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Non-Financial Measures, Aggregation and Performance Evaluation

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In this study we examine the operational use and the predictive power of aggregated data of performance. We argue that the decision-making process is enhanced by the use of contemporaneous operational data to approximate the ex-post indicators of success or failure as one may be able to effectively combine measures of various inputs to simulate an ex-ante measure of the outcome. An empirical examination of National Basketball Association (NBA) game statistics supports the predictive ability of aggregated performance indicators.

Key Words: Aggregated Measures, Fixed Effects, NBA.

I. Introduction

Quantitative information enhances the objectivity of the decision process. Useful and meaningful measures assist decision-makers with differentiation and rank-ordering of choices in a manner consistent with the objective function. Managers' choice of alternatives based on anticipated consequences may not be conclusive without reliance on some measurement process. Quantitative distinctions not only should reflect qualitative ones, i.e. nominal measures, but also must belong to a measurement system that is capable of confirming or refuting hypotheses about attributes of any variable that affect the managers' choices and the organizational utility function (Nourayi and Daroca 1996).

A growing body of literature addresses these issues. Horngren (2004), for example, highlights the relevance of non-financial measures in the managerial decision-making process. Horngren (2004) maintains that "financial measures focus on *outcomes* of decisions made under uncertainty" (p. 208) and emphasizes that although profitability measures may be the major objective of business organizations, such measures are not directly controllable at operational level. Elovici et al.(2006) use a framework frequently employed in information economics to aggregate the data from several information systems based on user's need. Elovici et al.(2006) demonstrate analytically that the proposed framework increases user's expected payoffs. Their experiment also shows precision of aggregated data is higher than the individual components; the recall of data is usually lower than the individual components. Lawry and He (2008) propose label semantics as an integrated representation framework for probabilistic uncertainty and fuzziness in multiple-attribute, decision-making problems. Within this framework they introduce linguistic decision trees as a tool for information aggregation in multi-attribute, decision-making problems and describe the process of information propagation through a hierarchy of linked decision trees.

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Empirical applications of analytics of attributes of measurement systems have also been discussed in the literature. Kahraman et al. (2003a), for example, recommends four different fuzzy multi-attribute group decision-making approaches to select the best facility location alternative. Jaganathan et al. (2007) use "fuzzy analytic hierarchy process" to deal with multiple-attribute investments in new manufacturing technologies. Their analysis implicitly recognizes the need to construct a decision-support system to adequately represent quantitative and subjective assessments. Similarly, Kahraman et al. (2003b) suggest dividing the decision process into several stages where a decision is required for each stage. The incremental nature of their approach reduces uncertainties associated with later stages of the decision process.

In general the analysis and the evaluation of various alternatives in a decision process may be simplified by summarizing, aggregating, and reducing the amount of data a decision maker has to process. Therefore, information aggregation is justified on economic grounds as well as from the perspective of human-information processing and on a behavioral basis. Aggregation is not, however, always a clear-cut solution because it may reduce information by averaging away the potential explanatory power embedded in various attributes of individual variables.

The decision maker may reduce the uncertainty inherent in economic decisions by evaluating the likely outcome of a choice process based on the contemporaneous data. In particular the aggregated operational data reduce uncertainty in the choice process by using contemporaneous data as the approximations for ex-post indicators of success or failure. The notion of information timeliness provides the support for use of information that is available during the operations. For example, we may be able to effectively combine measures of various input data to simulate an approximate ex-post measure of the outcome in order to deal with either the process deficiencies or the anticipated problem relative to the outcomes on a more timely manner. That is, process adjustment and/or anticipation of the outcome using aggregated operational measures, as oppose to ex-post financial measure helps a decision maker avoid delaying the assessment and evaluation activities until the end of an operation.

In this study we examine the explanatory power of aggregated measures of performance using data from professional basketball games of the National Basketball Association (NBA). NBA games offer an appropriate setting for examination of measurement concepts relative to the aggregated information because, given the high degree of substitutability of basketball skills and activities during a game, game statistics may be combined seamlessly to create meaningful measures. Game statistics data provide an appropriate setting for examination of aggregated operational measures because of the structure of the game and the way various players' actions are recorded during the game. That is, every game statistic resulting from a meaningful action of a player on the team is recorded and can eventually be mapped directly to the final game score. Thus, basketball statistics provide a very powerful measure of activities during a game and, therefore, may be aggregated seamlessly and, as an intermediate step during the game, can very accurately be mapped to the win/loss results for the game.

The rest of the paper proceeds as follows. A summary review of the relevant research in presented in Section 2. The data and the statistical methodology used in the empirical research are briefly discussed in Section 3. A summary of the statistical results is presented in Section 4. The conclusions and a few final remarks are presented in the final section.

II. Theoretical Framework and Relevant Literature

Qualitative attributes may be considered additive phenomena of a larger infrastructure that positively impacts overall organizational effectiveness. According to Gold et al. (2001) process capabilities of acquisition, conversion, application, and protection form an operational perspective for the framework of knowledge combination and exchange that underlies the theory of knowledge integration. They indicate "these dimensions also form an additive construct of process capability that is positively related to organizational effectiveness (p. 19.)" Grant (1996) provides a framework for defining the process aspects of knowledge integration. According to this framework, integration of knowledge is dependent upon the following three aspects: efficiency, scope, and flexibility of integration.

Analysis and evaluation of information about various alternatives in a decision setting may be simplified by summarizing, aggregating, and reducing the amount of data the decision maker has to consider. Although aggregated data favorably affects the costs of information processing, the extent to which data can be aggregated will depend on the properties of decision variables and the measurement process as well as the decision context. Fichman (2001) indicates that aggregation across perfect complements would have no substantive effect on the measurement of attributes, since the aggregated measure would be perfectly correlated with each of the individual variables included in the aggregate. Additionally, aggregating substitutes should lead to the greatest increase in predictive validity.

Aggregation in some cases can average away potential explanatory power of individual variables. However, with respect to a primary attribute, the aggregated measure can be the most powerful explanatory variable. Where such aggregation appears warranted, the tradeoffs related to robustness, generalization, and clarity of theoretical interpretation will tip toward aggregation of various attributes or variables. When such generalization contradicts plausible hypotheses, aggregation of attributes or variables should be avoided (Fichman 2001). If aggregated measures are used as the basis for the choice process, they must meet the required theoretical underpinning consistent with the decision framework. Neglecting the interaction among variables that affect overall organization objectives may result in ambiguous signals about ordering the consequences of various choices. In an aggregated design, by contrast, omitted specifications of relevant variables should pose less of a problem because their effects will tend to be smoothed out across variables. Benefits of aggregation can compensate for possible adverse effects caused by either misestimating or omitting specification of variables.

Theoretical aspects of information value and usefulness must ultimately be validated based on empirical examination of such concepts. However, the most significant challenge regarding empirical examination of aggregated business data is the availability of detailed information about business operations.

III. Data and Statistical Methodology

Three datasets of game statistics were originally constructed to examine the explanatory power of aggregated measures of team performance. The first dataset is composed of regular season attendance (ticket sales) data and win/loss statistics covering 13 regular seasons, 1991-92 through 2002-03 for 27 teams, and 9 regular seasons, 1995-96 through 2002-03 for the two expansion teams, Toronto Raptors and Vancouver Grizzlies (now Memphis Grizzlies), respectively. The data are used to examine the impact of win/loss statistics on regular season attendance. Attendance data were collected directly from each franchise office and the win/loss statistics are obtained from the NBA website (http://www.nba.com).

The second dataset is composed of team-by-team annual game statistics for 5 regular seasons, 1999-2000 through 2003-2004 for each of the 29 NBA teams. The choice of the time period is mainly dictated by the availability of detailed and consistent game statistics. This dataset is used to examine the relationship between regular season winning and aggregated measures. This dataset includes the following regular season NBA statistics: Field Goal Made (FGM), Field Goal Attempts (FGA), Field Goal Percentage (FG%), Free Throw Made (FTM), Free Throw Attempts (FTA), Free Throw Percentage (FT%), 3-Point Field Goal Made (3FGM), 3-Point Field Goal Attempts (3FGA), 3-Point Field Goal Percentage (3FG%), Assists (ASST), Steals (ST), Offensive Rebounds (OR), Defensive Rebounds (DR), Total Rebounds (TR), Turnover (TO), Team Rebounds, and Block Shots (BS), and Total Points (TP). These statistics are readily available and are published in daily newspapers. We obtained them from the daily editions of the Los Angeles Times. Based upon these game statistics, the NBA routinely constructs an aggregated measure of regular season players' performance called the Efficiency Score, ES^R, which is defined as follows:

$$ES^R = TP + TR + ASST + ST + BS - [(FGA - FGM) + (FTA - FTM) + TO] \quad (1)$$

This measure, however, has the drawback of including the final game score, TP. As such, its practical use in predicting outcomes is not plausible. We use the NBA efficiency measure for each team; but in addition, we construct four other *regular* season aggregated measures of performance, which we label M_1^R, M_2^R, M_3^R and M_4^R. These aggregated measures are defined as follows:

$$M_1^R = FGM + 0.5(3FGM + FTA) + DR + BS - TO \quad (2)$$

$$M_2^R = FGM + 0.2(ASST) + 0.8(3FGM + FTM) + 0.5(FGA + DR + ST + BS) \quad (3)$$

$$M_3^R = FGM + 0.2(ASST) + 0.8(3FGM + FTA) + 0.4(FGA + DR + ST + BS) \quad (4)$$

$$M_4^R = FGM + 0.2(ASST) + 0.5(3FGM + FTA) + 0.4(FGA + DR + ST + BS) \quad (5)$$

Clearly, M_2^R, M_3^R and M_4^R, are to a large extent equivalent; but their use in the empirical analysis is intended to examine the relevance of alternative weighting schemes of game statistics.

Finally, the third dataset is composed of data on two playoffs seasons--2003 and 2004. The dataset does not include the 1999-2002 playoffs because the playoffs format changed in 2003. The 2003 playoffs season is the first year the seven-game series for all four rounds of playoffs was implemented. This dataset is used to examine the relationship between playoff games point spread and aggregated measures. The playoff statistics include the point spread (PS) in addition to the game statistics listed earlier. The aggregated measures constructed for the playoffs games differ from those for the regular season games. The aggregated measures for the regular season games are based on the overall results for each season. These measures, however, need to be adjusted when we examine the playoffs competition because the post-season competitions do not follow the same pattern as the regular season games. Not all teams reach playoffs, not every playoff team plays in every round, and the number of games in a round varies from a minimum of four to a maximum of seven games. Therefore, both the Efficiency Score and the aggregated measures of performance must be computed on a game-by-game basis, as the difference between the aggregated measures for the opposing teams in each game. For example, the Efficiency Score ES^P for playoff is defined as $ES^P = ES_a^P - ES_b^P$ (6)

where ES_a^P is the efficiency score for team a in a playoff game (P), and ES_b^P is the efficiency score for team b, the opposing team in the same playoff game. Similarly, the remaining aggregated measures of performance for playoff P, M_1^P through M_4^P are obtained as follows:

$$M_1^P = M_{1a}^P - M_{1b}^P \quad (7)$$
$$M_2^P = M_{2a}^P - M_{2b}^P \quad (8)$$
$$M_3^P = M_{3a}^P - M_{3b}^P \quad (9)$$
$$M_4^P = M_{4a}^P - M_{4b}^P \quad (10)$$

The three datasets are panel data. Panel data have become increasingly relevant in applied research (Hsiao 2003; Baltagi 2001; Wooldridge 2002). A panel has spatial and temporal dimensions. The spatial dimension pertains to the set of cross-sectional units of observation. The temporal dimension pertains to periodic observations of a set of variables characterizing these cross-sectional units over a particular time span. The advantage of pooled estimators over heterogeneous estimators, such as, in our case, individual franchise regressions, is that individual regressions often yield unreliable and implausible coefficients. Panel data, instead, are more informative, display a higher degree of variability, suffer less from problems of multicollinearity, and have more degrees of freedom. If there are N units of observations and if the survey is undertaken T time periods, there are potentially NT observations consisting of time series of length T on N parallel units. This results in more efficient estimates. Furthermore, the use of panel data offers a solution to the problem of bias caused by unobserved heterogeneity. Unobserved heterogeneity refers to unobserved qualities present in the unit under consideration but unknown to the researcher. For example, it is rather obvious that all franchises are not the same. Each of them has certain traits, qualities, characteristics, etc., that are difficult to quantify. In cross-section analysis, unobserved heterogeneity is captured by the error term. However, the central assumption of regression theory is that the explanatory variable and the error term are uncorrelated, i.e., that the explanatory variable is exogenous. As unobserved heterogeneity is captured by the error term, this assumption is violated. With panel data, instead, it is possible to correctly identify the true effects, even in the presence of unobserved heterogeneity (Baltagi 2001).

In panel data estimation one may choose between the random effects and fixed effects models. According to Judge et al. (1988) the difference in results is rather small for a large T and a small N. In the case of a small T relative to N the fixed effects model is inefficient though consistent and, as such, a random effect model may be preferred. However, the correlation between characteristics pertaining to cross sections and explanatory variables may render estimates biased in the random effect model. For relatively smaller T the worst in applying the fixed effects model is its inefficiency. Above all, all teams included in the datasets constitute roughly 100 percent of the respective statistical populations; and as such, treating parameters as fixed is not an unreasonable assumption. Moreover, as Baltagi et al. (2000) point out, the fixed effects model performs better in prediction among the pooling techniques. Consequently, we employ the fixed effects model in the statistical analysis that follows.

With the growing popularity of panel data applications, the time series properties of the data, such as unit roots and cointegration analysis, have also received increasingly more attention. If a unit root exists in the panel data, the results of using data in their level form is suspect, as we risk estimating a spurious regression where the probability of making incorrect inferences about the estimated coefficients approach one asymptotically. Panel data unit root tests exploit the extra power in the cross-sectional dimension of the data. A variety of tests for panel unit roots have been proposed. Among those, the most common tests in practice are the LLC test (Levin, Lin and Chu 2002) and the IPS test (Im, Pesaran, and Shin 1997). The LLC test assumes a common unit root process, i.e., the unit root, is identical across cross-sections. Conversely, the IPS test allows for individual unit root processes, i.e., the unit root are allowed to vary across cross-sections.

IV. Statistical Analysis and Empirical Results

This section is divided into two main parts. First, we analyze the relationship between outcome measures and organizational objectives. Second, we address the issue of predicting game outcomes using aggregated measures of performance.

We analyze the first issue in the context of regular season games. The relevant hypothesis is that there exists a strong and positive link between the measure of performance and the franchise's financial success, as measured by the franchise capacity utilization percentage, (ticket sales as a percentage of arena capacity). The LLC and IPS panel unit root tests consistently reject the null of a unit root for both capacity utilization percentage (CUP_{it}) and the winning percentage (WP_{it}). Thus, the evidence suggests that both CUP_{it} and WP_{it} evolve as stationary processes. This result has two important implications for the empirical analysis. First, the rejection of the unit root hypothesis guarantees that the least squares approach to estimation does not suffer from the spurious regression problem, i.e., does not result in biased and inconsistent estimates. Second, it suggests that it is not necessary to turn to panel cointegration techniques in order to determine whether a long-run equilibrium relationship exists among CUP_{it} and WP_{it} .

Panel data fixed effects regression analysis is used to examine the relationship between winning percentage and attendance expressed by capacity utilization percentage (Nourayi 2006). Three alternative models are presented in Table 1. The first column reports a fixed effects regression of CUP_{it} on WP_{it} where CUP_{it} is capacity utilization percentage of franchise i at time t, WP_{it} is winning percentage of franchise i at time t. The results clearly indicate that the franchise winning percentage has a significant contemporaneous impact on capacity utilization percentage.

A one percentage point increase in the franchise winning percentage yields a 0.27 percentage point increase in capacity utilization percentage. The second column in Table 1 extends the model to include the lagged franchise winning percentage suggests that fan loyalty has also a significant impact on capacity utilization percentage, as previous year's winning percentage has also an impact on capacity utilization percentage. However, the effect is only about half the impact of the cotemporaneous effect. Furthermore, as the third column in Table 1 indicates, this lagged effect is transient and

Table 1

Relationship between Attendance and Winning Percentage
Fixed Effects Estimation

Dependent Variable: CUP_{it}			
Constant	0.7564 (42.53)	0.7036 (33.45)	0.6882 (27.48)
WP_{it}	0.2771 (8.03)	0.2309 (5.64)	0.2406 (5.74)
WP_{it-1}		0.1498 (3.61)	0.1505 (3.22)
WP_{it-2}			0.0181 (0.43)
Adjusted R^2	0.56	0.59	0.60

Note: The t-statistics are in parenthesis below the estimated coefficients. The statistics are computed using the Beck and Katz (1995) heteroskedasticity-adjusted standard errors (PCSE).

dies out after one year, as the estimated coefficient on WP_{it-2} is insignificant.

The second issue concerns the ability of aggregated measures of performance to predict the outcomes of the games. We analyze this problem in the context of both regular season games and playoff games. The relevant hypothesis concerns the issue of reliability of aggregated input measures in signaling the outcome of the game. Whitney (1988) describes the objective of professional sports competition and the difference between winning games and achieving the championship. In professional basketball competition the objectives of measurement processes for regular season games and playoff games differ. Teams are expected to increase their WP during regular seasons in order to (a) reach the playoffs and (b) enjoy the home-court advantage during playoff games; on the other hand, is winning the championship; and such a distinction is reached by a team that wins the requisite number of games in each round of competitions.

Winning percentage (WP) is used as the efficiency measure for regular season games. This approach produces one observation per team for each season or 145 overall observations. For the playoff games, teams were dichotomized into win/loss categories for each game; and the point-differential for each game was computed by comparing the final game scores for the two teams in each game. This process yields one observation per game and 170 observations overall. The outcome measures are expressed in the nominal measures for win/loss, and interval measures for point differential are then compared with aggregated measures of games statistics.

The usefulness of an aggregated measure of performance is directly related to its ability to predict an outcome, which in turn is contingent upon the detailed objective of the specific process. The analysis of the correlation between the outcome measures and the aggregated measures indicates that for the regular season games M_1^R has the highest correlation with WP (r = 0.67), while for the playoffs M_2^P has the highest correlation with PS. We based the evaluation of the predictive ability of the aggregated measures with respect to the outcome of the game during the regular season on the sign of the aggregated measures; whereby, a positive sign signals a win and a negative sign indicates a loss. On that basis, we counted the number of times a given aggregated measure predicted correctly the outcome of the game. We found that ES^P correctly predicted the outcome for the game 159 times out of 170 games, or 93.53 percent of the times. This was not unexpected, since the efficiency score represents ex-post measure, due to the fact that it comprises the game final score. Conversely, the remaining aggregated measures, i.e., M_1^P through M_4^P, which provide ex-ante signal of win/loss, correctly predicted the win/loss outcome of the games 152, 158, 155, and 155, respectively, implying that M_2^P is the strongest predictor among the four aggregated measures, with an accuracy rate of 92.94 percent, while M_1^P is the weakest predictor, with an accuracy rate of 89.41 percent. Similarly, M_3^P, and M_4^P, had an accuracy rate of 91.18 percent and 91.18 percent, respectively. A different approach was used to evaluate the ability of aggregated measures to predict the outcome of the games during the playoffs. We constructed two separate measures based on the difference between the value of an aggregated measure and the actual point spread for a given playoff game and computed the sum of the absolute value of the differences, i.e., $\sum_{i=1}^{n}|\Delta_i|$ and the sum of the square of the differences, i.e., $\sum_{i=1}^{n}\Delta_i^2$,

Table 2

Relationship between Regular Season Winning and Aggregated Measures: Fixed Effects Estimation

Dependent Variable: WP^R_{it}					
Independent Variables	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Constant	-0.2100 (-1.23)	-1.0139 (-5.36)	-0.6126 (-1.85)	-0.5643 (-1.71)	-0.5280 (-1.59)
ES^R	0.00008 (4.17)				
M_1^R		0.00026 (8.00)			
M_2^R			0.00013 (3.37)		
M_3^R				0.00011 (3.23)	
M_4^R					0.00012 (3.10)
Adjusted R^2	0.66	0.71	0.61	0.61	0.60
Note: The number in parenthesis below the estimated coefficients are t-statistics and are obtained using the Beck and Katz (1995) heteroskedasticity-adjusted standard errors (PCSE).					

where Δ_i represent the difference between the value of the aggregated measure and the actual point spread for a given playoff game i. M_2^P is the best predictor of the playoffs results, as it minimizes the sum of the difference between the value of the aggregated measure and the actual point spread for a given playoff game both in terms of absolute deviations and in terms of squared deviations. Interestingly, however, the efficiency score turns out to be a very poor predictor of the outcomes of the playoffs games.

The LLC as well as the IPS panel unit root tests reject the null hypothesis of unit root for each of the four aggregated measures as well as for the efficiency score computed based on NBA formula for both the regular season and the playoffs. The LLC tests also rejects the null hypothesis of unit root for WP for regular season, but this result is not confirmed by the IPS test. Table 2 presents the results of the fixed effects estimation of the relationship between the regular season winning percentage and aggregated measures of performance. Although all the aggregated measures, including ES^R, have a significant impact on WP^R, the statistical findings clearly indicate that M_1^R has more explanatory power than the remaining measures. As shown in Table 2, M_1^R explains approximately 71 percent of the variability of WP^R, based on the adjusted R^2, compared to approximately 66 percent for ES^R, 61 percent for M_2^R, M_3^R and 60 percent for M_4^R. Because of the possibility that WP^R contains a unit root, the fixed effects regressions were repeated using first differences. The findings do not alter the results based on the fixed effects regression results presented in Table 2 and confirm the superiority of the M_1^R measure in predicting the winning percentage for a franchise during the regular season.

Similar regression analysis for the playoff games confirmed the superiority of M_2^P in predicting the point spread (PS) for playoff games as shown in Table 3.

Table 3

Relationship between Playoff Games Point Spread and Aggregated Measures Fixed Effects Estimation

Dependent Variable: PS_{it}					
Constant	0.6743 (2.22)	0.4772 (1.24)	0.5632 (1.83)	0.0606 (0.15)	0.3269 (0.84)
ES^P	0.4163 (38.89)				
M_1^P		0.8348 (30.83)			
M_2^P			1.1003 (37.43)		
M_3^P				1.0478 (29.15)	
M_4^P					1.1180 (29.10)
Adjusted R^2	0.90	0.85	0.90	0.84.	0.85

Note: The numbers in parenthesis below the estimated coefficients are t-statistics, computed based upon the Beck and Katz (1995) heteroskedasticity-adjusted standard errors (PCSE).

V. Conclusions and Final Remarks

Aggregated operational measures can be helpful in implementing "continuous improvement strategies" by avoiding entirely piecemeal considerations. Likewise, an effective application of tools such as "activity-based management" may become more likely when the impact of aggregated measures is taken into account in the decision-making process. The results of this study indicate that, in line with Fichman (2001) analysis, the aggregation of game statistics provides a more parsimonious measure, which is as informative as disaggregated and detailed input measures. In aggregated measures, the effect of a particular piece of information is smoothed across large number of data points. Similarly, the impact of measurement noise, e.g., referees' error in judgment, and random events such as players' injuries, etc., is diluted.

This study also indicates that the aggregation of statistics measuring identical attributes of performance enhances the decision usefulness of measures. At the same time, the findings of this study show that aggregating game performance data that are complementary in nature have no substantive effect on the measurement results. This confirms Fichman's analysis (Fichman 2001) on aggregation across complementary measures.

Research analyses provide insight into use of knowledge with various perspectives. Gold et al. (2001) suggested insights into content (knowledge domain), use and impact of knowledge on individuals (decision making), creation, memory, use of knowledge within a firm (organizational), and exchange between individuals and organizations (market). In producing a meaningful measure, one must also be aware of the decision perspective, focus, and objective. It is conceivable that constructing aggregated measures may require subjective weighting of various components to increase the decision usefulness and predictive ability of the aggregate. Although this study underscores the use of knowledge from a decision-making perspective, the organizational and market perspectives are also very closely related frameworks for a study of aggregated measures. The use of aggregated operational measures represents a useful approach in understanding the significance of a variety of qualitative attributes of products or services. The effective deployment of this methodology, however, is not without risk, as it requires a careful consideration of the relevance and the reliability of such measures. As emphasized by Fichman (2001), however, aggregation produces measures that are less susceptible to the sources of noise, and, "to that extent these sources of noise are expected to be present and cannot be feasibly eradicated by other means, this should resolve the tradeoffs related to robustness of measurement and predictive validity in favor of greater aggregation." (p. 435)

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