differences in the information set available to them when the judgment is made. This adaptive behavior often is a rational reaction to the characteristics of the information set by a decision maker with limited cognitive processing capabilities (Anderson, 1990; Payne et al., 1993).

Eggleton (1976, 1982) specifies a three-process model of the conditional decision processes used to make intuitive extrapolations of time-series. These process are:
1. Pattern recognition -- the selection of key features of the time-series that might affect extrapolation method selection.

2. Pattern abstraction -- classification of the time-series into a time-series type based on the features selected.

3. Heuristic selection and application -- selection of an extrapolation heuristic associated in memory with the time-series type and applying it to the time-series.

Although Eggleton (1976, 1982) found some empirical support for this model, his results could not determine whether a subject's pattern recognition ability was related to forecasting accuracy (Cohen, 1976). Harvey (1988) tried to determine whether subjects' used a pattern recognition-based process or a pattern-independent process and found no relationship between pattern recognition and forecast accuracy. Harvey (1988), however, did not test pattern recognition knowledge directly but instead measured pattern generation knowledge. Also, Harvey used time-series that were generated with a first-order autoregressive algorithm where time-series characteristics like direction and rate of change were irrelevant to forecast accuracy.

Since Eggleton's (1976, 1982) model does not limit the definition of time-series pattern, the latter findings are not inconsistent with his model. That is, individuals could use heuristics that focus on the autoregressive properties of a time-series if the time-series is highly variability or discontinuous and could use heuristics that focus on trends in the time-series for more stable time-series. This study attempts to help resolve these conflicting views by directly testing the effects of pattern recognition knowledge on forecast accuracy.
Task Effects

We chose a seven-year period of annual sales as the length of the time-series because it is consistent with those used in the prior research (Biggs & Wild, 1985; Lawrence & Makridakis, 1989). We chose to study the effects of direction and rate of change in annual sales time-series trends because several studies have experimentally tested how the accuracy of intuitive time-series extrapolation judgments vary with these time-series characteristics (Biggs & Wild, 1985; Eggleton, 1982; Lawrence & Makridakis, 1989; Wagenaar & Sagaria, 1975; Wagenaar, Sagaria & Timmers, 1978).

The direction and rate of change also describe a majority of most annual sales' time-series properties. Consider the 1,654 firms on Compustat which have annual sales data for each year of the seven-year period 1984-1990 (the most recent seven year period available). Table 1 contains the percentages of these firms classified as having one of six sales time-series: an increasing or decreasing direction of change in annual sales, and an increasing, linear or decreasing rate of change in annual sales.¹ As shown, these six time-series describe 72% of the firms' annual sales. Thus, our use of these two characteristics of a time-series increases the consistency of our research with the prior research and the task characteristics that describe many firm's annual sales.

Table 1

4
The prior research finds that judgment accuracy is lower for
time-series with a direction of change that is decreasing
compared to increasing and for a rate of change that is
increasing rather than linear or decreasing (Biggs & Wild, 1985).
Direction and rate of time-series change also have been found to
interact: The decrease in judgment accuracy is larger between
increasing and decreasing direction time-series for increasing
rate time-series than for decreasing or linear rate time-series
(Biggs & Wild, 1985).

This analysis of the task characteristics of sales time-
series supports the following three expectations, which are
graphically presented in Figure 1:

1. Judgment accuracy is lower for decreasing direction sales
time-series than for increasing direction sales time-series
(i.e., 1<2 and 3<4 in Figure 1).

2. Judgment accuracy is lower for increasing rate sales time-
series than for decreasing or linear rate sales time-series
(i.e., 3<1 and 4<2 in Figure 1).

3. The difference in judgment accuracy between an increasing
rate sales time-series and a decreasing or linear rate sales
time-series is greater for a decreasing direction sales time-
series than for an increasing direction sales time-series
(i.e., (1-3)<(2-4) in Figure 1).

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**Figure 1**

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**Knowledge Effects**

Although no previous research has empirically tested the
effects of differences in knowledge on judgment accuracy in
intuitive time-series extrapolation, Eggleton’s (1976, 1982)
model implies that intuitive sales extrapolation accuracy should increase with the presence of, and the level of refinement in, procedures for identifying and extrapolating different sales time-series (direction, rate of change, and discontinuity). For example, different procedures should be used to extrapolate a sales time-series with a discontinuity than one without it. Sales time-series extrapolation judgment accuracy for sales time-series without a discontinuity should be based on procedures that are sensitive to the direction and rate of change in the sales time-series and do not adjust for discontinuities. Sales time-series extrapolation accuracy for sales time-series with a discontinuity should be based on procedures that can identify the discontinuity and adjust for it, as well as procedures which are sensitive to sales time-series direction and rate of change.

In summary, when making an intuitive sales time-series extrapolation, two types of pattern recognition knowledge about a sales time-series likely are determinants of judgment accuracy: (1) knowledge appropriate for continuous sales time-series identification and extrapolation (i.e., trend processing); and (2) knowledge appropriate for discontinuous sales time-series identification and adjustment (i.e., discontinuity processing). Hereafter, these types of knowledge are referred to as trend and discontinuity.

This analysis supports the expectation that high, compared to low, trend or discontinuity knowledge results in higher judgment accuracy. However, this analysis does not provide a basis for
making predictions about whether or how they might interact with task characteristics to affect judgment accuracy.

Knowledge by Task Interactions

Eggleton’s (1976, 1982) model implies that different intuitive extrapolation procedures are used for different time-series. Therefore, an ordinal interaction effect on the accuracy of intuitive sales time-series extrapolation should exist between sales time-series and knowledge. In this study, this interaction is modeled using four variables, each having two or three levels. Two variables specify the sales time-series: direction of change (increasing or decreasing) and rate of change (increasing, linear or decreasing). Two variables describe knowledge: trend and discontinuity (each with low and high levels).

Knowledge differences are expected to have a greater impact on judgment accuracy when the error rate for the task is higher than when it is lower. Prior research has shown that extrapolations of increasing rate sales time-series have higher error rates than linear or decreasing rate sales time-series (Biggs & Wild, 1985). Thus, we expect that knowledge should affect judgment accuracy more for an increasing rate sales time-series than for a linear or decreasing rate sales time-series. Prior research also has shown that extrapolations of decreasing direction time-series have higher error rates than increasing direction time-series (Biggs & Wild, 1985). Therefore, knowledge should affect judgment accuracy more for a decreasing direction
sales time-series than for an increasing direction sales time-series.

This analysis leads to the following expectation, which is graphically presented in Figure 2: Differences in judgment accuracy due to differences in task characteristics will be lower for high knowledge levels than for low knowledge levels (i.e., (6-8)<(2-4), (5-7)<(1-3), (8-7)<(4-3), and (6-5)<(2-1) in Figure 2). This expectation implies that extrapolation judgment accuracy is a function of two task-by-knowledge three-way ordinal interactions:

\[ H_1: \text{Intuitive sales time-series judgment accuracy in predicting next-period sales is a function of a sales time-series rate by sales time-series direction by discontinuity knowledge interaction.} \]

\[ H_2: \text{Intuitive sales time-series judgment accuracy in predicting next-period sales is a function of a sales time-series rate by sales time-series direction by trend knowledge interaction.} \]

Figure 2

EXPERIMENTAL DESIGN

The experimental design had four independent variables and judgment accuracy was the dependent variable. Below is a description of each variable, which is followed by the experimental procedure and a description of the subjects.
Independent Variables

The operationalization of the two between-subject task variables was based on the data used in Biggs & Wild (1985). They mathematically constructed six, seven-year, sales time-series based on a 3x2 design: increasing and decreasing direction of change, and increasing (exponential), linear and decreasing (logarithmic) rate of change. Their six sales time-series had no noise as they were deterministically generated from formulae.

To construct the six sales time-series used in this study, the following procedure was used. The Biggs & Wild (1985) data were adjusted to minimize demand effects of the sales time-series extrapolation task by randomly adding or subtracting either $10,000,000, $15,000,000 or $20,000,000 to every sales amount within a given sales time-series, with the only constraint being that the expected sales value for the eighth (prediction) year could not be negative. The six sales time-series are presented in Table 2.

Table 2

The operationalization of the two within-subject knowledge variables was as follows. The subjects were administered a two-part, knowledge test.

The first part measured trend knowledge. This test consisted of 12 seven-year continuous time-series (described as not being sales) that included two each of the six time-series which are
formed by crossing increasing and decreasing changes in direction with increasing, linear and decreasing rates of change. Each time-series was similar to the ones in Table 2. A subject was required to specify both the direction of change (increasing, decreasing or no-change in direction) and the rate of change (increasing, decreasing or linear). Thus, for each time-series a subject had to select one of nine possible responses. Trend knowledge was measured by the percentage of the 12 time-series which were correctly identified. For hypothesis testing purposes, trend knowledge was dichotomized at the median into low and high levels.

The second part of the knowledge test measured discontinuity knowledge. For each of ten seven-year time-series (described as not being sales), a subject had to indicate both the direction of any discontinuity (increasing, decreasing or neither) and the year of any discontinuity. The ten time-series were similar to the ones in Table 2. Eight of these time-series had a discontinuity and two did not. The discontinuity knowledge score was the number of time-series which were correctly identified. For hypothesis testing purposes, discontinuity knowledge was dichotomized at the median into low and high levels.

**Dependent Variable**

The dependent variable was judgment accuracy, which was measured for a subject’s response to each of the six sales time-series in Table 2. Accuracy for each sales time-series was the absolute difference between the expected annual sales for year
eight and a subject’s prediction. Thus, a lower value on this measure indicated higher judgment accuracy. The expected value of year eight was determined by the same formulae used to produce the sales time-series. Absolute difference was used as the accuracy measure because it did not allow positive and negative errors to offset.

Procedure

Each subject was provided with a booklet that identified the nature of the study and had three sections. The first section contained the six sales time-series cases which were used to measure judgment accuracy. Preceding these six cases were four practice cases. The six cases were presented in four randomized orders. No order effect was detected ($p < 0.05$). The second section contained the knowledge tests for trend and discontinuity. For each part, the sets of sales time-series were presented in four random orders and no order effects were detected ($p < 0.05$). The third section had some demographic and debriefing questions (see below). Subjects completed the booklet in the presence of the experimenter in an average of 40 minutes (range: 30 to 50 minutes).

Subjects

The subjects were 66 graduating seniors who were accounting majors enrolled at a large state university. Subjects voluntarily participated in this study during class time. The profile of the subjects was obtained from questions in the last part of the booklet. None of the subjects had any financial
analyst experience. In response to a question which asked about how hard they tried to give their best possible answers to all of the questions in the study, the mean response was 5.78 (range: 3-7) on a seven-point scale (1 = I did not try at all, and 7 = I tried as hard as I am able to).

RESULTS

Descriptive Statistics

Table 3 contains the cell means and standard deviations of judgment accuracy for the four-variable design. Inspection of the absolute-error distributions for the six sales time-series indicated that five of them had significant skewness for one or both of two reasons. First, each distribution had a lower bound of $0, and since their means were relatively close to $0 (in relation to their standard deviations), they were truncated, which created positive skew. To reduce this skew, the judgments for five of the six sales time-series were transformed by a base-10 log. For each of the distributions, this transformation reduced the level of skewness to be within the limits of normality.

Table 3

Second, four of the 396 (= 66 x 6) judgments were greater than three standard deviations above the mean of a distribution which increased positive skewness. Thus, using the "Winsorizing" procedure for outlier adjustment (Foster, 1986), these four
judgments were reset to be equal to three standard deviations above their respective means.

The subjects' mean judgment accuracy across all cells was an absolute error of $6,264,119 (= 6.1\% of the mean of the expected annual sales for the six sales time-series). There was considerable variation in the subjects' judgment accuracy across the 24 cells. Judgment accuracy was lowest (mean absolute error = $17,551,308) for the sales time-series that was decreasing at an increasing rate and trend knowledge was high while discontinuity knowledge was low. Judgment accuracy was highest (mean absolute error = $2,113,238) for the sales time-series that was decreasing at a linear rate and discontinuity and trend knowledge were high.

Consistent with prior research, the mean difference in absolute error between the increasing rate time-series and the decreasing and linear rate time-series was larger for time-series that had a decreasing direction than those that had an increasing direction. Collapsing across knowledge levels, the difference in means for the decreasing direction time-series was $8,888,250 versus $4,497,030 for increasing direction time-series ($t = 3.98$, one-tailed $p = 0.0001$).

Also as expected, collapsing over task variables, the absolute error in the high discontinuity knowledge condition was lower than in the low condition ($5,330,295$ versus $7,318,435$; $t = 2.18$, one-tailed $p = 0.015$). Collapsing over task variables, the mean absolute error rate also was lower in the high trend
knowledge condition than in the low condition, but the difference was not significant ($5,999,613 versus $6,545,156; t = 0.58, one-tailed p = 0.28).

Tests of Hypotheses

A 3x2^3 MANOVA was used to test the two hypotheses. It had two between-subject variables (high and low trend knowledge; and high and low discontinuity knowledge) and two within-subject variables (increasing and decreasing directions of changes in sales time-series; and increasing, linear and decreasing rates of sales time-series change).

The hypotheses predicted that judgment accuracy would be a function of two three-way interactions involving the task and knowledge variables (Figure 2). Figures 3 and 4 show the results graphically in relation to Figure 2.

Figures 3 and 4

The two three-way interactions that included the two task variables and either discontinuity knowledge (Figure 3: $F = 2.88$, $p = 0.06$) or trend knowledge (Figure 4: $F = 3.07$, $p = 0.05$) were significant. Visual comparisons of the predicted and observed interactions indicated that both three-way interactions had forms which approximated their predicted forms. T-tests, however, indicated that the interactions significantly deviated from their predicted forms (Table 4).
Each observed interaction would be consistent with the predicted interaction if the following inequalities in means were significant: \((6-8)<(2-4), (5-7)<(1-3), (8-7)<(4-3),\) and \((6-5)<(2-1),\) where the numbers are the segment end-points in Figures 2, 3, and 4. Table 4 presents a summary of the results of these tests. For the interactions which involved discontinuity knowledge, while two of the four inequalities were in the wrong direction, none were significant. For the interactions which involved trend knowledge, three of the four inequalities were in the wrong direction and two of those three were significant.

Overall, the results provided some support for H1 and H2. While evidence was found for task by knowledge ordinal interactions, the observed interactions were not exactly as predicted.

**DISCUSSION**

**Results**

The theoretical analysis in this paper developed two hypotheses regarding how two characteristics of sales time-series and two types of knowledge about sales time-series interactively affect the accuracy of intuitive time-series extrapolation of next-period sales. The results indicated that sales time-series characteristics and knowledge about sales time-series ordinally
interacted to affect judgment performance, although the observed forms of the two interactions were not exactly as predicted.

**Implications for Future Research**

Future research on how individuals form expectations about future values of a (financial) time-series could further study how time-series characteristics and knowledge about those characteristics independently and interactively affect judgment processes and performance. Such research could pursue two main directions. One would be to use process tracing methods to better determine the characteristics of the cognitive processes used to extrapolate time-series. Such studies could determine:

1. the time-series characteristics (if any) that are used to identify a pattern;
2. the category structure used to classify time-series and the role of base-rate information in the classification process;
3. the forecasting heuristics that are associated with each category;
4. how the cognitive demands of these heuristics affect heuristic selection; and
5. how task context variables such as time pressure, incentives and risk preferences affect judgment accuracy.

Based on what is learned in these processing studies about how task characteristics and knowledge interact, a second line of research would study how to improve intuitive extrapolation accuracy. Such research might determine how other types of knowledge interacts with additional task characteristics to influence accuracy; how different heuristics vary in extrapolation accuracy when they are mechanistically applied in a
simulated environment; what the relative importance of pattern recognition, categorization and heuristic selection accuracy are in determining extrapolation accuracy; and how improved extrapolation processes can be taught.

In conclusion, this experimental study has extended the research on the intuitive extrapolation of time-series by testing how task characteristics of time-series and knowledge about these characteristics interact to affect judgment accuracy. This research has also identified several additional opportunities for research to investigate further how task and task characteristics interact to affect judgment performance.
1. Each firm's seven-year sales time-series was classified into one of seven categories based on direction and rate of change using a statistical significance cutoff of 0.10. Time-series that could not be classified at this level of significance were assigned to the "other" category.

2. A discontinuity in a time-series is defined as a significant departure in a given year from the average rate and/or direction of change in the time-series.

3. In this study, judgment accuracy was measured by mean absolute error. Therefore, Figure 2 presents predictions in terms of error rates to be consistent with the presentation of observed error rates below.

4. This study employs a within-subjects design for task characteristics compared to Biggs and Wild's [1985] between-subjects design. Therefore, we had to modify the Biggs and Wild data to reduce the possibility of subjects guessing the manipulations of task characteristics.

5. Time-series used for the knowledge tests were described as not being sales data to avoid confounding base-rate sales knowledge with time-series extrapolation knowledge.

6. Direction of change was defined as:

"... Whether there was a statistically significant increase or decrease in sales over time. Statistically significant means that there is a 90% or greater chance that, in fact, the slope of the sales trend is different (i.e., increasing or decreasing) from a flat (horizontal) trend."

Rate of change was defined as:

"... whether the trend direction is constant over time, or whether it increases or decreases over time. Each type of rate of change (increasing, constant, decreasing) is defined as having a 90% or greater change that, in fact, that type of rate of change really is the true one."

7. High trend knowledge subjects' scores ranged from 7 to 12 (out of 12 possible) with a mean of 9.2 and a standard deviation of 1.66. Low trend knowledge subjects' scores ranged from 1 to 6 with a mean of 4.5 and a standard deviation of 1.30. The hypotheses also were tested with the two levels of trend knowledge formed by applying different splitting rules (e.g., lower and upper quartiles) and the results of those tests were qualitatively the same as those presented.
8. A discontinuity was defined as:

"... a change in value from one year to the next that exceeds 10% or more of the annual change in value between the years before and after the discontinuity."

9. High discontinuity knowledge subjects' scores ranged from 6 to 10 (out of 10 possible) with a mean of 7.7 and a standard deviation of 1.13. Low discontinuity knowledge subjects' scores ranged from 0 to 4 with a mean of 2.7 and a standard deviation of 1.18. The hypotheses also were tested with the two levels of discontinuity knowledge formed by applying different splitting rules (e.g., lower and upper quartiles) and the results of those tests were qualitatively the same as those presented.

10. Cell contents of Table 3 are arranged with knowledge variables as columns and task variables as rows. Within each variable, levels are ordered top to bottom and left to right by decreasing expected effect on accuracy (e.g., increasing above decreasing trend direction, low knowledge to the left of high knowledge).
BIBLIOGRAPHY


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### TABLE 4
Predicted and Observed Knowledge by Task Characteristic Differences

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Fig. 1. Predicted Time Series Direction by Rate Interaction
Fig. 2. Predicted Knowledge by Task Characteristics Interaction
Fig. 3. Observed Discontinuity Knowledge by Task Characteristics Interaction
Fig. 4. Observed Trend Knowledge by Task Characteristics Interaction