How Appraisers Do Their Work: A Test of the Appraisal Process and the Development of a Descriptive Model

*Julian Diaz III**

Abstract. **Actual decisionmaking behavior is rarely the focus of real estate valuation research, but this paper argues the need for just such investigations and reports the results of one study. Two hypotheses concerning the relationship between the appraisal process and the actual behavior of expert appraisers are developed. An experimental test of these hypotheses reveals evidence that the behavior of expert appraisers deviates significantly from the prescribed appraisal processs. Based upon the experimental observations, a model of actual expert behavior is built and compared to the prescribed model. Some implications of the observed behavioral divergence are discussed.**

Introduction

While all academic disciplines within the business domain are rightfully considered behavioral, a relatively neglected area of inquiry within real estate is the study of actual decisionmaking behavior. Study of the behavior of real estate appraisers for example largely has been confined to prescriptive interests (i.e., has focused on the normative "what ought to be done" as opposed to the descriptive "what actually is done"). There are exceptions.

Cole, Guilkey and Miles [6] measured the reliability of one group of commercial appraisals by comparing the value judgments of appraisers to actual sales prices. Ferguson [9] discovered evidence that under certain conditions residential appraisal values are correlated with contract prices. Smith [18] explored nine discrepancies between the behavior of appraisers and appraisal theory.

The paucity of behavioral research in real estate belies its importance. Brightman [5] has pointed out that normative research must be grounded in descriptive models. More simply stated, the quality of decisions and decisionmaking cannot be improved until actual decisionmaking processes are clearly understood. The study of outputs, such as in Cole, Guilkey and Miles and in Ferguson, generates important hypotheses but offers no glimpse into the black box of behavior. The detection of certain inconsistencies between normative and actual behavior, such as in Smith, offers a glimpse but fails to provide the descriptive foundation needed for effective prescriptive research. The purpose of this paper is to

*Department of Real Estate, Georgia State University, P.O. Box 4020, Atlanta, Georgia 30302-4020.
Date Revised—September 6, 1989; Accepted—November 16, 1989.

compare models of behavior prescribed to real estate appraisers with actual appraisal problem-solving behavior and to provide a testable model of the actual behavior of real estate appraisers.

The investigation of the relationship between prescribed and actual behavior is initiated by the development of research hypotheses. A brief introduction to human problem-solving research and its unique problems is offered next. Procedures that would permit the statistical examination of the research hypotheses are presented as are the research methods of this study. Following the reporting and discussion of the results of the statistical examination, a model of actual appraiser behavior is built. The paper concludes with a statement summarizing the major findings and discussing implications.

Development of Research Hypotheses

The American Institute of Real Estate Appraisers [1] prescribes the appraisal process as a set of procedures to be used in the valuation of real estate. The model has been adapted for residential appraisal use in Bloom and Harrison [4]. Theories of memory suggest that the problem-solving behavior of novices may be guided by stored facts, such as the appraisal process, that are used in a recipe fashion.[1] However, the problem-solving behavior of experts is highly efficient and is driven by subconscious procedures, called production rules, learned gradually with practice.[2]

The production rule theoretical construct suggests that an expert solving a routine problem automatically, even unconsciously commences the next step whereas a novice must consciously deliberate what next to do.[3] Production rules can be ruthlessly efficient, and when moving from recipe behavior to production rule-driven behavior, steps can be altered, recombined or even eliminated. An expert eventually may come to solve problems in a manner that is quite different from the way in which he/she learned to solve them as a novice. Once in place, production rules are dictatorial in determining routine problem-solving behavior. An expert appraiser's behavior therefore may consistently deviate from the appraisal process.

When faced with ever increasing problem uniqueness, an expert may abandon routinized, production rule-driven behavior in favor of more conscious, deliberate behavior (i.e., may be driven toward the normative appraisal process), but the strength of production rules suggests that such shifts in expert behavior are sticky. Whereas moving appraisal settings from these geographic areas familiar to the expert into unfamiliar areas injects uniqueness into an appraisal problem, the uniqueness of unfamiliar geographic settings is hypothesized to be insufficient to drive expert behavior toward the appraisal process. The research hypotheses of this study are therefore stated as follows: (I) The behavior of expert real estate appraisers solving routine appraisal problems set in familiar geographic areas will deviate from the prescribed appraisal process. (II) The behavior of expert real estate appraisers solving routine appraisal problems set in unfamiliar geographic areas will deviate from the prescribed appraisal process.

The Nature of Research into Human Problem Solving

While providing statistical precision, many traditional research paradigms have proved inadequate for the purposes of descriptive research (i.e., research into actual problem-solving behavior). Measurement techniques wedded to conventional statistics cannot capture the richness of human problem solving. How does a single-point quantitative variable or even a vector of single-point quantitative variables represent the dynamics of a complex problem-solving process? This problem has contributed to the development of the process-tracing research tradition.

Newell and Simon [14] provided the theoretical base for the process-tracing tradition and illustrated the use of a methodology designed to describe or trace human cognitive processes in problem solving. This methodology is a verbal protocol technique that requires subjects to think aloud. Payne [17] introduced the use of an information board technique with the similar goal of revealing cognitive processes in information acquisition and processing. Russo and Rosen [19] employed an eye fixation method to study information processing in multi-attribute choice and judgment tasks.

These three process-tracing methods (verbal protocol, information board, eye fixation) form the methodological backbone of the process-tracing tradition. The tradition aims to describe and explain cognitive problem solving by employing methods that allow the direct observation of problem-solving behavior. The major shortcoming of the process-tracing methods is the lack of standardized statistics. Without statistical procedures, precise conclusions are not possible, meaningful comparison among and within studies is difficult, and the process-tracing methods reduce to a "typical subject" or case study analysis.

A Statistical Technique for Intrastudy Comparisons

Single-point quantitative statistics are too restrictive to be applied to complex cognitive processes, but statistical procedures that examine the nature of distributions hold more promise. These procedures address questions such as whether the sampled population follows some specified distribution and whether two independent samples come from identically distributed populations. If decisionmaking processes can be represented by distributions, statistical comparisons of subject behavior can be made.

Jacoby, Chestnut, Weigl and Fisher [12] developed a process statistic for experiments in well-structured information search. Their technique was based upon building models of "transitions". Subjects were required to select the optimal choice from among a set of alternatives. Several items of information, called cues, were available for each alternative, and subjects searched the information one cue at a time until willing to make the selection of the optimal alternative. These researchers identified four possible transitions that a subject could make while searching through the available information: (1) immediate reaccess of a cue, (2) same alternative but different information, (3) same type of information but for a different alternative, and (4) different alternative and different type of information.

Using this scheme, a subject's information search behavior can be portrayed as a vector each element of which has a possible value of 1, 2, 3, or 4. Jacoby, et al. aggregated these transition values and calculated the proportion of total transitions devoted to each transition type. Five post-hoc models of expected transition probabilities were hypothesized and compared to subject behavior. Chi-square statistics were calculated to offer indications of goodness-of-fit between hypothesized and observed models.

A similar transition concept can be used to represent the solution processes of real estate appraisers. The normative appraisal process prescribes the solution path to be taken in solving appraisal problems. The steps of this prescribed solution can be divided into major categories that can be numbered sequentially (see Exhibit 1). According to the normative model, steps within these major categories need not be completed in any prescribed order, but each step should be completed before moving on to the next major category of steps.

Moving from one step to another step within a category would constitute no transition and would be given a value of zero. A transition from one step within a category to a step within another category can be labeled by subtracting from the current step number the previous step number. A total of k-1 transition values exist in a solution process of k steps. If the normative model is followed, each of the k-1 transitions will have a value of 0 or +1. If the normative model is not followed, at least some transitions will have a value equal to neither 0 nor +1. Distributions of the proportion of transition values can be constructed for the normative model as well as for actual subject solution processes.

As an example, Exhibit 1 presents the normative sequence for solution of a residential appraisal task. Categories and steps are assigned, and transition values are calculated. There are a total of twenty-one steps and twenty transitions. Thirty percent of the transition values are +1 while 70% are 0.

Assume that a subject completes a task by taking the following steps: 1D, 1A, 1C, 1B, 4A, 4B, 3, 4E, 4D, 5A, 6A, 5B, 5C, 6B, 5D, 5E, 6C, 7. This solution path can be characterized by the following transitions: 0, 0, 0, +3, 0, −1, +1, 0, +1, +1, −1, 0, +1, −1, 0, +1, +1. Also note that of the twenty-one prescribed steps, only eighteen were taken. When a prescribed step is not taken, a transition value of −7 is given because the absolute value of −7 is one greater than the absolute value of the greatest possible negative

Exhibit 1
Normative Solution Sequence of a Residential Appraisal Task

Category	Step	Transition	Step Description
1	1A	—	Identification of RE to be Appraised
	1B	0	Identification of Property Rights
	1C	0	Date of Appraisal
	1D	0	Appraisal Objective
	1E	0	Definition of Value
2	2	+1	Regional and City Data
3	3	+1	Neighborhood Data
4	4A	+1	Description of Subject Site
	4B	0	Description of Subject Improvements
	4C	0	Subject Title Data
	4D	0	Subject Taxes
	4E	0	Subject Zoning (Highest and Best Use)
5	5A	+1	Comparable Sales
	5B	0	Comparable Lot Sales
	5C	0	Cost Data
	5D	0	Comparable Rentals
	5E	0	Gross Monthly Rent Multipliers
6	6A	+1	Sales Comparison Approach
	6B	0	Cost Approach
	6C	0	Income Approach
7	7	+1	Reconciliation

difference $(7-1)$ between prescribed steps. Fifteen percent of the transition values (three of twenty) of this hypothetical solution path are -7; 15% are -1 (three of twenty); 35% are 0 (seven of twenty); 30% are $+1$ (six of twenty); 5% are $+3$ (one of twenty).

Jacoby, et al. used chi-square goodness-of-fit tests for comparisons. This statistical procedure is not an option for the present study because the chi-square test statistic is calculated by dividing the difference between observed and expected frequency by the expected frequency. The normative (expected) distribution has several zero frequency cells which would lead to division by zero.

The Kolmogorov-Smirnov (K-S) goodness-of-fit tests avoids the division by zero problem and employs cumulative distribution functions. There are acutally two K-S tests for goodness-of-fit. The K-S one-sample test compares an hypothesized cumulative distribution with an observed cumulative distribution. The K-S two-sample test examines the hypothesis that two independent samples come from identically distributed populations.[4] The K-S tests were designed for continuous data and are approximate tests for discrete data such as the transition values. Daniel [7] and Gibbons [10] report that the K-S test is conservative for discrete data meaning that p-values are overestimated. The discovery of significant differences (the rejection of nulls) therefore becomes more difficult.[5]

Using K-S tests for goodness-of-fit, statistical comparisons can be made between the expected or normative cumulative distributions of transition values and observed cumulative distributions of transition values. Similarly, by comparing transition cumulative distributions, the behavior of different subjects can be statistically compared. Distributions could be aggregated over multiple observations so that the behavior of different samples of subjects can be compared.

The inability to compare process results is a problem that continues to hamper the wider application of the process-tracing methodologies. The procedure suggested here provides an alternative to the "typical subject" or case study method. Clearly the use of the procedure involves the loss of some information contained in a complex problem-solving protocol, but the technique does provide a method of aggregating and comparing human problem-solving processes that will be used in this study.

Research Methods

A one-factor repeated measures experimental design was employed to investigate the hypothesis that the behavior of expert real estate appraisers solving routine appraisal problems in familiar and unfamiliar geographic settings will deviate from the appraisal process. The factor, or independent variable of interest, was locational familiarity, and it was fixed at two levels, high positive locational familiarity and high negative locational familiarity. These two factor levels were selected to maximize the potential impact of the independent variable (locational familiarity) on the measured responses (solution processes as represented by the set of observed transition values).

To operationalize the factor levels, two appraisal cases were constructed. High positive locational familiarity was operationalized by designing a case set in a well-known Atlanta neighborhood. High negative locational familiarity was operationalized by designing an experimental case set in Austin, Texas.

Elstein, Shulman and Sprafka [8] identified two significant dimensions of task construction in process-tracing research, (1) degree of fidelity to real world situations and (2) freedom of subjects to determine quantity and sequence of information acquisition. The experimental tasks were designed to be representative of real world residential appraisal assignments. A residential instead of a commercial task was selected because of the greater complexity associated with commercial appraisal problems and the resulting complexity of analyzing commercial appraisal solution processes. Experimental cases were also designed so that subjects would have complete freedom to determine quantity and sequence of information acquisition and utilization.

The Atlanta case (high positive locational familiarity) was developed from an actual demonstration report submitted in partial fulfillment of the requirements for a professional residential appraisal designation. The Austin, Texas case (high negative locational familiarity) was developed from a report submitted in an appraisal course offered at the University of Texas at Austin. The report was similar to a demonstration report and was judged by the course instructor, a Ph.D. and an M.A.I., to be of highest quality.

All factual data from these reports were extracted and broken down into individual categories of data as suggested by the prescribed appraisal process. These data items, called cues, included (in alphabetical order) appraisal objective (purpose), comparable lot sales, comparable rentals, comparable sales (four sets of three sales each), cost data, date of valuation, definition of value, description of subject improvements, description of subject site, gross monthly rent multipliers, identification of property rights, identification of real estate to be appraised, neighborhood data, regional and city data, subject tax data, subject title data, and subject zoning. Expert appraisers not used as experimental subjects verified the representativeness of the appraisal cases.

A total of twelve expert appraisers participated as experimental subjects. Expert appraisers were defined as having no less than five years of residential appraisal experience in Atlanta and as possessing either or both of the major residential appraiser professional designations (RM of the American Institute of Real Estate Appraisers or SRA of the Society of Real Estate Appraisers). Experts were selected at random from membership rolls of the Atlanta area chapters of the two professional appraisal organizations and were asked to participate in the study. The first twelve who agreed were used as subjects. Two experts contacted declined to participate, one for health reasons, one due to scheduling conflicts. Participating subjects performed both the Atlanta case, located in an area familiar to them, and the Austin case, located in an area unfamiliar to them. The order of task performance was totally randomized.

Experimental sessions were initiated by presenting the subject with a brief written introduction and request for basic demographic information. When the demographic information sheet was returned to the experimenter, the experimenter gave the subject detailed written instructions for the experiment followed by a worksheet that briefly restated the instructions and provided a list of available cues. These alphabetically ordered cue labels represented the information available to the subject during the experiment. The subject was required to select verbally one desired cue label. The experimenter then recorded the request, provided the subject with the requested information, and began to time cue usage. When finished with the information, the subject returned it to the experimenter and requested the next desired information. The experimenter refiled the used information, recorded the time of usage, recorded the new request, provided the newly requested information, and began to time usage of the new cue.

Each task required the subject to estimate future sale price based upon the set of available cues. Each subject was given absolute freedom to determine quantity and sequence of cue acquisition, but only one cue could be accessed at a time. This procedure allowed for the recording of sequence and duration of cue utilization. From these recordings, the experimenter was able to construct a distribution of transition values which represented the process followed by a particular subject to solve a particular task. The experimenter also observed the non-cue-acquisition behavior of the subject so that as much as possible of the subject's entire decisionmaking process could be recorded. Extensive debriefing sessions were also conducted.

To minimize deviation in the response variable due to extraneous factors, strict quality control was observed. The same written instructions and the same administrator were employed throughout the experiment. All verbal communications between experimenter (i.e., administrator) and subject were minimized. Settings were the normal work place of the subject. All experimental sessions were conducted between January 5, 1987 and February 27, 1987.

Results

Transition values recorded during experimental sessions were accumulated into distributions. Exhibit 2 represents the distribution of transition values for the familiar task aggregated across all subjects. Exhibit 3 represents the distribution of transition values for the unfamiliar task across all subjects. Exhibit 4 is the distribution of transition values suggested by the normative model (i.e., the appraisal process).

To test the research hypotheses, Kolmogorov-Smirnov one-sample tests were employed. The one-sample K-S test compares a hypothesized or theoretical distribution, such as the transition values distribution suggested by the appraisal process, with an observed or empirical distribution such as the familiar and unfamiliar task transition values distri-

Exhibit 2
Transition Values Distribution for Familiar Task

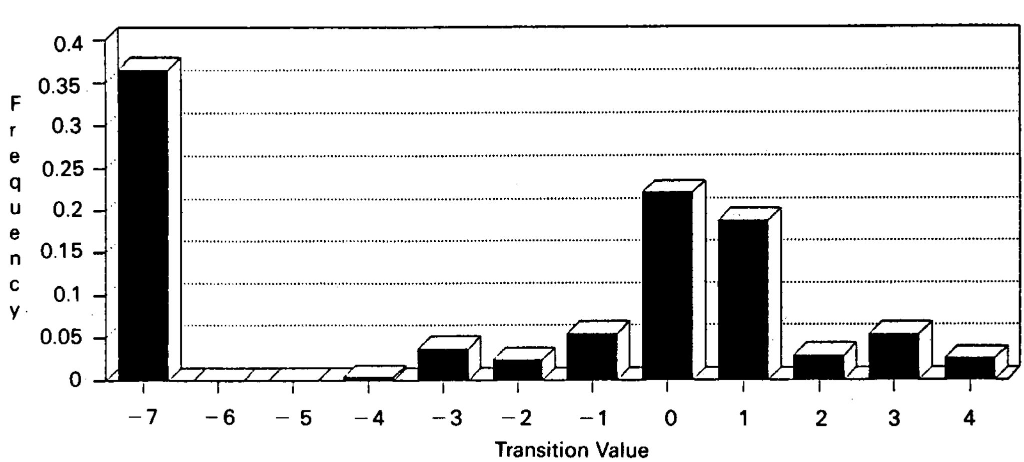


Exhibit 3
Transition Values Distribution for Unfamiliar Task

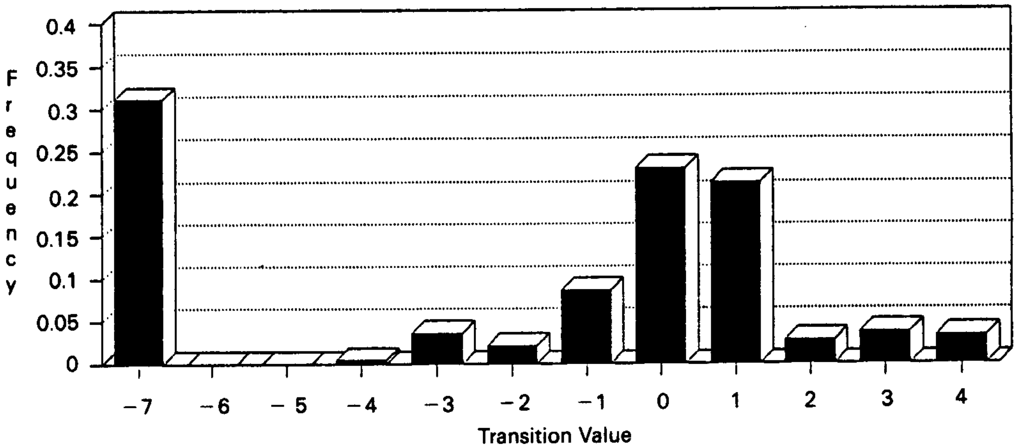
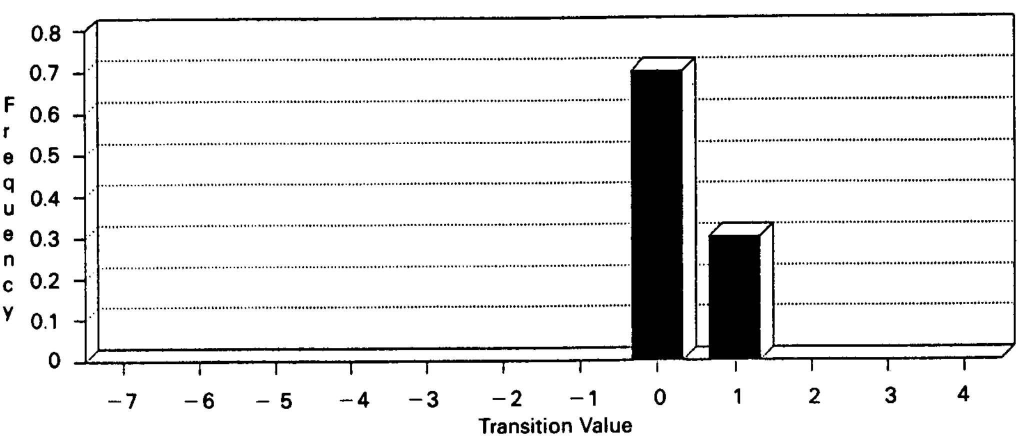


Exhibit 4
Distribution of Transition Values Suggested by the Normative Model



butions yielded from the experiments. The comparison seeks to answer whether the observed sample of transition values (represented by the empirically constructed distribution) comes from the theoretical population of transition values suggested by the appraisal process. The geographically familiar case is addressed first.

The first research hypothesis is that the behavior of expert real estate appraisers solving routine appraisal problems set in familiar geographic areas will deviate from the prescribed appraisal process. From this research hypothesis a null and an alternative hypothesis for the experiment are constructed. The null hypothesis (i.e., the opposite of the research hypothesis) is that the distribution of familiar task transition values will be equal to the distribution of transition values suggested by the appraisal process. The alternative hypothesis is that the distribution of familiar task transition values will not be equal to the distribution of transition values suggested by the appraisal process. Symbolically the experimental hypotheses are given below.

$$Ho: \ Ff(x) = Fo(x)$$

$$Ha: \ Ff(x) <> Fo(x)$$

where:

$Ff(x)$ is the cumulative distribution of familiar task transition values.
$Fo(x)$ is the cumulative distribution of transition values suggested by the appraisal process.

The one-sample K-S test statistic, denoted D, is calculated by subtracting $Fo(x)$ from $Ff(x)$ at every possible transition value (i.e., from -7 to $+4$). The largest absolute difference resulting from this series of subtractions then becomes D, the one-sample K-S test statistic. For the familiar task case these calculations are shown in Exhibit 5. D is 0.484, and since $D(0.01)$ is 0.104, the p-value for 0.484 is less than 0.01 leading to a rejection of the

Exhibit 5
Calculations of K-S Test-Statistic for Familiar Task versus Normative Model

Ho: Ff (x) = Fo (x) *Ha: Ff (x) <> Fo (x)*

Trans. Value	Familiar Task Observations	*Ff (x)*	Normative Model Num. of Trans.	*Fo (x)*	*D*
−7	89	0.365	0	0.0	0.365
−6	0	0.365	0	0.0	0.365
−5	0	0.365	0	0.0	0.365
−4	1	0.369	0	0.0	0.369
−3	9	0.406	0	0.0	0.406
−2	6	0.430	0	0.0	0.430
−1	13	0.484	0	0.0	0.484
0	54	0.705	14	0.7	0.005
1	46	0.893	6	1.0	0.107
2	7	0.922	0	1.0	0.078
3	13	0.975	0	1.0	0.025
4	6	1.0	0	1.0	0.0
	244				

$D = 0.484$; $D0.01 = 0.104$; p-value < 0.01, therefore reject *Ho* (See Gibbons, 1976, p. 388 for calculation of percentiles.)

Ff (x) = Cumulative probabilities for the familiar task
Fo (x) = Cumulative probabilities for the normative model
D = Absolute value of *Ff (x)* − *Fo (x)*

null hypothesis and to support for the research hypothesis that the behavior of experts performing appraisal tasks set in familiar geographic areas is not normative.

The second research hypothesis, the behavior of expert real estate appraisers solving routine appraisal problems set in unfamiliar geographic areas will deviate from the prescribed appraisal process, generates the experimental hypotheses stated below.

$$Ho\colon \quad Fu\,(x) = Fo\,(x)$$

$$Ha\colon \quad Fu\,(x) <> Fo\,(x)$$

where:

$Fu(x)$ is the cumulative distribution of unfamiliar task transition values.
$Fo(x)$ is the cumulative distribution of transition values suggested by the appraisal process.

The calculations for the K-S test statistic for the unfamiliar case are shown in Exhibit 6. A D-statistic of 0.459 and its *p*-value of less than 0.01 lead to the rejection of the null and support the contention of the second research hypothesis that the behavior of experts performing appraisal tasks set in unfamiliar geographic areas is not normative.

If expert behavior is not normative under conditions of geographic familiarity or

Exhibit 6
Calculation of K-S Test-Statistic for Unfamiliar Task versus Normative Model

Ho: *Fu (x)* = *Fo (x)* *Ha*: *Fu (x)* < > *Fo (x)*

Trans. Value	Unfamiliar Task Observations	*Fu (x)*	Normative Model Num. of Trans.	*Fo (x)*	*D*
−7	76	0.311	0	0.0	0.311
−6	0	0.311	0	0.0	0.311
−5	0	0.311	0	0.0	0.311
−4	1	0.316	0	0.0	0.316
−3	9	0.352	0	0.0.	0.352
−2	5	0.373	0	0.0	0.373
−1	21	0.459	0	0.0	<u>0.459</u>
0	56	0.689	14	0.7	0.011
1	52	0.902	6	1.0	0.098
2	7	0.93	0	1.0	0.07
3	9	0.967	0	1.0	0.033
4	8	1.0	0	1.0	0.0
	244				

D = 0.459; $D0.01$ = 0.104; *p*-value. < 0.01, therefore reject *Ho* (See Gibbons, 1976, p. 388 for calculation of percentiles.)
Fu (x) = Cumulative probabilities for the unfamiliar task
Fo (x) = Cumulative probabilities for the normative model
D = Absolute value of *Fu (x)* − *Fo (x)*

Exhibit 7
Calculation of K-S Test Statistic for Familiar versus Unfamiliar Task

Trans. Value	*Ff (x)*	*Fu (x)*	*D*
−7	0.365	0.311	0.054
−6	0.365	0.311	0.054
−5	0.365	0.311	0.054
−4	0.369	0.316	0.053
−3	0.406	0.352	0.054
−2	0.430	0.373	<u>0.057</u>
−1	0.484	0.459	0.025
0	0.705	0.689	0.016
1	0.893	0.902	0.009
2	0.922	0.93	0.008
3	0.975	0.967	0.008
4	1.0	1.0	0.0

$D = 0.057$; $D0.20 = 0.097$ (See Gibbons, 1976, p. 391.)

Since $D < 0.20$, p-value $D > 0.20$; therefore fail to reject *Ho*.

Ff (x) = Cumulative probabilities for the familiar task
Fu (x) = Cumulative probabilities for the unfamiliar task
D = Absolute value of *Ff (x)* − *Fu (x)*

unfamiliarity, is it the same under both conditions? The production rule theoretical construct suggests that behavior will be the same. A two-sample K-S test was employed to examine the hypothesis that the two-sample transition value distributions (i.e. the familiar task distribution and the unfamiliar task distribution) came from identically distributed populations. Test hypotheses are *Ho*: $Ff(x) = Fu(x)$ and *Ha*: $Ff(x) <> Fu(x)$. The test-statistic for the two-sample test is the greatest difference between the two observed cumulative distributions and is calculated in Exhibit 7.

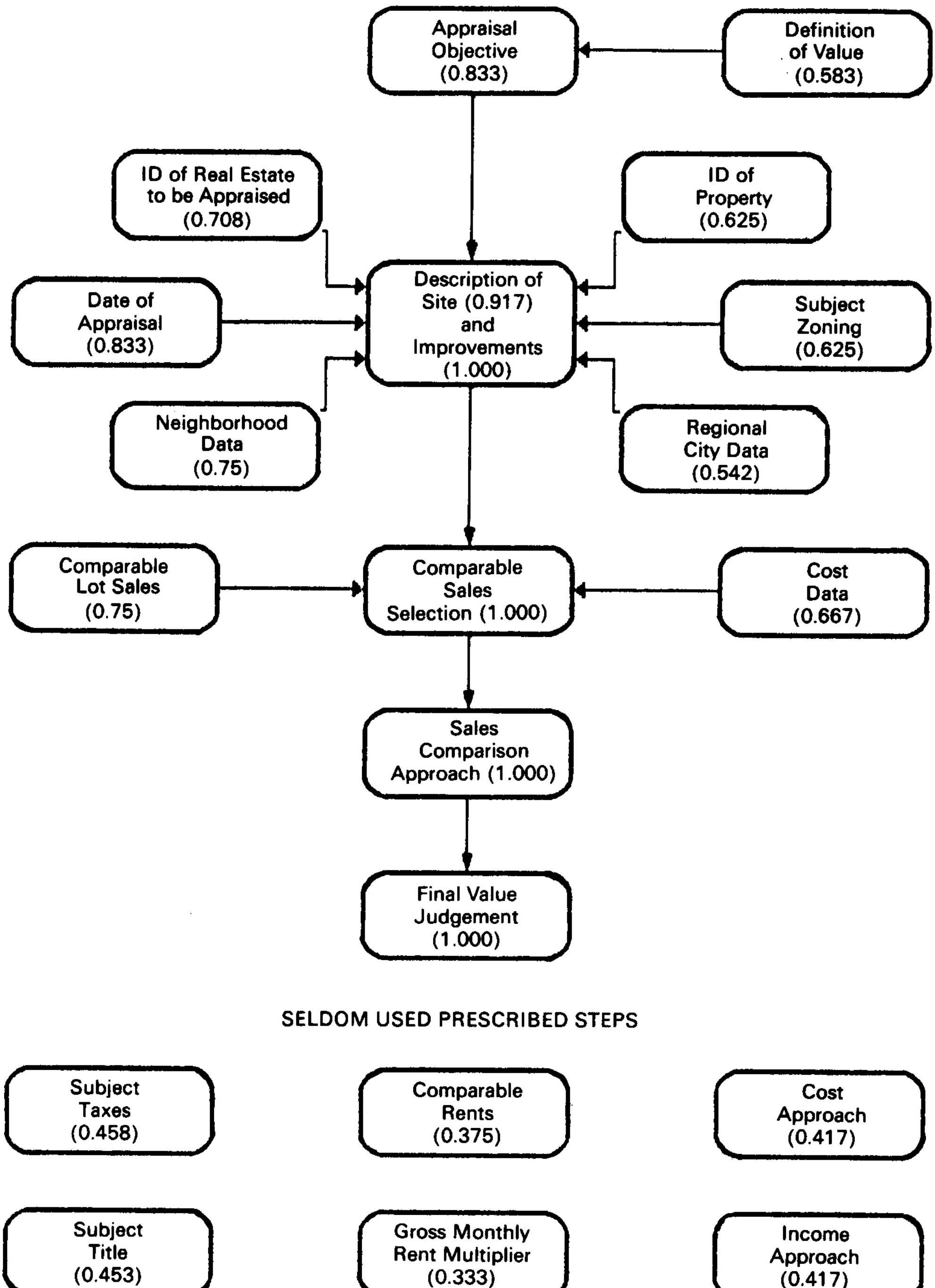
A p-value greater than 0.20 results, leading to the statistical decision not to reject the null and to the conclusion that expert behavior may be the same for tasks in familiar and unfamiliar settings.

The statistical tests thus indicate that the behavior of expert residential real estate appraisers does not conform to the appraisal process. Further, the evidence does not reveal any differences between geographically familiar task behavior and geographically unfamiliar task behavior. Findings of non-normativity lead to the desire for models of actual behavior, and information gathered during the experiments provides the basis for the development of such a model.

Development of a Descriptive Model of Expert Behavior

The appraisal process advocates a solution procedure the focus of which begins with the most general information (regional, area, neighborhood data) and attenuates gradually to the specifics of the subject property being appraised. Unlike the prescribed process, the experts of this study quickly focused on the specifics of the subject property and broadened their inquiry only when questions warranted an investigation into more general inform-

Exhibit 8
Descriptive Model of Residential Appraiser Behavior



ation. The procedure held while experts performed the locationally familiar task (Atlanta) as well as the locationally unfamiliar one (Austin, Texas). The average time taken to complete the unfamiliar task was 34.85 minutes; the familiar task took an average of 33.47 minutes.

Based upon frequency of use, six steps of the appraisal process appear to dominate the behavior of the expert subjects. These dominant steps were used to build a preliminary five-step descriptive model of expert residential appraisal behavior (see Exhibit 8). Because of their close association, two steps prescribed by the appraisal process were combined into one descriptive step. The descriptive model steps and the frequency of their observed use are (1) appraisal objective (0.833), (2) description of subject site (0.917) and improvements (1.0), (3) comparable sales selection (1.0), (4) sales comparison approach (1.0), and (5) reconciliation or final value judgment (1.0).

Other steps prescribed by the appraisal process were employed to a lesser extent and appear to be considered optional, only to be accessed if the expert felt that the particular case warranted their consideration. Six steps of the appraisal process were employed in less than 50% of the expert tasks and are judged therefore to be unimportant in routine residential appraisal problems represented by the experiment. These six seldom used prescribed steps and their frequency of use are (1) subject taxes (0.458), (2) subject title (0.458), (3) comparable rentals (0.375), (4) gross monthly rent multipliers (0.333), (5) the cost approach (0.417), and (6) the income approach (0.208).

The developed descriptive model is a skeletal one upon the five steps of which the other prescribed steps are suspended as needed. Experts generally began an experimental task by accessing information on the appraisal objective (descriptive step number 1). Closely associated with this step in 58.3% of expert cases was access of information concerning the definition of value relevant to the task. Following a determination of the appraisal objective, experts generally accessed information on the subject property including description of improvements and description of site (descriptive step number 2). Optional steps that appear to be associated with the second descriptive step (in descending order of frequency of access) were date of appraisal (0.833), neighborhood data (0.75), identification of real estate to be appraised (0.708), identification of property rights (0.625), subject zoning (0.625), and regional and city data (0.542).

After collecting subject property data, experts accessed optional information only if needed. This approach seems more cognitively efficient than the appraisal process which dictates the collection of all information. If a need for a particular data item does not arise in the mind of an expert, he/she does not expend the cognitive effort to collect, analyze and digest it. Reversing the order of data selection from general-to-specific (appraisal process) to specific-to-general allows the expert quickly to perceive the appraisal problem and to make judgments of data relevancy.

The next major step in the descriptive expert model is the selection of comparable sales. This step was conducted by all expert subjects in all tasks. Associated with this step was the collection by experts of other data as well. The collection of comparable lot sales appeared in 75% of expert tasks, the collection of cost data in 66.7%. These data were used in the next major step of the descriptive model, the sales comparison approach. Cost data was used as a support for the sales comparison approach, primarily to develop adjustments for items of dissimilarity between subject property and comparable properties. For example, if the comparable sale property had an extra half-bath and a half-bath cost $1500, a negative $1500 adjustment was made to the comparable sale to make the sale price representative of the subject property value. The reconciliation was the final step employed. Because only the sales comparison approach was used in a majority of tasks, the reconciliation reduced to a simple statement of the final value judgment.

Conclusions

This paper presents strong evidence that expert residential real estate appraisers do not follow the appraisal process when solving routine appraisal tasks. While extension of these findings to commercial real estate experts is tempting, confident generalization cannot be made. A model developed within the paper that describes actual expert behavior differs from the appraisal process in both usage and order of usage of information.

The discovery of expert behavior significantly different from normative behavior leads to serious questions about the efficacy of the appraisal process and has important educational implications. The modeling of descriptive expert behavior sets the stage for the examination of the issue. If non-normative expert behavior leads to suboptimal valuation judgments, students and practitioners must be cautioned against this natural but biasing behavior. Conversely, if the expert model proves to be more efficient than the normative model and if its use does not bias results, the appraisal process must be seriously reexamined as a prescription for appraisal problem solving. And models based upon actual expert behavior must serve as guides to a new definition of appraisal problem-solving methodology.

Notes

[1]See, for example, the ACT* theory of memory most completely presented in J. R. Anderson, *The Architecture of Cognition* (Cambridge, Mass.: Harvard University Press, 1983).

[2]The seminal work on production rules is Allen Newell's. See, for example, Allen Newell, Production Systems: Models of Control Structures, in William Chase, editor, *Visual Information Processing* (New York: Academic Press, 1973), 463–526 and Allan Newall and Herbert Simon, *Human Problem Solving* (Englewood Cliffs, N.J.: Prentice-Hall, 1972).

[3]This potential difference in behavior is reflected in the well-known learning taxonomy of Benjamin S. Bloom, Max D. Engelhart, Edward J. Furst, Walker H. Hill and David R. Krathwohl, *Taxonomy of Educational Objectives: Handbook I, The Cognitive Domain* (New York: Longmans, Green and Co., 1956).

[4]For further discussion of the K-S tests see Wayne W. Daniel, *Applied Nonparametric Statistics* (Boston, Mass.: Houghton Mifflin Company, 1978) and Jean D Gibbons, *Nonparametric Methods for Quantitative Analysis* (New York: Rinehart and Winston, 1976). For a more theoretical treatment see Jean D. Gibbons, *Nonparametric Statistical Inference* (New York: Marcel Dekker, Inc., second edition 1985).

[5]Several references discussing this point are offered by Daniel including G. E. Noether, Note on the Kolmogorov Statistic in the Discrete Case, *Metrika* 7 (1963), 115–16 and G. E. Noether, *Elements of Nonparametric Statistics* (New York: John Wiley and Sons, 1967).

References

[1] American Institute of Real Estate Appraisers. *The Appraisal of Real Estate*. Chicago: Author, eighth edition 1987.

[2] J. R. Anderson. *The Architecture of Cognition*. Cambridge, Mass: Harvard University Press, 1983.

[3] B. S. Bloom, M. D. Engelhart, E. J. Furst, W. J. Hill and D. R. Krathwohl. *A Taxonomy of Educational Objectives: Handbook I, The Cognitive Domain*. New York: Longmans, Green and Co., 1956.

[4] G. F. Bloom and H. S. Harrison. *Appraising the Single Family Residence*. Chicago: American Institute of Real Estate Appraisers, 1978.

[5] H. J. Brightman. Differences in Ill-Structured Problem Solving Along the Organizational Hierarchy. *Decision Sciences* 9:1 (January 1978), 1–18.

[6] R. Cole, D. Guilkey and M. Miles. Toward an Assessment of the Reliability of Commercial Appraisals. *The Appraisal Journal* 54 (July 1986), 422–32.

[7] W. W. Daniel. *Applied Nonparametrics Statistics*. Boston: Houghton Mifflin Company, 1978.

[8] A. S. Elstein, L. E. Shulman and S. A. Sprafka. *Medical Problem Solving: An Analysis of Clinical Reasoning*. Cambridge, Mass.: Harvard University Press, 1978.

[9] J. T. Ferguson. After-sale Evaluations: Appraisals or Justifications. *The Journal of Real Estate Research* 3:1 (Spring 1988), 19–26.

[10] J. D. Gibbons. *Nonparametric Methods For Quantitative Analysis*. New York: Holt, Rinehart and Winston, 1976.

[11] ———. *Nonparametric Statistical Inference*. New York: Marcel Dekker, Inc, second edition 1985.

[12] B. Jacoby, R. W. Chestnut, K. C. Weigl and W. Fisher. Pre-purchase Information Acquisition: Description of a Process Methodology, Research Paradigm, and Pilot Investigation. In B. B. Anderson, editor, *Advances in Consumer Research*, Vol. 3, 306–14. Chicago: Association for Consumer Research, University of Illinois, 1976.

[13] A. Newell. Production Systems: Models of Control Structures. In W. G. Chase, editor, *Visual Information Processing*, 463–526. New York: Academic Press, 1973.

[14] ——— and H. A. Simon. *Human Problem Solving*. Englewood Cliffs, N.J.: Prentice-Hall, 1972.

[15] G. E. Noether. Note on the Kolmogorov Statistic in the Discrete Case. *Metrika* 7 (1963), 115–16.

[16] ———. *Elements of Nonparametric Statistics*. New York: John Wiley and Sons, 1967.

[17] J. W. Payne. Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis. *Organizational Behavior and Human Performance* 16 (1976), 366–87.

[18] H. C. Smith. Inconsistencies in Appraisal Theory and Practice. *The Journal of Real Estate Research* 1:1 (Fall 1986), 1–17.

[19] J. E. Russo and L. D. Rosen. An Eye Fixation Analysis of Multialternative Choice. *Memory and Cognition* 3:3 (Summer 1975), 267–76.

The author thanks John B. Corgel and Terry V. Grissom for helpful comments on earlier drafts of this paper.