Evaluating Local Studies of Barriers to Fair Housing

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Abstract:

Analyses of Impediments to Fair Housing (AIs) are Federally-mandated studies intended to develop an agenda for remedies to structural and operational barriers to fair housing in the U.S. There are few existing evaluations of AI quality, and there is little understanding of how AI results influence fair housing policy.

We have developed an evaluation instrument that determines the extent to which AIs meet statutory requirements and use appropriate data and methods. We have applied this instrument to a small national sample of AIs using multiple readers. We find that while there is broad agreement across readers as to whether specific questions are addressed or not, there is considerable variation regarding more detailed measurements of AI quality. Nevertheless, the evaluation instrument appears to provide reliable measures of AI quality across topic areas. This research will enable jurisdictions that perform AIs to develop well-defined quality metrics and to address unique local characteristics.

Keywords:

Fair housing, analysis of impediments, housing policy

I. Introduction

Analyses of Impediments to Fair Housing (AIs) are studies that must be performed by American jurisdictions that receive Community Development Block Grant funds from the U.S. Department of Housing and Urban Development (HUD). AIs are intended to develop an agenda
for remedies to structural and operational barriers to fair housing that leverages local knowledge of housing markets and policy implementation and avoids an approach relying on centralized authority and policy mandates. The legal foundation for these studies is Title VIII of the Civil Rights Act, also known as the “Fair Housing Act” (42 U.S.C sections 3601-3619), which states, in part: “[i]t is the policy of the United States to provide, within constitutional limitations, for fair housing throughout the United States.” In addition, fair housing laws have been enacted by many states and local jurisdictions.

Fair housing laws apply civil rights protections to specific members of the population: those members of defined “protected classes”. Seven Federal protected classes are: race, color, religion, national origin, sex, familial status and disability. These definitions can be extended through state and local laws. For example, the Pennsylvania Human Relations Act defines three additional protected classes to those listed above: ancestry, age, and use of guide- or support-animal because of blindness, deafness, or physical handicaps; the Pittsburgh, Pennsylvania City Code defines five additional protected classes: ancestry, place of birth, sexual orientation, age (declared policy but not actually in legal code), and use of support animals because of the handicap or disability of the user.

While AIs have been performed by many jurisdictions over the past decade, few evaluations of the quality of AIs have been performed, and there is little understanding of how, or whether, AI results influence fair housing policy. In the experience of these authors, who have performed AIs for the City of Pittsburgh (Martin and Johnson, 1999) and suburban Allegheny County, PA (Martin, Johnson and Williams Foster, 2000), AIs are often viewed as a government requirement separate from policy design and law enforcement related to fair housing.
A research and policy gap exists on the subject of evaluating AIs. Although HUD and private fair housing organizations such as the National Fair Housing Alliance have historically promoted standardization of AIs as a way to improve the quality of reporting, there is little available data to assess whether, in fact, reporting jurisdictions heed these recommendations. Proposals for AI standardization are uncomplicated. For example, in its *Fair Housing Planning Guide* (U.S. Department of Housing and Urban Development, 1996), HUD recommends a “Suggested AI Format” to jurisdictions receiving CDBG funds. HUD’s Suggested AI Format encourages jurisdictions to report the following data:

- Demographic Data
- Income Data
- Employment
- Housing Profile
- Maps

HUD also recommends a standardized “Suggested Format for the Analysis of Impediments,” composed as follows:

- Introduction and executive summary
- Jurisdictional background data
- Evaluation of current fair housing status
- Impediments to fair housing choice
- Public and private fair housing programs and activities
- Conclusions and recommendations

Details of the AI Format are contained in the Appendix.
HUD’s proposed model for standardization presents useful guidelines for constructing AIs. It also suggests a framework for evaluating the quality of AIs and their use in developing fair housing policy. More explicit and extensive guidance on evaluation of AIs is given in a web page provided the National Low Income Housing Coalition (2001). However, neither of these two resources provides a concise, easy-to-apply methodology by which local organizations can determine the extent to which their studies confirm to widely-accepted standards.

Our experience in performing AIs has led us to three fundamental insights. First, we have realized that there is little guidance available to practitioners or researchers who seek to measure the quality of a particular AI, or a group of AIs on a regional, or national basis (an analysis of impediments “report card”). Second, there is no means known to us to apply the extensive data collected in the process of creating the AI to a model that might measure, in some consistent fashion, the extent to which a particular region provides fair housing opportunity to its residents (a fair housing “report card”). Finally, we believe that “futile gesture”, that is, of a desire of protected class members to avoid looking for housing in certain areas, in anticipation of potential discriminatory acts, or to avoid pursuing legal remedies for suspected discriminatory acts is an important but little-understood issue in fair housing. These insights form the basis of a research agenda in fair housing; this paper represents a preliminary investigation into the first of these topics.

In the absence of a rigorous evaluation instrument, the collection, selection, and evaluation of data across AI jurisdictions is an empirically difficult undertaking. Recognizing the need for an evaluation instrument, and using HUD’s recommended model for standardization, we have designed an evaluation instrument to assess the quality and policy utility of AIs. This instrument, called the Analysis of Impediments Evaluation Index (EI),
determines the extent to which an AI examines a broad range of housing concerns, such as: housing types, structural barriers to fair housing opportunities, testing, zoning, lending and insurance practices and media treatment. Our fundamental goal is to apply the Evaluation Index to a representative national sample of AIs and to provide insight into distinctions in the quality of AIs across housing concerns, geography and demographic characteristics of study areas within the U.S. This research will enable researchers to determine the extent to which (a) topics addressed meet statutory requirements; (b) impediments identified are justified by data used; and (c) the impediments identified and recommendations made can increase access to fair housing. In addition, we hope that jurisdictions can use this research to perform AIs that address unique jurisdiction-area characteristics and that are likely to result in appropriate, actionable recommendations.

In this paper, we have applied the Evaluation Index to a very small national sample of AIs. Our goals are to gain insight into variations in AI quality and sources of that variation, to measure the validity and reliability of the Evaluation Instrument, to assess the extent to which the AIs chosen are representative of a much larger set of AIs, as well as the quality of these AIs, and to make recommendations regarding operational use of the EI and policy implications associated with the EI.

Our study has generated the following results. First, evaluations by fair housing experts of our evaluation instrument are positive. Second, the study areas of AIs selected from the large collection maintained by NHFA are broadly representative of the United States as a whole. Third, application of the EI to the five AIs results in clear distinctions in quality across question categories, response components and AI study areas. Finally, a measure of AI quality associated with the number of questions in the EI that are considered “addressed” or “not addressed” shows
consistency across multiple evaluators, as compared to a more complex scaled measure, though this latter measure, combined with more consistent training of evaluators, holds the promise of significant insights that can result in specific changes in AI practice.

We can make a number of research recommendations based on these preliminary encouraging results. We believe that the relational database application used to store information about AIs, and to apply the EI to specific AIs, is worth sharing with other researchers. We also believe that the data we have collected, both on AIs and the EI applied to AIs, has clear potential for GIS mapping, though we have not done so as yet. Finally, we believe that the EI can assist jurisdictions in distinguishing between components of AIs that record historical facts and those that perform more open-ended analyses, and in performing both of these tasks more effectively than is currently the case.

These preliminary results and recommendations provide a motivation for us to refine the EI further, to apply it to the entire sample of AIs and to make clear recommendations as to best practice for fair housing program evaluation. Research in this direction is ongoing.

II. Case Study: the Greater Pittsburgh Region

In this section we briefly review findings from two analyses of impediments to fair housing in the Pittsburgh metropolitan area: the city of Pittsburgh (Martin, Johnson and Williams Foster, 2000), and Allegheny County, PA, excluding the cities of Pittsburgh and McKeesport and the municipality of Penn Hills (Martin and Johnson, 1999). We do so in order to identify the motivations for the present study, and to preview a number two themes that recur in evaluation of AIs: the distinction between the quality of an AI and the quality of a region’s fair housing
environment, and the distinction between recording “facts” about fair housing practice and performing “analyses” of the fair housing environment.

Both of these analyses of impediments took place in a fair housing environment that is best described as lacking a compelling political, social or academic motivation to address systemic inequities or inefficiencies in fair housing provision, enforcement or evaluation. For example, AIs can be local in scope, focusing on a particular city, or regional in scope, addressing a collection of nearby municipalities, or perhaps an entire county. HUD’s Fair Housing Planning Guide recommends that regional analyses be written. Even though Allegheny County is composed of over 130 municipalities, it was determined that a regional AI was not appropriate. Instead, separate AIs for the cities of Pittsburgh and McKeesport, the municipality of Penn Hills and the remainder of suburban Allegheny County were asserted to result in more accountability for each jurisdiction or collection of jurisdictions.

There are three main actors concerned with regional fair housing policy in Allegheny County: The Allegheny County Department of Economic Development, The City of Pittsburgh Department of City Planning and The Fair Housing Partnership of Greater Pittsburgh, a nonprofit advocacy and enforcement organization. While these organizations have differing, and at times competing policy concerns, we found no significant institutional barriers to completion of the studies themselves, nor did we encounter pressure to modify our results to address political concerns.

Both studies followed the HUD AI guidelines where possible, and attempted to combine quantitative data analysis, using geographic information systems for mapping and relational databases for data management, with qualitative data analysis, using well-defined interview protocols and a preliminary content analysis.
The two studies reported similar findings. Housing is highly segregated by race in the Pittsburgh region. There is strong evidence of discrimination against protected classes, especially those defined by race, disability, familial status and sex. In addition, there is substantial evidence of discrimination on the basis of source of income, in particular, the inability of families using tenant-based housing subsidies to rent otherwise acceptable units of their choosing. (This last form of discrimination is not illegal under fair housing law, however.) While constituent-serving agencies feel that fair housing laws are adequate, there was evidence that these agencies lack sufficient expertise to apprise clients of their rights under fair housing law, nor to pursue allegations of housing discrimination using available remedies. Constituent-serving agencies reported substantial levels of “futile gesture” behavior on the part of clients, whereby clients do not seek housing in certain communities in anticipation of discriminatory behavior, or do not pursue legal remedies to allegations of housing discrimination.

We found that fair housing issues are under-reported in the local media, and what reporting does exist tends to be focused on a specific kind of housing issue: introduction of subsidized housing, whose residents are African-American, into majority-white suburban communities. We also found that while zoning codes in the city of Pittsburgh had been revised to eliminate restrictions on specific disabilities and had eased restrictions on group living facilities, zoning codes in suburban Allegheny County had mechanisms that could limit availability of group housing arrangements.

There was extensive evidence of disparities in home mortgage and insurance denial rates between whites and blacks, and evidence of “predatory lending” in lower-income or racially segregated communities.
Finally, we determined that, aside from specific acts of housing discrimination, or evidence as to the possibility of housing discrimination, there appeared to us to be other, widespread barriers to fair housing which we refer to as “structural impediments”. Two examples of these impediments are: a lack of information about fair housing opportunities, for example, regions with desirable local amenities and available, affordable rental housing, and physical barriers to access these fair housing opportunities, for example inconvenient mass transit service between suburban municipalities and from the central city to the suburbs.

Our two studies make similar recommendations. We endorse better training of media and staff at constituent-serving agencies in fair housing law and policy, and greater cooperation between agencies, in sharing fair housing expertise, referring clients for services and addressing allegations of housing discrimination. We recommend better data collection regarding housing markets, especially rental housing, and the incidence of housing discrimination at all stages of the housing search process. These data collection practices would help identify the reasons for disparities in access to housing and would help in designing appropriate policy interventions. We recommend more intensive study of the phenomenon of “futile gesture”. We endorsed the notion of publicly available data repositories, perhaps using the World Wide Web, along with mentoring, that would enable constituent-serving agencies to provide consistent, comprehensive fair housing counseling and support.

Similarities between these studies inspired us to ask three fundamental questions:

- How well did we execute these AIs?
- How do the fair housing environments we examined to those in other regions in the country?
- How can we better understand study the phenomenon of “futile gesture”?
The first question is the motivation for this study. The second question inspired the design of an
“Impediment Index” for the Pittsburgh AI, a collection of measures related to fair housing which
could be combined to produce a single, numerical measure of housing market openness. Many of
the data components of the Impediment Index served as components of the Analysis of
Impediments Evaluation Index. The third question is the basis for ongoing research.

III. Evaluation Framework for AIs

In designing the Analysis of Impediments Evaluation Index, we relied on two sources:
the Guideline for Evaluating the Analysis of Impediments (National Low Income Housing
Coalition, 2001) and the Impediments Index, contained in the Pittsburgh, Pennsylvania AI
(Martin, Johnson and Williams Foster, 2000). The NLIHC Guideline contains the following
categories for evaluation:

1. Activities Utilizing CDBG funds to "Affirmatively Further Fair Housing"
2. Classify Areas for Potential Discriminatory Practices and Identify Impediments
3. Employment Opportunities
4. Educational Opportunities
5. Transportation Networks
6. Fair Housing Complaint Profile
7. Identify actions initiated by Department of Justice/HUD Against City, Company, or
Corporation within Jurisdiction
8. National, State, or Local Fair Housing Laws
9. Fair Housing Education Programs
11. Housing Availability & Affordability Profiles

12. Population Profiles

This exhaustive set of evaluation categories includes many complex questions. For example, question 6(a)(iv) asks:

“Have there been other indicators of housing discrimination? Have racial or ethnic hate crimes been reported in local media outlets? Have there been other reports of civil rights housing issues, since as indexes of discrimination, media "exposes" of discrimination, or reports of individuals encountering discrimination or harassment? Does the community have a hate crimes reporting mechanism which might provide indicators of the extent of discrimination? Have those reports been the subject of follow-up enforcement action by a local, federal or state agency?”

Clearly, a concise, easy-to-use AI evaluation instrument would require one to greatly simplify the questions proposed by NLIHC, but the document provides no guidance in this direction.

The Pittsburgh AI’s Impediments Index, designed to generate a single numeric measure of housing market openness, contains the following categories of measures:

1. Environmental Sites
2. Public and Assisted Housing
3. Zoning
4. Real Estate and Home Lending Policies and Practices
5. Fair Housing Law Enforcement
6. Fair Housing Services and Education and Outreach
7. Housing Tenure

For example, within “Public and Assisted Housing” the measure “Relative Affordable Housing Supply/Demand” is described as “Is the municipality’s rental market able to absorb new Section
“8 certificates?” and is defined as 1 minus the ratio of affordable housing supply to demand. This measure is typical of others in the Impediment Index in that while it may be difficult to measure accurately, it represents an important policy concern. These measures inspired us to use some of them in the EI in a slightly different way: instead of computing the performance of a region according a certain measure, we would determine the extent to which the AI itself attempted to address the question.

Thus, we have selected and simplified (from the NLIHC document) or selected and transformed (from the Impediments Index) a wide variety of questions relevant to assessing the quality of an AI. This iterative process has resulted in a list of over 150 questions in the following categories:

A. Housing Types
B. Fair Housing-Related
C. Jurisdiction-Level Role
D. Advertising
E. Local and Regional Amenities
F. Zoning
G. Lending Practices, Institutions and Financial Services
H. ADA/Disabilities Issues
I. Insurance
J. Media Reporting of Fair Housing Issues
K. Demographic Profiles
We then separately chose a “short list” of questions most relevant to the task of AI evaluation, and combined these questions into a master list of 53 questions, in the 11 categories listed above and divided further into 29 subcategories.

We provided the EI to three fair housing experts for review, along with seven rating categories. Responses by the panelists are contained in Table 1.

[Table 1: Analysis of Impediments Evaluation Index Ratings]

Overall, the consensus of the panelists was that our EI was likely to provide insight to practitioners and academics, both for policy analysis and policy design. The complete EI is available in Appendix B of Martin, Johnson and Williams Foster (2002).

An important component of AI evaluation is the formulation of EI question response choices that provide insight into the extent to which an AI addresses a particular question correctly and in full. We distinguish between two types of EI questions: those that capture the historical reality of jurisdiction behavior regarding affirmatively furthering access to fair housing opportunity, and those that measure the quality of the AI in measuring efforts a jurisdiction has made to increase access to fair housing. The first measure, which we refer to as “Quantitative/Qualitative Assessment”, measures (a) the extent to which a particular activity in question was actually performed, and (b) the quality (or, level of compliance with administrative or legal guidelines) of the activity. The second measure, which we refer to as “Data Analysis”, measures

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1 One reviewer supplied extensive comments regarding the ability of the EI to identify long-term housing market segregation. Our response is that the EI is not an analytical tool designed to process primary data or test hypotheses, but rather an evaluative tool designed to assess the quality by which AIs address key fair housing issues.
(a) the extent to which the data in the AI associated with the jurisdiction’s action in question
provides insight into the historical reality of the action, and (b) the extent to which the AI
provides a means by which outcomes associated with the action in question (or, perhaps, the
level of performance of the action itself) can be assessed.

For example, question 11 of the EI:

“Characterize the provision of fair housing education & outreach (E&O) or
counseling services”

would be classified as “Quantitative/Qualitative Assessment” since the quality of an AI’s
response to this question would be measured using an analyst’s assessment of the quality
of documented evidence as to the jurisdiction’s provision of these services (and not the
effectiveness of the documented services). On the other hand, question 27 of the EI:

“Characterize the distribution of hazardous waste sites”

would be classified as “Data Analysis” since the quality of an AI’s response to this question
would be measured by using an analyst’s assessment of the means by which analytic tools have
been deployed to characterize a quantity that varies over space and time according to statistical
distributions.

An additional concern for the EI is the scale used to measure the quality of AI responses
to various questions. We feel that the response scales should be consistent within question
categories, independent of the subject of particular questions and indicative of the quality of the
data used to formulate a response as well as substance of the response. Thus, we have devised a
novel technique that decomposes the response to an EI question into four components, and
computes a response “score” by adding binary values associated with each of the four
components. For example, Quantitative/Qualitative Assessment response components are defined as:

- Correct data sources (0 or 1)
- Frequency of efforts to collect data in question (0 or 1)
- Quantity of data collected (0 or 1)
- Quality of data collected (0 or 1)

while Data Analysis response components are defined as:

- Data for analysis available in AI or indicated as available by authors (0 or 1)
- Method for analyzing data clearly identified (0 or 1)
- Data analysis method consistent in nature or applied consistently to entire data set (0 or 1)
- Data analysis method appropriate for identified task (0 or one)

In both cases, the score for a particular response is computed as:

- 0: None of the four data components was addressed in any meaningful way by the AI
- 1: Any one of four data components is apparent in the AI response
- 2: Any two of four data components are apparent in the AI response
- 3: Any three of four data components are available in the AI response
- 4: All four data components are available in the AI response

We feel that these AI evaluation instrument response scales provide insight into the distinction between what a jurisdiction does and how a jurisdiction’s actions are recorded and evaluated.

In order to apply the EI to a potentially large number of AIs, we designed a relational database application to facilitate entry of AI characteristics and responses to specific EI questions. This application can eventually be used to compute numerical quality indices,
generate descriptive statistics and display data using geographic information systems. Additional
details on this application are available in Martin, Johnson and Williams Foster (2002); the
application is available at http://www.andrew.cmu.edu/user/johnson2/AI14-030402.mdb.

IV. Review of AIs

Selection of AI Sample

The National Fair Housing Alliance (NHFA), in Washington, D.C. has received nearly
1,000 completed AIs from many municipalities across the country over the past 10 years. NHFA
shared with us a list of AIs in their possession, and a preliminary, in-house analysis of AI quality.
NHFA also agreed to let us apply the Analysis of Impediments Evaluation Index to a sample of
their AIs.

We selected the AIs to request from NHFA using a stratified random sample. The target
population was the set of all AIs conducted in the nation. Given the limitations in accessing this
target population, we defined the sampling population as AIs available from the National Fair
Housing Alliance (NFHA). The total number of AIs in the sampling population is the 670
studies documented by NHFA in an internal database (other AIs in their files had not yet been
entered into the database at the time of our request). The regional distribution\(^2\) of AIs is
presented in Table 2.

\(^2\) Regions are defined as follows: Caribbean – Puerto Rico; Midwest – Illinois, Indiana, Iowa, Kansas, Michigan,
Minnesota, Nebraska, North Dakota, Ohio, Oklahoma, South Dakota, Wisconsin; Mountain West – Colorado,
Idaho, Montana, Utah, Wyoming; Northeast – Connecticut, Delaware, District of Columbia, Maine, Maryland,
Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont; Pacific Northwest
– Alaska, Oregon, Washington; South – Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi,
We stratified on region to assure each region was represented in the final sample. We randomly selected 5 AIs in each of the 8 regions to yield a final sample of 40 AIs. As evidenced in Table 2, while the Caribbean, Mountain West, Pacific Northwest, and Southwest regions were substantially underrepresented in the sampling population, they are proportionally represented in the final sample.

Demographic characteristics of the AIs in the sample, based on the 2000 Census, are presented in Table 3, along with demographic characteristics for all metropolitan statistical areas (MSAs) in the United States. These results indicate that the populations of MSAs containing jurisdictions that were subjects of our sample AIs are much larger than the populations of MSAs overall, and median house values were larger than those of MSAs overall, but the MSAs associated with AIs in our sample are generally representative with MSAs overall in terms of percent black/non-Hispanic, percent Hispanic, median family income and percent homeowners.

We have constructed a subsample of 5 AIs for preliminary analysis. This sample includes three AIs randomly selected from the final sample (Tampa, Florida; Rome, New York; and

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North Carolina, South Carolina, Tennessee, Texas, Virginia, West Virginia; **Southwest** – Arizona, Nevada, New Mexico; **West Coast** – California, Hawaii.

3 Fewer AIs (33) were actually retrieved from NHFA than specified by the sampling scheme due to administrative error and specified AIs missing from NFHA's files.
Tempe, Arizona) and the Pittsburgh and Allegheny County AIs described earlier. All subsequent results related to the EI refer to this smaller sample.

**Analysis of AI Sample**

The Evaluation Index was initially applied by a single reader to the five AIs in our limited sample using a simple binary response code: EI questions were simply judged as “addressed” or “not addressed”, with comments appended, and with no distinction made between “data analysis” and “qualitative/quantitative analysis” EI questions. Based on responses to the EI questions (described in detail in Martin, Johnson and Williams Foster, 2002), we then constructed the more elaborate EI described in the previous section, and applied it to the same set of five AIs, this time using three readers in such a way that each AI was reviewed by at least two readers. We added to the EI a sample “ideal response” to each question in order to give the readers a context for evaluating the various questions.

The first analysis we performed compares EI results in the second wave of analysis using a composite “binary” measure (i.e. coding a score of 0 as “not addressed” and coding scores of 1 through 4 as “addressed”) to the full 0-to-4 measure. The maximum score using the binary measure is 53, the number of questions in the EI; the maximum score using the full scaled measure is 212. Results are shown in Table 4, below.

|Table 4: EI Scores, Binary and Full, Across AIs and Readers|

There are two results of note. First, on average, and with respect to the binary and scaled measures, readers gave the highest scores to the Pittsburgh and Allegheny County AIs; the Rome and Tempe AIs performed worst on the binary measure and the Tempe and Tampa AIs
performed worst on the scaled measure. Second, there appears to be significantly more consistency between evaluators when using the binary score than when using the scaled score.

An examination of the scaled score responses and presence of comments provided by the readers provides some additional insight to these results. Table 5, below, indicates that reader B appears to be more conservative in his scoring and much less likely to accompany his numeric scores with explanatory comments than his colleagues, while reader D tends to be more liberal than her colleagues. It appears that of the three readers, E is the most judicious in his scoring and most consistent in providing explanatory comments.

[Table 5: Distribution of Scaled Scores and Presence of Comments, By Reader]

Results of Tables 4 and 5 indicate that reader B is a clear outlier in terms of the scaled scores assigned to EI questions. We observed that the correlation between the percent of questions addressed and the total scaled numeric score over all readers was 0.63; when we removed reader E from the sample, the correlation rose to 0.97.

Another perspective on EI results is that of measured performance of AIs by evaluation category. Table 6 contains average values, across readers, for the fraction of questions in each evaluation category that were evaluated as “addressed” as well as the fraction of the total possible scaled score.

[Table 6: Distribution of Binary and Scaled Scores, by AI and Evaluation Category]
These results indicate that, according to the “addressed”/”not addressed” classification, main categories B (“Fair Housing-Related”), F (“Zoning”) and K (“Demographic Profiles”) tend to addressed best by the AIs we have studied, while main categories D (“Advertising”) and I (“Insurance”) tend to be addressed most poorly. The distribution of scaled score results is much narrower, with maximum possible values rarely achieved. It is striking that the Rome AI has two categories (D and I) for which no effort appears to have been made to address fair housing concerns, while Tampa and Tempe have three such categories apiece. It appears that a better effort could be made by HUD and other agencies to encourage jurisdictions to examine issues of advertising and media reporting with respect to fair housing, even if fair housing is typically most notable for its absence from consideration in these areas.

We explore in detail the consistency of evaluations in three ways: across AIs, within evaluation categories, and over time, for the one reader who evaluated the same set of AIs twice. Table 7 shows that, on average, readers agreed on EI questions being addressed over two-thirds of the time, and that this level of agreement did not vary much across AIs.

[Table 7: Consistency of Evaluations, Binary Scores, Summary AI Results]

The level of agreement across readers and within question categories varies more widely, however. There is no evidence that the level of agreement within question categories is significantly associated with the number of questions within each category; we conjecture that variance in this measure is a result of the varying levels of fair housing domain knowledge possessed by readers before performing the AI evaluations. Results in Table 7 are an indication that, overall, the Evaluation Instrument has a moderately high level of reliability.
Finally, we examine the extent to which changes in EI responses over time indicate some measure of “learning”. As we have already mentioned, reader E read four AIs—Rome, Tampa, Tempe and Allegheny County—twice, once when using the “addressed”/“not addressed” binary score, and again when applying the scaled score. Results in Table 8, below, indicate a slight downward trend over time in the percentage of questions judged as “addressed”. In addition, consistency in responses appears not to be a function of the quality of the AIs: the AI with the highest consistency measure, Tempe, was rated next-to-last (in Fall 2002) and last (in Spring 2003) in terms of percent of questions addressed, whereas the AI with the next-highest consistency measure, Allegheny County, was rated highest in both time periods in terms of percent of questions addressed.

[Table 8: Consistency in EI Responses over Time, Reader E]

Does this trend represent a better grasp of relevant fair housing policy and AI requirements over time? To answer this question, we examined those questions that were either judged “addressed” in Fall 2002 and “not addressed” in Spring 2003 or judged “not addressed” in Fall 2002 and “addressed” in Spring 2003 for which comments were supplied (the Tempe and Allegheny County AIs). Based on our reading of the AIs, the EI and the reader’s comments, we judged that only one out of the 7 (14%) Spring 2003 responses for the Tempe AI that were inconsistent with respect to the corresponding Fall 2002 EI questions were correctly classified in the spring, while seven out of the 13 (53.8%) inconsistent Spring responses for the Allegheny County AI were correctly classified in the spring. Thus, we cannot conclude that a significant amount of “learning” with respect to the EI has taken place over time.
Policy Implications

Results in this paper motivate two specific uses for the Evaluation Instrument. First, HUD can use the EI to pinpoint questions that are more likely to generate disagreements or misunderstandings by AI readers and thus to provide better quality guidelines and requirements for AIs. Second, jurisdictions can use the EI to isolate classes of analyses that tend to be poorly addressed or well addressed in order to assign technical resources to improve the quality of AIs.

Results related to the reliability and consistency of EI results also motivate recommendations for use of the EI in practice. Despite the simplicity of the binary response score as compared to the scaled score, and the lower level of variance in total scores using the binary score as compared to the scaled score, we do not believe that the former is preferred to the latter in terms of reliability. Indeed, through use of the scaled score, we are able to identify readers who are unusually likely to be liberal or conservative in judging the relative quality of AI responses, and we are able to identify portions of individual AIs that are judged to be of relatively higher quality than others. Thus, if the EI with the scaled score were to be used in practice, analysts would likely be able to identify AI topics that require better quality data collection and analysis. Also, the fact that a question is addressed, alone, provided no indication as to the quality of an AI’s response—the scaled score could range from 1 (only one out of the four response components identified) to 4 (all of the response components identified). We have observed this discrepancy multiple times when evaluating readers’ EI responses.

Observed variation in the scores assigned by readers to the various AIs is indicative of varying levels of quality of the readers in evaluating AIs—recall our result that when reader E was dropped from the sample of EI results, the correlation between the percent of questions judged as “addressed” and the total scaled score was very close to one. We would not have
gained this insight if we had relied on one or perhaps two readers. Thus, we recommend that the EI be used in practice with at least three readers in order to identify a measure of “central tendency” with respect to evaluation trends. It is likely that better and more consistent training of AI readers may reduce variation in scores.

Evaluation results reported in this paper give no indication as to the openness of the housing market in the various regions; the Pittsburgh and Allegheny County AIs are quite critical of the state of fair housing in the Pittsburgh region, even as they were judged by the readers to be the best quality of the five AIs read. Thus, this exercise in AI evaluation must be performed in tandem with another tool to summarize the quality of the fair housing environment.

V. Conclusion and Next Steps

This paper has established a conceptual framework for evaluating the quality of Federally-mandated studies called Analyses of Impediments to Fair Housing (AIs). This framework can provide guidance to jurisdictions seeking to affirmatively further access to fair housing. We have argued that existing resources for evaluating AIs do not provide clear, succinct guidance to practitioners and academics. We have developed an evaluation instrument, the Analysis of Impediments Evaluation Index (EI), as a means to generating such guidance. Based on feedback from housing experts, we believe that the EI addresses key needs of housing analysts and is worthy of further study. The EI includes an innovative means by which responses to two types of EI questions can be classified along four dimensions yet aggregated onto a meaningful four-point scale.

We have applied the EI to a small representative national sample of AIs, and have demonstrated that the EI is a robust, consistent analysis instrument that identifies variations in AI
quality along a number of dimensions of AI policy concerns. For example, we have identified three areas of fair housing-related inquiry—advertising, insurance and media reporting—for which HUD might provide more guidance to jurisdictions in assessing housing market quality and identifying impediments to fair housing.

We have found that EI scores computed using a binary measure (“addressed” versus “not addressed”) has some advantages as compared to a 0-to-4 scaled score, both from the perspective of the reader of an AI and in terms of analysis of EI results. However, we believe that the additional complications associated with a score for each EI question comprising four distinct components provides substantial insight into proclivities of readers and relative quality of AIs themselves. Similarly, we believe that use of multiple readers provides additional insight as to trends in EI responses. However, we do not believe that much is gained regarding AI quality by applying the EI to the same AI at two or more time points.

This study has three main benefits. First, it enables policy-makers to understand how to: (a) better perform AIs in the field given resource limitations, (b) encourage stakeholders to take action based on AI results and (c) to identify specific needs for improved training of fair housing practitioners. Second, it enables researchers to: (a) better measure the quality of fair housing studies, (b) better evaluate AI process outcomes, and (c) to better communicate amongst each other regarding AI evaluation using a standard database of AI characteristics, evaluation questions and outcome variables. More generally, this research will help enable policy-makers and researchers to better understand the relationship AI quality and the local fair housing environment and how specific recommendations influence changes in local fair housing policy, enforcement and outcomes.
We plan to apply the EI to the larger sample of AIs provided by the National Fair Housing Alliance in order to amplify and refine the operational and policy insights contained here.

Acknowledgements:

Thanks to the Kathy Fletcher, Director of Member Services, National Fair Housing Alliance for her organization’s generosity in providing AIs and practitioner insight and support for this research project. Thanks to the following students for their research assistance: Richard Barbour and Judith Derenzo (University of Pittsburgh); Peter Edelman, Xiaoyan Li and Hsin-Yi Teng (Carnegie Mellon University).
References:


Appendix: HUD’s Suggested Format for the Analysis of Impediments

I. Introduction and Executive Summary of the Analysis
   A. Who Conducted
   B. Participants
   C. Methodology Used
   D. How Funded
   E. Conclusions
      1. Impediments Found
      2. Actions to Address Impediments

II. Jurisdictional Background Data
   A. Demographic Data
   B. Income Data
   C. Employment Data
   D. Housing Profile
   E. Maps
   F. Other Relevant Data

III. Evaluation of Jurisdiction’s Current Fair Housing Legal Status
   A. Fair housing complaints or compliance reviews where the Secretary has issued a charge or made a finding of discrimination
   B. Fair housing discrimination suit filed by the Department of Justice or private plaintiffs
   C. Reasons for any trends or patterns
   D. Discussion of other fair housing concerns or problems

IV. Identification of Impediments to Fair Housing Choice
   A. Public Sector
      1. Zoning and Site Selections
      2. Neighborhood Revitalization, Municipal and Other Services, Employment-Housing-Transportation Linkage
      3. PHA and Other Assisted/Insured Housing Provider Tenant Selection Procedures; Housing Choices for Certificate and Voucher Holders
      4. Sale of Subsidized Housing and Possible Displacement
      5. Property Tax Policies
      6. Planning and Zoning Boards
   B. Private Sector
      1. Lending Policies and Practices
   C. Public and Private Sector
      1. Fair Housing Enforcement
      2. Informational Programs
   D. Where there is a determination of unlawful segregation or other housing discrimination by a court or a finding of noncompliance by HUD under Title VI of the Civil Rights Act of 1964 or Section 504 of the Rehabilitation act of 1973, or where the Secretary has issued a charge under the Fair Housing Act regarding assisted housing within a recipient’s jurisdiction, an analysis of the actions which could be taken by the recipient to help remedy the discriminatory condition, including actions involving the expenditure of funds by the jurisdiction.

V. Assessment of Current Public and Private Fair Housing Programs And Activities in the Jurisdiction

VI. Conclusions and Recommendations

Source: Fair Housing Planning Guide. (U.S. Department of Housing and Urban Development 1996)
### Question Categories

<table>
<thead>
<tr>
<th>Question</th>
<th>Rating Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall Quality of Evaluation Instrument (EI):</td>
<td>Low</td>
</tr>
<tr>
<td>Ability of EI to provide measurable results:</td>
<td>1</td>
</tr>
<tr>
<td>Likelihood that EI will enable researchers to determine the extent to which Analyses of Impediments can identify specific barriers to fair housing across different jurisdictions:</td>
<td>1</td>
</tr>
<tr>
<td>Appropriateness of EI for HUD’s policy towards conducting Analysis of Impediments:</td>
<td>1</td>
</tr>
<tr>
<td>Ability of EI to inform public policy on analysis of impediments to fair housing:</td>
<td>1</td>
</tr>
<tr>
<td>Likelihood EI will benefit governmental agencies receiving CDBG funds:</td>
<td>1, 2, 3</td>
</tr>
<tr>
<td>Ability of EI to be applied to AIs across different jurisdictions, now and in the near future:</td>
<td>1, 2, 3</td>
</tr>
<tr>
<td>Quality of EI as a tool to be applied consistently by researchers with differing levels of housing expertise to AIs of differing levels of quality, lengths and presentation styles:</td>
<td>1, 2, 3</td>
</tr>
</tbody>
</table>

[Table 1: Analysis of Impediments Evaluation Index Ratings]
### Table 2: Regional Distribution of AIs in the Sampling Population and the Final Analysis Sample

<table>
<thead>
<tr>
<th>Region</th>
<th>Sampling Population</th>
<th>Final Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number</td>
<td>Percent</td>
</tr>
<tr>
<td>Caribbean</td>
<td>11</td>
<td>2%</td>
</tr>
<tr>
<td>Midwest</td>
<td>161</td>
<td>24%</td>
</tr>
<tr>
<td>Mountain West</td>
<td>26</td>
<td>4%</td>
</tr>
<tr>
<td>Northeast</td>
<td>127</td>
<td>19%</td>
</tr>
<tr>
<td>Pacific Northwest</td>
<td>22</td>
<td>3%</td>
</tr>
<tr>
<td>South</td>
<td>176</td>
<td>26%</td>
</tr>
<tr>
<td>Southwest</td>
<td>20</td>
<td>3%</td>
</tr>
<tr>
<td>West Coast</td>
<td>127</td>
<td>19%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>670</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>

[Table 2: Regional Distribution of AIs in the Sampling Population and the Final Analysis Sample]
<table>
<thead>
<tr>
<th>Data Category</th>
<th>AI Sample*</th>
<th>U.S. Metropolitan Statistical Areas **</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Units</td>
<td>35</td>
<td>284</td>
</tr>
<tr>
<td>Average Study Area Population</td>
<td>319,157.77</td>
<td>-</td>
</tr>
<tr>
<td>Standard Deviation of Study Area Population</td>
<td>457,947.84</td>
<td>-</td>
</tr>
<tr>
<td>Average MSA Population</td>
<td>3,108,985.80</td>
<td>678,613.84</td>
</tr>
<tr>
<td>Standard Deviation of MSA Population</td>
<td>5,063,967.61</td>
<td>1,642,503.10</td>
</tr>
<tr>
<td>Average Number of Years Since Study</td>
<td>6.16</td>
<td>-</td>
</tr>
<tr>
<td>Average MSA Percent Black/Non-Hispanic</td>
<td>14.64%</td>
<td>19.33%</td>
</tr>
<tr>
<td>Average MSA Percent Hispanic</td>
<td>9.28%</td>
<td>6.79%</td>
</tr>
<tr>
<td>Average MSA Median Family Income</td>
<td>$31,237.17</td>
<td>$33,686.07</td>
</tr>
<tr>
<td>Average MSA Percent Homeowners</td>
<td>62.98%</td>
<td>65.00%</td>
</tr>
<tr>
<td>Average MSA Median House Value</td>
<td>$100,162.86</td>
<td>$73,523.24</td>
</tr>
</tbody>
</table>

*Source: National Fair Housing Alliance, 2001. Includes Pittsburgh, PA and Allegheny County, PA, not part of original sample of AIs provided by NHFA.


[Table 3: Summary Characteristics of AIs in Actual Sample]
<table>
<thead>
<tr>
<th>AI</th>
<th>Reader</th>
<th># Addressed</th>
<th>Scaled Score</th>
<th>% Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rome</td>
<td>D</td>
<td>18</td>
<td>54</td>
<td>17.0</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>16</td>
<td>33</td>
<td></td>
</tr>
<tr>
<td><strong>Mean, All Readers</strong></td>
<td></td>
<td></td>
<td><strong>43.5</strong></td>
<td></td>
</tr>
<tr>
<td><strong>% Deviation</strong></td>
<td></td>
<td></td>
<td><strong>64.8%</strong></td>
<td></td>
</tr>
<tr>
<td>Pittsburgh</td>
<td>B</td>
<td>36</td>
<td>37</td>
<td>34.5</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>33</td>
<td>121</td>
<td></td>
</tr>
<tr>
<td><strong>Mean, All Readers</strong></td>
<td></td>
<td></td>
<td><strong>79.0</strong></td>
<td></td>
</tr>
<tr>
<td><strong>% Deviation</strong></td>
<td></td>
<td></td>
<td><strong>227.2%</strong></td>
<td></td>
</tr>
<tr>
<td>Tampa</td>
<td>B</td>
<td>26</td>
<td>27</td>
<td>20.0</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>14</td>
<td>31</td>
<td></td>
</tr>
<tr>
<td><strong>Mean, All Readers</strong></td>
<td></td>
<td></td>
<td><strong>29.0</strong></td>
<td></td>
</tr>
<tr>
<td><strong>% Deviation</strong></td>
<td></td>
<td></td>
<td><strong>14.9%</strong></td>
<td></td>
</tr>
<tr>
<td>Tempe</td>
<td>B</td>
<td>18</td>
<td>19</td>
<td>14.5</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>11</td>
<td>21</td>
<td></td>
</tr>
<tr>
<td><strong>Mean, All Readers</strong></td>
<td></td>
<td></td>
<td><strong>20.0</strong></td>
<td></td>
</tr>
<tr>
<td><strong>% Deviation</strong></td>
<td></td>
<td></td>
<td><strong>9.7%</strong></td>
<td></td>
</tr>
<tr>
<td>Allegheny County</td>
<td>D</td>
<td>35</td>
<td>118</td>
<td>32.0</td>
</tr>
<tr>
<td></td>
<td>E</td>
<td>29</td>
<td>74</td>
<td></td>
</tr>
<tr>
<td><strong>Mean, All Readers</strong></td>
<td></td>
<td></td>
<td><strong>96.0</strong></td>
<td></td>
</tr>
<tr>
<td><strong>% Deviation</strong></td>
<td></td>
<td></td>
<td><strong>59.3%</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Mean, All Readers, All Jurisdictions</strong></td>
<td></td>
<td></td>
<td><strong>20.9</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Average % deviation, All Jurisdictions</strong></td>
<td></td>
<td></td>
<td><strong>53.5</strong></td>
<td></td>
</tr>
<tr>
<td><strong>38.2%</strong></td>
<td></td>
<td></td>
<td><strong>75.2%</strong></td>
<td></td>
</tr>
</tbody>
</table>

"% deviation" is measured as (high score – low score)/low score

[Table 4: EI Scores, Binary and Full, Across AIs and Readers]
<table>
<thead>
<tr>
<th>Reader</th>
<th>Question Response Scale</th>
<th>Questions with Comments</th>
<th>Questions Without Comments</th>
<th>Total (Number)</th>
<th>Total (Percent)</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>0</td>
<td>71</td>
<td>8</td>
<td>79</td>
<td>50.3</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>52</td>
<td>23</td>
<td>75</td>
<td>47.8</td>
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<tr>
<td></td>
<td>2</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>1.9</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>124</td>
<td>33</td>
<td>157</td>
<td>100.0</td>
</tr>
<tr>
<td>D</td>
<td>0</td>
<td>61</td>
<td>12</td>
<td>73</td>
<td>47.7</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>1</td>
<td>4</td>
<td>5</td>
<td>3.3</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>2</td>
<td>8</td>
<td>10</td>
<td>6.5</td>
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<tr>
<td></td>
<td>3</td>
<td>7</td>
<td>7</td>
<td>14</td>
<td>9.2</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>45</td>
<td>6</td>
<td>51</td>
<td>33.33</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>116</td>
<td>37</td>
<td>153</td>
<td>100.0</td>
</tr>
<tr>
<td>E</td>
<td>0</td>
<td>96</td>
<td>46</td>
<td>142</td>
<td>67.0</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>0</td>
<td>21</td>
<td>21</td>
<td>9.9</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>0</td>
<td>20</td>
<td>20</td>
<td>9.4</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>0</td>
<td>18</td>
<td>18</td>
<td>8.5</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>0</td>
<td>11</td>
<td>11</td>
<td>5.2</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>96</td>
<td>116</td>
<td>212</td>
<td>100</td>
</tr>
</tbody>
</table>

[Table 5: Distribution of Scaled Scores and Presence of Comments, By Reader]
<table>
<thead>
<tr>
<th>Main Category</th>
<th>Rome Mean % Addressed</th>
<th>Mean % Score of Max</th>
<th>Pittsburgh Mean % Addressed</th>
<th>Mean % Score of Max</th>
<th>Tampa Mean % Addressed</th>
<th>Mean % Score of Max</th>
<th>Tempe Mean % Addressed</th>
<th>Mean % Score of Max</th>
<th>Allegheny County Mean % Addressed</th>
<th>Mean % Score of Max</th>
<th>All Jurisdictions Mean % Addressed</th>
<th>Mean % Score of Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: Housing Types</td>
<td>27.5%</td>
<td>19.5%</td>
<td>83.5%</td>
<td>50.0%</td>
<td>44.5%</td>
<td>11.0%</td>
<td>22.0%</td>
<td>8.0%</td>
<td>83.5%</td>
<td>58.0%</td>
<td>52.2%</td>
<td>29.3%</td>
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<tr>
<td>B: Fair Housing-Related</td>
<td>36.0%</td>
<td>22.5%</td>
<td>86.5%</td>
<td>49.0%</td>
<td>73.0%</td>
<td>29.5%</td>
<td>36.0%</td>
<td>15.0%</td>
<td>73.0%</td>
<td>54.5%</td>
<td>60.9%</td>
<td>34.1%</td>
</tr>
<tr>
<td>C: Jurisdiction-Level Role</td>
<td>16.5%</td>
<td>4.0%</td>
<td>66.5%</td>
<td>50.0%</td>
<td>67.0%</td>
<td>33.5%</td>
<td>33.0%</td>
<td>8.0%</td>
<td>33.0%</td>
<td>25.0%</td>
<td>43.2%</td>
<td>24.1%</td>
</tr>
<tr>
<td>D: Advertising</td>
<td>0.0%</td>
<td>0.0%</td>
<td>16.5%</td>
<td>4.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>33.0%</td>
<td>25.0%</td>
<td>9.9%</td>
<td>5.8%</td>
</tr>
<tr>
<td>E: Local and Regional Amenities</td>
<td>40.0%</td>
<td>20.0%</td>
<td>60.0%</td>
<td>32.5%</td>
<td>30.0%</td>
<td>7.5%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>80.0%</td>
<td>60.0%</td>
<td>42.0%</td>
<td>24.0%</td>
</tr>
<tr>
<td>F: Zoning</td>
<td>33.5%</td>
<td>29.0%</td>
<td>100.0%</td>
<td>62.5%</td>
<td>33.0%</td>
<td>12.5%</td>
<td>66.5%</td>
<td>20.5%</td>
<td>100.0%</td>
<td>91.5%</td>
<td>66.6%</td>
<td>43.2%</td>
</tr>
<tr>
<td>G: Lending Practices, Institutions and</td>
<td>36.0%</td>
<td>20.0%</td>
<td>41.0%</td>
<td>17.0%</td>
<td>18.0%</td>
<td>5.5%</td>
<td>18.0%</td>
<td>4.5%</td>
<td>22.5%</td>
<td>18.0%</td>
<td>27.1%</td>
<td>13.0%</td>
</tr>
<tr>
<td>Financial Services</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>H: ADA/Disabilities Issues</td>
<td>37.5%</td>
<td>28.0%</td>
<td>37.5%</td>
<td>25.0%</td>
<td>12.5%</td>
<td>6.5%</td>
<td>50.0%</td>
<td>16.0%</td>
<td>75.0%</td>
<td>47.0%</td>
<td>42.5%</td>
<td>24.5%</td>
</tr>
<tr>
<td>I: Insurance</td>
<td>0.0%</td>
<td>0.0%</td>
<td>50.0%</td>
<td>31.5%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>25.0%</td>
<td>6.5%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>15.0%</td>
<td>7.6%</td>
</tr>
<tr>
<td>J: Media for Reporting of Fair Housing</td>
<td>50.0%</td>
<td>37.5%</td>
<td>100.0%</td>
<td>62.5%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>0.0%</td>
<td>100.0%</td>
<td>75.0%</td>
<td>50.0%</td>
<td>35.0%</td>
</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>K: Demographic Profiles</td>
<td>100.0%</td>
<td>87.5%</td>
<td>100.0%</td>
<td>62.5%</td>
<td>100.0%</td>
<td>37.5%</td>
<td>100.0%</td>
<td>50.0%</td>
<td>100.0%</td>
<td>87.5%</td>
<td>100.0%</td>
<td>65.0%</td>
</tr>
<tr>
<td>Average</td>
<td>34.3%</td>
<td>24.4%</td>
<td>67.4%</td>
<td>40.6%</td>
<td>34.4%</td>
<td>13.0%</td>
<td>31.9%</td>
<td>11.7%</td>
<td>63.6%</td>
<td>49.2%</td>
<td>46.3%</td>
<td>27.8%</td>
</tr>
</tbody>
</table>

[Table 6: Distribution of Binary and Scaled Scores, by AI and Evaluation Category]
<table>
<thead>
<tr>
<th>Main Category</th>
<th>Number of Questions</th>
<th>Percent of Questions for which Readers Agree</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rome</td>
<td>Pittsburgh</td>
</tr>
<tr>
<td>A: Housing Types</td>
<td>9</td>
<td>88.9</td>
</tr>
<tr>
<td>B: Fair Housing-Related</td>
<td>11</td>
<td>81.8</td>
</tr>
<tr>
<td>C: Jurisdiction-Level Role</td>
<td>3</td>
<td>66.7</td>
</tr>
<tr>
<td>D: Advertising</td>
<td>3</td>
<td>100.0</td>
</tr>
<tr>
<td>E: Local and Regional Amenities</td>
<td>5</td>
<td>60.0</td>
</tr>
<tr>
<td>F: Zoning</td>
<td>3</td>
<td>33.3</td>
</tr>
<tr>
<td>G: Lending Practices, Institutions and Financial Services</td>
<td>11</td>
<td>63.6</td>
</tr>
<tr>
<td>H: ADA/Disabilities Issues</td>
<td>4</td>
<td>25.0</td>
</tr>
<tr>
<td>I: Insurance</td>
<td>2</td>
<td>100.0</td>
</tr>
<tr>
<td>J: Media Reporting of Fair Housing Issues</td>
<td>1</td>
<td>0.0</td>
</tr>
<tr>
<td>K: Demographic Profiles</td>
<td>1</td>
<td>100.0</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>53</strong></td>
<td><strong>69.8%</strong></td>
</tr>
</tbody>
</table>

[Table 7: Consistency of Evaluations, Binary Scores, Main Evaluation Categories]
<table>
<thead>
<tr>
<th>AI</th>
<th>% Consistent Responses</th>
<th>% Addressed (Fall 2002)</th>
<th>% Addressed (Spring 2003)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rome</td>
<td>69.8</td>
<td>26.4</td>
<td>30.2</td>
</tr>
<tr>
<td>Tampa</td>
<td>66.1</td>
<td>41.5</td>
<td>26.4</td>
</tr>
<tr>
<td>Tempe</td>
<td>86.8</td>
<td>30.2</td>
<td>20.8</td>
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<tr>
<td>Allegheny County</td>
<td>75.5</td>
<td>56.6</td>
<td>54.7</td>
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</tbody>
</table>

[Table 8: Consistency in EI Responses over Time, Reader E]