# REGRESSION AND CONTEXT:
## Contextual Analysis, Interpretation, and Limitations



The purpose of this section is to see how well, and in what ways, HLM addresses concerns about contextual analysis previously raised by Bob Hauser in the early 1970s.[1] I concentrate here not on longitudinal data, but rather on clustered data. I will focus the discussion on datasets where residents are clustered within a neighborhood, or within a streetblock. I think the same points may apply, with some variations, similarly for individuals within an institution, or agencies clustered within a broader context, such as different police departments in different states. The discussion is further focused in that the contextual predictors considered come from aggregated, individual-level predictors. The aggregated measures are intended to reflect normative properties of the group or setting in question

The structure of the section is as follows. First I review five criticisms made by Bob Hauser some time ago, of contextual analysis.[2] Then I consider how these concerns may apply to HLM. In what ways does HLM help us with these concerns, or provide additional information, or reframe the consequences emerging from these concerns? Then, I will illustrate some results comparing results using the two different approaches.

### Stating the Five Concerns

Bob Hauser in two papers in the 1970s raised five concerns about contextual analysis. These concerns blended theoretical and analytical concerns. Subsequent statements on contextual analysis, such as Boyd and Iversen's 1979 book, have not provided clear resolutions for these concerns.

Hauser's concerns focus specifically on a particular variety of contextual analysis: situations where a individual level predictor is aggregated to the group level, and then used as a contextual predictor of an outcome. So he is focusing specifically on compositional variables. He indicated the first and last of the concerns were most important.

#### Problem 1: Meaning

The first concern is with interpreting the effects. "Contextual effects are partial 'ecological' correlations or regressions" (Hauser, 1974, 366). Their interpretation is difficult for two reasons. First, there are "inherent problems in defining constructs as residuals" (Hauser, 1974, p. 367, citing Blalock, 1968). In other words, the group effect is defined as impacts occurring after individual level impacts have occurred; the predictor has been partialled. Second, "contextual analysis depends on the identification of residually measured group effects with normative environments which are in turn characterized by group composition" (Hauser, 1974, 367). In other words, the partialled aggregate variable is intended to closely correspond to a specific feature of the group setting.

Related to this latter point is the amount of variance associated with this aggregated variable. Is the variance substantial enough to "warrant identification of the normative environment with group composition." (Hauser, 1974, 367). If there are other variables showing similar or greater segregation across groups, should they be used as the group indicator?

So in short, two related problems arise: using a partialled variable to represent a construct, and linking the partialled variable with a feature of the group context. The researcher may be committing the **contextual fallacy** which arises when "residual differences among a set of social groups, which remain after the effects of one or more individual attributes have been partialled out, are interpreted in terms of social or psychological mechanisms correlated with group levels of one of the individual attributes" (Hauser 1970, 659). In short, the effect is being unwarrantedly attributed to context rather than residual variation in individual differences, which so happens to differ somewhat from group to group.

Problem 2: Size of effects

Hauser, although recognizing that numerous policy, theoretical, and study-related factors influence whether an effect is worthy of attention, suggests that often contextual effects can be trivial. Hauser argues forcefully that the only rationale for retaining a contextual, compositional variable, in contrast to the arguments put forth by Farkas, is that it substantially influences the outcome, after controlling for relevant individual impacts, **and** that the variable has an "unambiguous and distinctively sociological interpretation" (Hauser, 1974, 369). He rejects arguments to retain it for reasons of statistical control; if there is no interest in group dynamics, the regression should be run solely on pooled, within-group covariances.

Problem 3: Omitted Variables

This caution against mis-specification is familiar to many. The point here is that if the researcher omits individual-level variables that are a) correlated with the group level variable and b) relevant to a complete, individual-level model, then the contextual impact for the compositional variable will be overstated. In short, the "theory of relations among individual attributes [should be] complete and correct, or at least defensible in relation to some explicit criterion, before speculating about residual group differences" (Hauser 1970, 659). Presumably, to test for this problem one would add additional theoretically relevant individual-level variables to learn if they dilute the impact of the context variable, or at least be prepared to argue the theoretical completeness of the individual-level model.

Problem 4: Measurement error

The problem here is that random measurement error, will, under certain conditions, cause the contextual variable to have a stronger impact, and the individual level variable to have a weaker impact. This can occur when the individual and contextual variable have coefficients with the same sign. In short, all else equal, when the above condition is met, and measurement errors are random, the more poorly measured variable will have stronger contextual impacts.

Problem 5: Selection on the dependent variable

"The membership of social organizations is typically subject to processes of social selection in recruitment and in attrition which partly determine the character of the members" (Hauser 1970 374-375). Therefore, a contextual impact may appear that describes not impact of group context, but rather selection and attrition processes leading people into and out of certain groups. In the case of neighborhood-clustered data, selection and selective attrition are undoubtedly occurring, although the selection pressures are probably not as strong as found in formal institutions or formal organizations.

A Brief Overview of the Relevant HLM Models

The HLM model contains several submodels, in addition to the "full" model with intercepts and slopes as outcomes. For discussion purposes here, we are interested in some submodels including: the one-way ANOVA with random effects, the intercepts and slopes-as-outcomes model, and the latter, but with fixed, Level I slopes.

## Looking at HLM in Context of Hauser's Concerns

### Problem 1: Meaning

HLM does not directly address how the researcher should establish the construct validity of his/her compositional variable. However, by explicitly offering the researcher the option of group-mean centering Level I predictors, the researcher can separate the Level II group predictor from its Level I counterpart. This presumes that a group mean centered Level I predictor makes sense theoretically for the researcher. The modeling process encourages the researcher to think about the different theoretical implications of group level vs. group-mean-adjusted individual level indicators,

HLM does not solve, however, the problem identified by Hauser, of being sure the compositional variable corresponds to an important feature of the normative group context. Avoiding the contextual fallacy requires careful theory and variable selection, and is not a problem "solved" by HLM.

### Problem 2: Size of Effects

HLM provides significant help in dealing with the size of effects, in two ways.

First, if a oneway ANOVA is conducted, the researcher learns if the group-level variation in the outcome, after correcting for data quality, is significantly larger than zero, and hos much it actually is. If it is not significantly greater than zero, then there is no point in the researcher seeking to identify contextual effects. If the Level II variance **is** significantly larger than zero, that does not necessarily mean the identified variance will be practically sizable, nor does it mean that a compositional variable is warranted, or that the specific one chosen by the researcher is the correct one. But at least HLM tells us when it makes no sense, after correcting for data quality, to attempt construction of contextual models.

In addition, HLM helps in a second way because it tells us when we need no more contextual variables. After we have entered Level II predictors, or even un-centerd Level I predictors, we can see if any significant variation in estimated group scores remains to be explained, or if the remaining variance is indistinguishable from zero.

### Problem 3: Omitted Variables

HLM provides significant advantages in dealing with this concern because it separates Level I and Level II variance "at the front end" of the modeling process. As long as all Level I predictors are group mean centered, so that they focus solely on within-group variation, and this is theoretically meaningful, contextual predictors do not rate a better or worse chance of significance depending on the inclusion or exclusion of specific Level I predictors. If Level I predictors are not group-mean centered, then the same possibilities for inappropriately mis-identifying context effects still remain. One additional diagnostic feature provided by HLM that may be helpful here is contrasting residual, Level II variance in a oneway ANOVA with residual, Level II variance in an ANCOVA model with a grand-mean centered predictor. Comparing the two T00s indicate how much of the Level I predictor is operating at Level II.

Nevertheless, in these types of models Hauser's suggestion remains helpful; one still wants to test impacts of the contextual variables under different sets of Level I predictors, if the Level I predictors are not group-mean centered.

### Problem 4: Random Measurement Error in Predictor

Hauser's suggestion still applies when using HLM -- in HLM increased random error in the predictor will weaken the Level I coefficient and strengthen the Level II coefficient, all else equal. But I think additional consequences follows as well in HLM.

In the full HLM model, with intercepts and slopes as outcomes regression, slopes of Level I coefficients are allowed to vary across groups, and then Level II predictors are used to predict those variations in slopes. The variance in these Level I slopes is captured in T11. As measurement error increases with a predictor variable, and Level I coefficients are thereby attenuated, the weaker slopes will result in smaller estimates of T11. The researcher can test the significance of the variance associated with these slopes, using a chi square test. The increased measurement error will make it more difficult for the researcher to reject the null hypothesis that the variance in the slopes is zero. Finally, the weaker Level I slopes will make it more difficult to find significant Level II predictors of those varying slopes.

Empirical Bayes estimates of slopes are shrunken considerably from the observed OLS coefficients anyway. Increased measurement error will contribute further to that shrinkage at Level I, make it more difficult to find significant variation, and make it more difficult to find significant Level II predictors of those varying slopes.

Problem 5: Selection on the Dependent Variable

If group membership results completely from selection and/or attrition processes on the dependent variable, and the dependent variable is not influenced by any causal factors separate from these processes, and you collect your data at a time when these processes have completed their cycles on all members of all groups, then in every group everyone would score equally on the outcome, and there would be no variance around each group's mean. Everyone has migrated into the group that perfectly matches their score on Y, and/or been expelled from the group that does not match their score on Y.

On the other hand, if there were no selection and/or attrition processes operating, and no causal determinants of Y apart from these processes, there would be no agreement among group members on Y, every group mean would be at the grand mean, and the variance in each group on Y, assuming equal group sizes, would be equal. Obviously, these conditions do not occur in actual settings.

But HLM does provide a diagnostic, in terms of reliability and the related intraclass correlation, that provides at least indirect evidence on this concern.

HLM provides us with a reliability estimate of the group means. These tell us how well the observed group means on Y approximate the "true" scores on Y. Reliability also can be examined after predictors have been entered in the model. If, after all the theoretically relevant predictors have been entered into the model, and you have good reason to think that your model is theoretically the strongest one and is accepted as relatively complete, and the **conditional** reliability of the group means remains sizable, it suggests that some unknown selection and/or attrition processes, unrelated to the variables already entered into the model, are responsible for some amount of "selection" or "attrition" on Y. If these processes are related to the contextual variable you wish to use, conditional reliability should drop markedly after that predictor has been entered.

## The High School and Beyond Data Set

In their book Bryk and Raudenbush refer extensively to examples from the HSB data set. These data also are provided with the program. The HSB file represents a representative sample of 160 public and Catholic high schools, nationwide, completed in the early 1980s (R&B, p. 68). There is a level 1 or individual data file (HSB1.SAV), and a level 2 or school level data file

(HSB2.SAV). Information on the variables follows. I suggest you copy these SPSS data files

Of course, you would want to spend some time in each file looking at univariate and bivariate descriptive statistics and graphical data displays to begin to get a feel for these data.

See 012001.sps (SYNTAX FILE) for some examples)

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```
 List of variables on the working file: HSB1

Name                                                                Position

ID$       SCHOOLID                                                         1
          Print Format: A5

MINORITY  STUDENT ETHNICITY                                                2
          Value    Label
              0    0THER
              1    MINORITY

FEMALE    STUDENT GENDER                                                   3
          Value    Label
              0    MALE
              1    FEMALE

SES       STUDENT SES INDEX                                                4

MATHACH   MATH ACHIEVEMENT                                                 5

================================================================================

            List of variables on the working file: HSB2

Name                                                                Position
ID$        SCHOOL ID CODE                                                  1
          Print Format: A5
          Write Format: A5

SIZE      SCHOOL ENROLLMENT                                                2

SECTOR    CATHOLIC DUMMY                                                   3
          Value    Label
              0    PUBLIC
              1    CATHOLIC

PRACAD    PROPORTION IN ACADEMIC TRACK                                     4

DISCLIM   DISCIPLINARY CLIMATE                                             5

HIMNTY    HIGH MINORITY ENROLLMENT                                         6
          Value    Label
```

.000 LESS THAN 40%
1.000 MORE THAN 40%

MEANSES MEAN SES OF STUDENTS IN L1 FILE 7

## Correlations

If we were to put both these files together, we would have a number of individual variables, and a number of level 2 variables. In regression terminology, we would call the level 2 variables contextual predictors. The correlation matrix includes correlations between individual level variables, between school level variables, and cross-level correlations; the latter represent connections between individuals and contexts.

- - Correlation Coefficients - -

| | HIMNTY | MEANSES | DISCLIM | PRACAD | SECTOR | MINORITY |
|---|---|---|---|---|---|---|
| HIMNTY | 1.0000 | -.3987** | .0211 | -.0618** | .0545** | .5814** |
| MEANSES | -.3987** | 1.0000 | -.3583** | .6373** | .3573** | -.3167** |
| DISCLIM | .0211 | -.3583** | 1.0000 | -.6260** | -.7204** | .0225 |
| PRACAD | -.0618** | .6373** | -.6260** | 1.0000 | .6811** | -.0551** |
| SECTOR | .0545** | .3573** | -.7204** | .6811** | 1.0000 | .0496** |
| MINORITY | .5814** | -.3167** | .0225 | -.0551** | .0496** | 1.0000 |
| SES | -.2115** | .5306** | -.1901** | .3382** | .1896** | -.2715** |
| SIZE | .1209** | -.1268** | .3403** | -.3253** | -.4237** | .0794** |
| FEMALE | .0436** | -.0589** | -.0906** | -.0492** | .0065 | .0140 |
| MATHACH | -.1731** | .3437** | -.2051** | .2921** | .2040** | -.2680** |

| | SES | SIZE | FEMALE | MATHACH |
|---|---|---|---|---|
| HIMNTY | -.2115** | .1209** | .0436** | -.1731** |
| MEANSES | .5306** | -.1268** | -.0589** | .3437** |
| DISCLIM | -.1901** | .3403** | -.0906** | -.2051** |
| PRACAD | .3382** | -.3253** | -.0492** | .2921** |
| SECTOR | .1896** | -.4237** | .0065 | .2040** |
| MINORITY | -.2715** | .0794** | .0140 | -.2680** |
| SES | 1.0000 | -.0673** | -.0679** | .3608** |
| SIZE | -.0673** | 1.0000 | -.0388** | -.0506** |
| FEMALE | -.0679** | -.0388** | 1.0000 | -.1231** |
| MATHACH | .3608** | -.0506** | -.1231** | 1.0000 |

* - Signif. LE .05 ** - Signif. LE .01 (2-tailed)

**QUESTIONS**

What is the connection between student ses and school ses? Between individual and school race? What contextual factors look relevant to the math achievement outcome?

Summary of regression models appearing below C=contextual predictor; outcome= math achievement

REGRESSION 1
FEMALE
MINORITY
SES

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```
REGRESSION 2
FEMALE
MINORITY
SES
MEANSES (C)

REGRESSION 3
FEMALE
MINORITY
SES
MEANSES    (C)
HIMNTY     (C)

REGRESSION 4
MEANSES      (C)
HIMNTY       (C)
FEMALE
SES

REGRESSION 5
MEANSES    (C)
MINORITY
FEMALE
```

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## An Individual-Level Regression

We can start our exploration of mathach using just individual level predictors. The results appear below.

```
      Equation Number 1    Dependent Variable..   MATHACH   MATH ACHIEVEMENT
Block Number  1.  Method:  Enter      FEMALE   MINORITY SES
Multiple R           .41390
R Square             .17131
Adjusted R Square    .17097
Standard Error      6.26273
Analysis of Variance
                    DF      Sum of Squares      Mean Square
Regression           3         58225.34687      19408.44896
Residual          7181        281651.58781         39.22178
F =     494.83858       Signif F =  .0000
------------------ Variables in the Equation ------------------
Variable              B        SE B       Beta         T  Sig T
FEMALE        -1.376645     .148347   -.099920    -9.280  .0000
MINORITY      -2.836513     .171976   -.184096   -16.494  .0000
SES            2.682990     .098726    .304002    27.176  .0000
(Constant)    14.253890     .117752              121.050  .0000
```

**QUESTIONS**

Interpret b weight and t ratio of each predictor
Interpret r squared
Interpret F test
Interpret t test of each variable
What null hypotheses have we rejected?

## A Comment on the Assumptions of Regression

What assumptions of OLS regression are being violated by the above regression?

3 assumptions about residuals:
- identical distributions at different values of x
- independent: unrelated to x or errors of other cases
- normally distributed

How about the assumption that each observation is sampled independently of each other observation?

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## Adding a Contextual Predictor

Now let=s add a contextual predictor; meanses of the school, based on the students sampled. The results appear below. We also include some collinearity diagnostics, including VIF, to be sure we are not creating severe multicollinearity problems.

```
Dependent Variable..   MATHACH   MATH ACHIEVEMENT
Block Number  1.  Method:  Enter      FEMALE   MINORITY SES      MEANSES
Multiple R           .43783
R Square             .19169
Adjusted R Square    .19124
Standard Error      6.18567
Analysis of Variance
                    DF      Sum of Squares      Mean Square
Regression           4         65152.47281      16288.11820
Residual          7180        274724.46187         38.26246
F =     425.69449       Signif F =  .0000
------------------------- Variables in the Equation -------------------------
Variable              B         SE B       Beta  Tolerance        VIF          T
FEMALE        -1.320010     .146582   -.095810    .994554      1.005     -9.005
MINORITY      -2.340960     .173807   -.151934    .884701      1.130    -13.469
SES            1.955114     .111511    .221529    .705176      1.418     17.533
MEANSES        2.867486     .213114    .172407    .685678      1.458     13.455
(Constant)    14.070331     .117100                                      120.156

Collinearity Diagnostics
Number  Eigenval     Cond  Variance Proportions
                    Index  Constant    FEMALE MINORITY      SES  MEANSES
    1    2.17438    1.000    .05770    .06333   .08252   .01689   .01632
    2    1.54656    1.186    .02514    .02356   .00232   .18303   .18405
    3     .57355    1.947    .00659    .21047   .68565   .14728   .00040
    4     .46365    2.166    .00001    .02007   .04441   .64486   .77487
    5     .24187    2.998    .91056    .68258   .18510   .00794   .02436
```

**QUESTIONS**

How much has R squared changed? How are we to interpret that?
What happened to the standard error of ses?

VIF is defined as [1/(1 - r squared)] where r squared is how much of **that** predictor is predictable from the other predictors; it is the reciprocal of tolerance (proportion of predictor that is unique). When we are close to 1 - 1.5 we are ok; when it gets above 1.5 or 2 or so there may be problems.

The **condition index** shows us if the matrix of predictors is ill conditioned. A matrix is ill-conditioned if some of Athe eigenvalues of the scaled, uncentered cross-products matrix .. Are much larger than others@ (SPSS base manual, 6.0, 356). It suggests that some predictors verge on being dependent on -- easily predicted by -- others. Basically you look for really small eigenvalues and really large indexes. Note that the next to last eigenvalue accounts for 65% of SES and about 78% of MEANSES. This suggests these two variables are somewhat dependent upon each other.

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Adding Another Contextual Predictor

Now we add racial composition of the school, using the HIMINTY dummy variable. Results appear below.

```
Dependent Variable..   MATHACH   MATH ACHIEVEMENT
Block Number  1.  Method:  Enter
   FEMALE   MINORITY SES      MEANSES  HIMNTY
Multiple R           .44013
R Square             .19372
Adjusted R Square    .19316
Standard Error      6.17835
Analysis of Variance
                    DF      Sum of Squares      Mean Square
Regression           5         65840.24891      13168.04978
Residual          7179        274036.68577         38.17199
F =     344.96633       Signif F =  .0000
------------------------ Variables in the Equation -------------------------
```

| Variable | B | SE B | Beta | Tolerance | VIF | T |
|---|---|---|---|---|---|---|
| FEMALE | -1.340245 | .146486 | -.097278 | .993501 | 1.007 | -9.149 |
| MINORITY | -2.799042 | .204410 | -.181664 | .638112 | 1.567 | -13.693 |
| SES | 1.916672 | .111747 | .217173 | .700544 | 1.427 | 17.152 |
| MEANSES | 3.130947 | .221726 | .188248 | .631948 | 1.582 | 14.121 |
| HIMNTY | .884905 | .208471 | .057771 | .606331 | 1.649 | 4.245 |
| (Constant) | 13.957462 | .119946 | | | | 116.364 |

Collinearity Diagnostics

| Number | Eigenval | Cond Index | Variance Proportions Constant | FEMALE | MINORITY | SES | MEANSES | HIMNTY |
|---|---|---|---|---|---|---|---|---|
| 1 | 2.76135 | 1.000 | .03007 | .03154 | .04111 | .00983 | .01215 | .03987 |
| 2 | 1.55098 | 1.334 | .03046 | .03141 | .00055 | .16773 | .16004 | .00058 |
| 3 | .69757 | 1.990 | .02929 | .21222 | .13080 | .21475 | .00130 | .13544 |
| 4 | .46984 | 2.424 | .00001 | .04557 | .14216 | .49154 | .63121 | .01015 |
| 5 | .28011 | 3.140 | .00008 | .00929 | .64521 | .11537 | .14163 | .77136 |
| 6 | .24014 | 3.391 | .91010 | .66997 | .04016 | .00078 | .05367 | .04260 |

**QUESTIONS**

Interpret each b weight. Each beta weight.
Comment on the change in r squared. What does this mean?
How do we interpret the contextual race predictor? (Remember it is a dummy variable) Compare the b (**not beta)** weight to the 0-order correlation; what is happening here?
What has happened to VIF? The condition index?
How do you interpret the tolerance of HIMINTY?

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## Taking out Individual Race

Suppose we decide we want to get a clearer view of the impact of racial context. So we drop out individual race, and just use the contextual race predictor. The results appear below.

```
Dependent Variable..   MATHACH   MATH ACHIEVEMENT
Block Number  1.  Method:  Enter      MEANSES  HIMNTY   FEMALE   SES
Variable(s) Entered on Step Number  1..    SES       STUDENT SES INDEX
                                    2..    FEMALE    STUDENT GENDER
                                    3..    HIMNTY    HIGH MINORITY ENROLLMENT
                                    4..    MEANSES   MEAN SES OF STUDENTS IN L1 FILE
Multiple R           .41552          Analysis of Variance
R Square             .17266                              DF      Sum of Squares      Mean
Square
Adjusted R Square    .17220          Regression           4         58682.81591
14670.70398
Standard Error      6.25808          Residual          7180        281194.11877
39.16353

                                     F =     374.60120       Signif F =  .0000
```

---------------------------- Variables in the Equation ----------------------------

| Variable | B | SE B | Beta | Tolerance | VIF | T | Sig T |
|---|---|---|---|---|---|---|---|
| MEANSES | 3.206792 | .224517 | .192808 | .632342 | 1.581 | 14.283 | .0000 |
| HIMNTY | -.622189 | .179335 | -.040619 | .840638 | 1.190 | -3.469 | .0005 |
| FEMALE | -1.287715 | .148325 | -.093465 | .994182 | 1.006 | -8.682 | .0000 |
| SES | 2.149144 | .111875 | .243514 | .717096 | 1.395 | 19.210 | .0000 |
| (Constant) | 13.582240 | .118281 | | | | 114.830 | .0000 |

Collinearity Diagnostics

| Number | Eigenval | Cond Index | Variance Proportions Constant | MEANSES | HIMNTY | FEMALE | SES |
|---|---|---|---|---|---|---|---|
| 1 | 2.19467 | 1.000 | .05612 | .01775 | .07887 | .06232 | .01461 |
| 2 | 1.54717 | 1.191 | .02594 | .17085 | .00215 | .02416 | .18247 |
| 3 | .60731 | 1.901 | .01023 | .05441 | .44191 | .13118 | .37610 |
| 4 | .40888 | 2.317 | .00279 | .67524 | .26962 | .15551 | .42556 |
| 5 | .24197 | 3.012 | .90492 | .08175 | .20745 | .62683 | .0012 |

Notice how the above results contrast with a regression containing only the individual race predictor

**QUESTIONS**

Interpret the b weight for himinty (remember it is a dummy variable).

---

## Swap out Individual SES, Put in Individual Race

Now let’s put individual race back in, but take out individual SES. The argument here might be that we are interested in school SES, but the effects of BOTH school and individual race.

```
Dependent Variable..   MATHACH   MATH ACHIEVEMENT
Method:  Enter      MEANSES  MINORITY FEMALE
Multiple R           .39634
R Square             .15709
Adjusted R Square    .15674
Standard Error      6.31625
```

F = 446.09149 Signif F = .0000

------------------ Variables in the Equation ------------------

| Variable | B | SE B | Beta | T | Sig T |
|---|---|---|---|---|---|
| MEANSES | 4.680129 | .190291 | .281392 | 24.595 | .0000 |
| MINORITY | -2.733856 | .175995 | -.177433 | -15.534 | .0000 |
| FEMALE | -1.433747 | .149530 | -.104065 | -9.588 | .0000 |
| (Constant) | 14.227503 | .119222 | | 119.337 | .0000 |

**QUESTIONS**

- What has happened to the b weight for meanses? How different is it now? What are we to conclude?

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[1] Hauser, P. M. 1970. "Context and consex." *American Journal of Sociology*:645-664.
Hauser, P.M. 1974. "Contextual analysis revisited." *Sociological Methods and Research* 2:365-375.

[2] Boyd, L. H., and G. R. Iversen. 1979. *Contextual analysis: Concepts and statistical techniques*. Wadsworth.