SOS3003
Applied data analysis for social science
Lecture note 03-2009

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Today

Lecture

- Hamilton, Lawrence C. 2008. A Low-Tech Guide to Causal Modelling. http://pubpages.unh.edu/~lch/causal2.pdf
- Principal components and factor analysis
  - Hamilton Ch 8 p249-282
- Also see:

  Winship, Chrisopher, and Stephen L. Morgan 1999 "The Estimation of Causal Effects from Observational Data", Annual Review of Sociology Vol 25: 659-707

Causal analysis

- Experiment
  - Randomized causal impacts (”treatment”) provide precise causal conclusions about effects (”response”) if there is significant differences in means
  - This can be impossible to achieve due to
    - Practical conditions
    - Economic constraints
    - Ethical judgements
- Instead one tries to obtain quasi-experiments
  - Using for example regression analysis

Model of causal effects Ref.:

- Research using observations utilize concepts from experimental design
  - “Treatment”, “Stimulus”
  - “Effect”, “Outcome”

Ref.:
Winship, Chrisopher, and Stephen L. Morgan 1999 “The Estimation of Causal Effects from Observational Data”, Annual Review of Sociology Vol 25: 659-707

Experiments allocate ”cases” randomly to one of two groups:

- **TREATMENT (T)**
  with observation
  - before treatment
  - after treatment
- **CONTROLL (C)**
  with observation
  - before non-treatment
  - after non-treatment

The counterfactual hypothesis for the study of causality

- Individual “i” can a priori be assumed selected for one of two groups
  - Treatment group, T, or control group, C.
- Treatment, t, as well as non-treatment, c, can a priori be given to individuals both in the T- and C-group
- In reality we are able to observe t only in the T-group and c in the C-group

Modelling of causal effects:
The counterfactual hypothesis (1)

- There are for each individual ”i” four possible outcomes
  - **Y_i(c,C)** or Y_i(t,C); if allocated to a control group
  - Y_i(c,T) or **Y_i(t,T)** ; if allocated to a treatment group

  - Only **Y_i(c, given that ”i” is a member of C)** or
  - **Y_i(t, given that ”i” is a member of T)** can be observed for any particular individual

Modelling of causal effects:
The counterfactual hypothesis (2)

More formally one may write the possible outcomes for person no i:

	Treatment: t	Non-treat.: c
T-group	$\mathbf{Y^t_i \in T}$	$Y^c_i \in T$
C-group	$Y^t_i \in C$	$\mathbf{Y^c_i \in C}$

Modelling of causal effects:
The counterfactual hypothesis (3)

- Then the causal effect for individual i is
- $\delta_i = Y_i\,(t) - Y_i\,(c)$
- Only one of these two quantities can be observed for any given individual
- This leads to the "counterfactual hypothesis"

The counterfactual hypothesis: concluding

- "The main value of this counterfactual framework is that causal inference can be summarized by a single question: Given that the δ_i cannot be calculated for any individual and therefore that Y^t_i and Y^c_i can be observed only on mutually exclusive subsets of the population, what can be inferred about the distribution of the δ_i from an analysis of Y_i and T_i ?" (Winship and Morgan 1999:664)

Modelling of causal effects: from individual effects to population averages

- We can observe
  Y_i (c |i∈C), but not Y_i (t |i∈C)

- The problem may be called a problem of missing data
- Instead of individual effects we can estimate average effects for the total population

Modelling of causal effects (1)

- Average effects can be estimated, but usually it involves difficulties
- One assumption is that the effect of the treatment will be the same for any given individual independent of which group the individual is allocated to
- This, however, is not self-evident

Modelling of causal effects (2)

The counterfactual hypothesis assumes:

- That changing the treatment group for one individual do not affect the outcome of other individuals (no interaction)
- That treatment in reality can be manipulated (e.g. sex can not be manipulated)

Modelling of causal effects (3)

- One problem is that in a sample the process of allocating person no i to a control or treatment group may affect the estimated average effect (the problem of selection)
- In some cases, however, the interesting quantity is <u>the average effect for those who actually receive the treatment</u>

Modelling of causal effects (4)

- It can be shown that there are two sources of bias for the estimates of the average effect

1. An established difference between the C- and T- groups
2. The treatment works in principle differently for those allocated to the T-group compared to those in the C-group
   - To counteract this one has to develop models of how people get into C- and T-groups (selection models)

Modelling of causal effects (5)

- A general class of methods that may be used to estimate causal effects are the regression models
- These are able to "control for" observable differences between the C- and T- groups, but not for unequal response to treatment

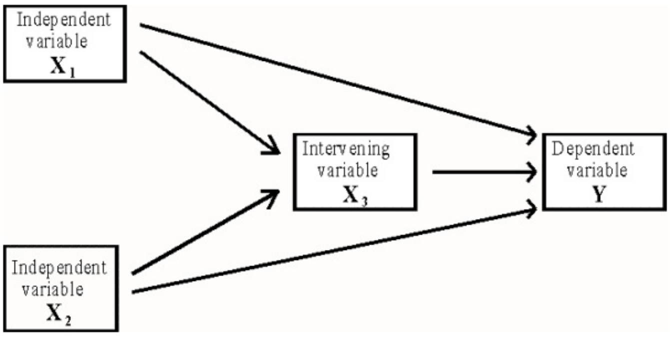
Causal modelling

- “path analysis” or “structural equations modelling” go back to the 60ies
- Jöerskog and Sörbom: LISREL
  - Use maximum likelihood to estimate model parameters maximising fit to the variance-covariance matrix
  - Commonly available in statistical packages
    - Covariance structural modelling
    - Structural equation modelling
    - Full information maximum likelihood estimation

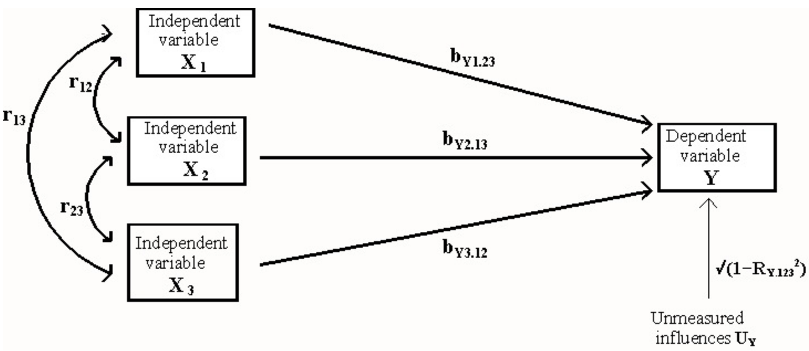
Low-Tech approach

- Uses OLS to do simple versions of the structural equations models
- The key assumption is the causal ordering of variables. In survey data this ordering is supplied by theory
- The causal diagram visualize the order of causation:
  - Causality flows from left to right
  - Intervening variables give rise to indirect effects
  - “reverse causation” creates problems

Low-Tech causal modelling
Figure 1



Multiple regression as a causal model
Figure 2



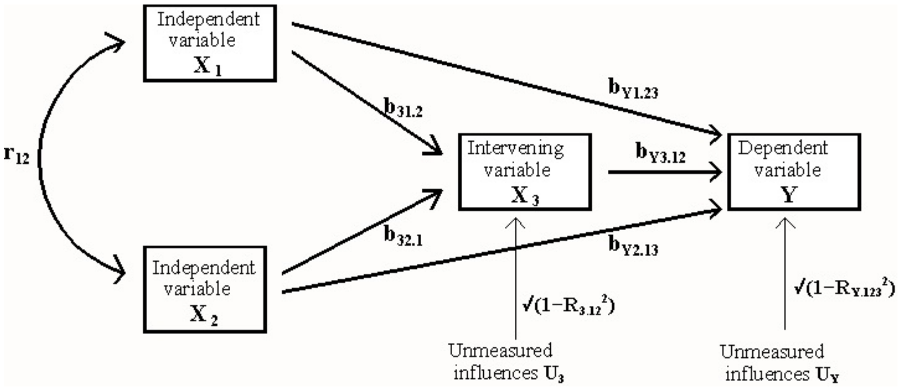
Quantities in the diagram

r_{12}, r_{13}, r_{23}	Pearson correlations among x-variables
$b_{Y1.23}$, etc.	Usually a standardized regression coefficient (“beta weight”) taken from the regression of Y on X_1, and “.” means controlled for X_2, X_3
$R_{Y.123}^2$	Coefficient of determination R^2 from the regression of Y on X_1, X_2, X_3
$\sqrt{\{1-R_{Y.123}^2\}}$	Is an estimate of unmeasured influences called error term or disturbance

Multiple regression

- All assumptions and all problems apply as before
  - Note in particular that error terms must be uncorrelated with included x-variables (no relevant variable has been omitted)
- If some of the X-es are intervening in figure 2 the model is too simple, but it matters only if we are interested in causality

Path coefficients
Figure 3



New elements in figure 3

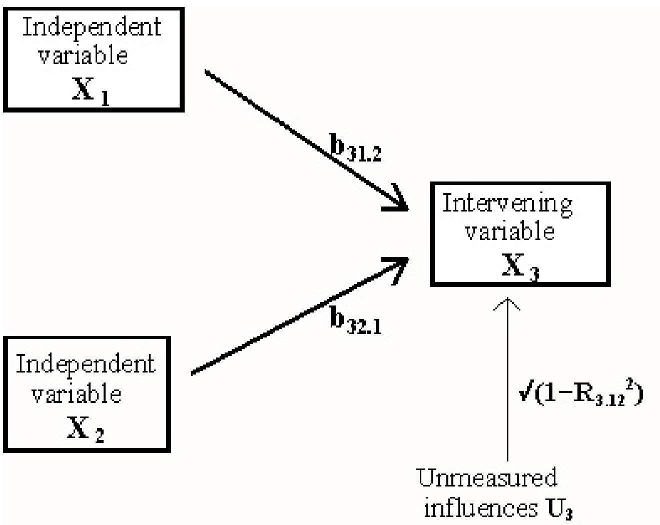
$b_{31.2}$, $b_{32.1}$	Standardized regression coefficients ("beta weight") from the regression of X_3 on X_1 controlled for X_2 and from the regression of X_3 on X_2 controlled for X_1
$R_{3.12}^2$	Coefficient of determination (R^2) from the regression of X_3 on X_1 and X_2
$\sqrt{\{1-R_{3.12}^2\}}$	The error term from the regression of X_3 on X_1 and X_2

The structural model of figure 3

- $\hat{Y} = b_{Y1.23}X_1 + b_{Y2.13}X_2 + b_{Y3.12}X_3$
- $\hat{X}_3 = b_{31.2}X_1 + b_{32.1}X_2$

- In structural equations variables and coefficients are standardized
- That means that variables have an average of 0 and a standard deviation of 1 and that coefficients vary between -1 and +1

Figure 5: the regression of X_3 on X_1 and X_2



Direct, Indirect and Total Effects

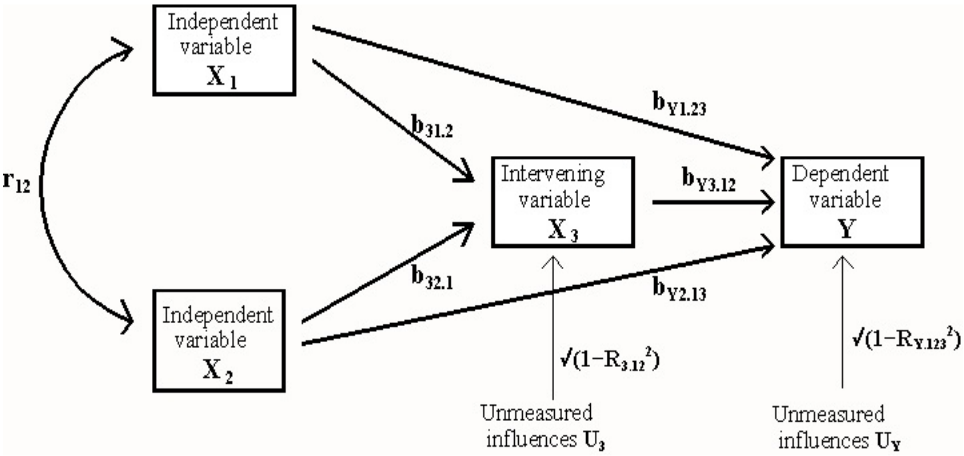
- *Indirect effects* equal the product of coefficients along any series of causal paths that link one variable to another
- *Total effects* equal the sum of all direct and indirect effects linking two variables

Indirect effects as products of path coefficients

- $\hat{Y} = b_{Y1.23}X_1 + b_{Y2.13}X_2 + b_{Y3.12}X_3$
- $\hat{X}_3 = b_{31.2}X_1 + b_{32.1}X_2$
- Means that we have
- $\hat{Y} = b_{Y1.23}X_1 + b_{Y2.13}X_2 + b_{Y3.12}X_3$
- $= b_{Y1.23}X_1 + b_{Y2.13}X_2 + b_{Y3.12}(b_{31.2}X_1 + b_{32.1}X_2)$
- $= b_{Y1.23}X_1 + b_{Y2.13}X_2 + b_{Y3.12}b_{31.2}X_1 + b_{Y3.12}b_{32.1}X_2$
- $= (b_{Y1.23} + b_{Y3.12}b_{31.2})X_1 + (b_{Y2.13} + b_{Y3.12}b_{32.1})X_2$

- Compare compound coefficients to the diagram

Structural model



Path Coefficients

- X_1 to Y: $\mathbf{b_{Y1.23}}$ (regression coefficient of Y on X_1, controlling for X2 and X3)
- X_2 to Y: $\mathbf{b_{Y2.13}}$ (regression coefficient of Y on X_2, controlling for X_1 and X3)
- X_3 to Y: $\mathbf{b_{Y3.12}}$ (regression coefficient of Y on X_3, controlling for X_1 and X_2)
- X_1 to X_3: $\mathbf{b_{31.2}}$ (regression coefficient of X_3 on X_1, controlling for X_2)
- X_2 to X_3: $\mathbf{b_{32.1}}$ (regression coefficient of X_3 on X_2, controlling for X_1)

Direct effects

X_1 to Y: $\mathbf{b_{Y1.23}}$	regression coefficient of Y on X1, controlling for X2 and X3
X_2 to Y: $\mathbf{b_{Y2.13}}$	regression coefficient of Y on X2, controlling for X1 and X3
X_3 to Y: $\mathbf{b_{Y3.12}}$	regression coefficient of Y on X3, controlling for X1 and X2
X_1 to X_3: $\mathbf{b_{31.2}}$	regression coefficient of X3 on X1, controlling for X2
X_2 to X_3: $\mathbf{b_{32.1}}$	regression coefficient of X3 on X2, controlling for X1

Indirect and total effects

Indirect effects	
X_1 to Y, through X_3:	$\mathbf{b_{31.2} \times b_{Y3.12}}$
X_2 to Y, through X_3:	$\mathbf{b_{32.1} \times b_{Y3.12}}$
Total effects	
X_1 to Y:	$\mathbf{b_{Y1.23} + (b_{31.2} \times b_{Y3.12})}$
X_2 to Y:	$\mathbf{b_{Y2.13} + (b_{32.1} \times b_{Y3.12})}$

Additions to multiple regressions

- We learn something new if the indirect effects are large enough to have substantial interest
- More than two steps of causation tends to become very weak
  - 0.3*0.3*0.3 = 0.027
  - 0.3 standard deviation change in causal variables leads to a 0.027 standard deviation change in the dependent variable

Variables and measurement

- All interval scale variables used in multiple regression (including non-linear transformed variables and interaction terms) can be included in structural equations models
- But interpretation becomes tricky when variables are complex. Conditional effect plots are very useful
- Robust, quantile, logit, and probit regression should not be used
- Categorical variables should not be used as intervening variables
- Scales or index variables can be used as usual in OLS regression

Concluding on structural equations modelling

- Including factors from factor analysis as explanatory variables make it possible to approximate a LISREL type analysis
- If assumptions are true LISREL will perform a much better and more comprehensive estimation, but too often assumptions are not true then the low-tech approach has access to the large toolkit of OLS regression for diagnostics and exploratory methods testing basic assumptions and discovering unusual data points
- Simple diagnostic work sometimes yields the most unexpected, interesting and replicable findings from our research

Principal components and factor analysis

- Principal components and factor analysis are both methods for data reduction
- They seek underlying dimensions that are able to account for the pattern of variation among a set of observed variables
- Principal components analysis is a transformation of the observed data where the idea is to explain as much as possible of the observed variation with a minimum number of components

Factor analysis

- Estimates coefficients on - and values of - unobserved variables (Factors) to explain the co-variation among an observed set of variables
- The assumption is that a small set of the unobserved factors are able to explain most of the co-variation
- Hence factor analysis can be used for data reduction. Many variables can be replaced by a few factors

Factor analysis

- $Z_k = \ell_{k1}F_1 + \ell_{k2}F_2 + \dots + \ell_{kj}F_j + \dots + \ell_{kJ}F_J + u_k$
  - $k = 1, 2, 3, \dots, K$
- Symbols
  - K observed variables, Z_k ; $k=1, 2, 3, \dots, K$
  - J unobserved factors, F_j ; $j=1, 2, 3, \dots, J$ where $J<K$
  - For each variable there is a unique error term, u_k, also called unique factors while the F factors are called common factors
  - For each factor there is a **standardized** regression coefficient, ℓ_{kj}, also called factor loading; k refers to variable no, j refers to factor no. An index denoting case no has been omitted here.

Correlation of factors

- Factors my be correlated or uncorrelated
  - Uncorrelated: they are then called **orthogonal**
  - Correlated: they are then called **oblique**
- Factors may be rotated
  - Oblique rotations create correlated factors
  - Orthogonal rotations create uncorrelated factors

Principal components

- Represents a simple transformation of variables. There are as many principal components as there are variables
- Principal components are uncorrelated
- $Z_k = \ell_{k1}F_1 + \ell_{k2}F_2 + \dots + \ell_{kj}F_j + \dots + \ell_{kK}F_K$
- If the last few principal components explain little variation we can retain J<K components. Thus Principal Components also can be used to reduce data.
- $Z_k = \ell_{k1}F_1 + \ell_{k2}F_2 + \dots + \ell_{kj}F_j + \dots + \ell_{kJ}F_J + v_k$
  where J<K and
  the residual v_k has small variance and consist of the discarded principal components

Principal components vs factor analysis

- Principal components analysis attempts to explain the observed variation of the variables
- Factor analysis attempts to explain their intercorrelations
- Use principal components to generate a composite variable that reproduce the maximum variance of observed variables
- Use factor analysis to model relationships between observed variables and unobserved latent variables and to obtain estimates of latent variable values
- The choice between the two is often blurred, to some degree it is a matter of taste

The number of principal components

- K variables yield K principal components
- If the first few components account for most of the variation, we can concentrate on them and discard the remaining
- The eigenvalues of the standardized correlation matrix provides a guide here
- Components are raked according to eigenvalues
- A principal component with an eigenvalue $\lambda<1$ accounts for less variance than a single variable
- Thus we discard components with eigenvalues below 1
- Another criterion for keeping components is that each component should have substantive meaning

Eigenvalues and explained variance

- In a covariance matrix the sum of eigenvalues equals the sum of variances.
- In a correlation matrix this = K (the number of variables) since each standardized variable has a variance of 1
- Thus the sum of eigenvalues of the principal components
- $\lambda_1 + \lambda_2 + \lambda_3 + \ldots + \lambda_K = K$ and
- λ_j / K = proportion of variance explained by component no j

Uniqueness and communality

- If K-J components are discarded and we have only J factors
- $Z_k = \ell_{k1}F_1 + \ell_{k2}F_2 + \ldots + \ell_{kj}F_j + \ldots + \ell_{kJ}F_J + v_k$
- And an error term v_k
- The variance of the error term is called the uniqueness of the variable
- Communality is the proportion of a variable's variance shared with the components
- Communality = h_k^2 = 1 - Uniqueness = $\Sigma_j \lambda_{kj}^2$, j=1,…, J ; k = variable number

Rotation to simple structure

- The idea is to transform (rotate) the factors so that the loadings on each components make it easier to interpret the meaning of the component
- If the loading are close either to 1 or -1 on one factor and close to 0 on all others the structure is simpler to interpret: we rotate to “simple structure”. The rotated factors fit data equally well but are simpler to interpret
- Rotations may be
  - Orthogonal (method typically: varimax)
  - Oblique (method typically: oblimin, promax)

Why rotate?

- Underlying unobserved dimensions may in theory be seen as correlated
- Allowing correlated factors may provide even simpler structure than uncorrelated factors, thus easier to interpret
- All rotations fit data equally well
- Hence the one chosen depends on a series of choices done by the analyst
- Try different methods to see if results differ

SPSS output

- For rotated factor solutions with correlated factors SPSS provides two matrixes for interpretation
- The pattern matrix provides the direct regression of the variables on the factors. The coefficients tells about the direct contribution of a factor in explaining the variance of a variable. Due to the correlations of the factors there are also indirect contributions
- The structure matrix provides the correlations between the variables and the factors

Factor scores

- Both principal components and factor analysis may be used to compute composite scores called factor scores
- Recall that variables and factors are assumed to be related like
  - $Z_k = \ell_{k1}F_1 + \ell_{k2}F_2 + \dots + \ell_{kj}F_j + \dots + \ell_{kK}F_K$
- Then it is possible to find values c_{ij} making
  - $\hat{F}_j = c_{1j}Z_1 + c_{2j}Z_2 + \dots + c_{kj}Z_j + \dots + c_{Kj}Z_K$
- The coefficients c_{ij} are the factor score coefficients. They come from the regression of the factor F_j on the variables

Methods for extracting factors

- Principal factor analysis
  - The original correlation matrix **R** is replaced by **R*** where the original 1-values of the diagonal has been replaced by estimates of the communality (the shared variance)
  - The factors extracted tries to explain the co-variance or correlations among the variables.
  - The unexplained variance is attributed to a unique factor (error term). The uniqueness may reflect measurement error or something that this variable measure that no other variable measure
  - The most common estimate of communality is R_k^2 the coefficient of determination from the regression of Z_k on all other variables

How many factor should we retain?

- In principal component analysis factors with eigenvalues above 1 is recommended
- In principal factor analysis factors with eigenvalues above 0 is recommended
- Procedure:
  - Extract initial factors or components
  - Rotate to simple structure
  - Decide on how many factors to retain
  - Obtain and use scores for the retained factors, ignoring discarded factors

Concluding (1)

- Principal components
  - transformation of the data, not model based. Appropriate if goal is to compactly express most of the variance of k variables. Minor components (perhaps all except the first) may be discarded and viewed as a residual.
- Factor analysis
  - Estimates parameters of a measurement model with latent (unobserved) variables.

Concluding (2)

- Types of factor analysis
  - Principal factoring – principal components of a modified correlation matrix R* in which communality estimates (R_k^2) replace one's on the main diagonal
    - Principal factoring without iteration
    - Principal factoring with iteration
  - Maximum likelihood estimation – significance tests regarding number of factors and other hypotheses, **assuming multivariate normality**

Concluding (3)

- Rotation
  - If we retain more than one factor rotation simplifies structure and improves interpretability
    - Orthogonal rotation (varimax) maximum polarization given uncorrelated factors
    - Oblique rotation (oblimin, promax) further polarization by permitting interfactor correlations. The results may be more interpretable and more realistic than uncorrelated factors
- Scores
  - Factor scores can be calculated for use in graphs and further analysis, based on rotated or unrotated factors and principal components

Concluding (4)

- Factor analysis is based on correlations and hence as affected by non-linearities and influential cases as in regression
  - Use scatter plots to check for outliers and non-linearities
  - In maximum likelihood estimation this becomes even more important since it assumes multivariate normality making it even less robust than principal factors

Principal components of trust in Malawi

- Survey of 283 households in 18 villages in Malawi, 2007
- There are 8 related questions asked in one group
- Are there 1, 2 or more underlying dimensions shaping the attitudes expressed?
- The questions:

M3 Would you say you trust all, most, some or just a few people in the following groups? (All=1 – None=5)

a	Your family members	*All*	*Most*	*Some*	*Only a few*	*None*	*Do not know*
b	Your relatives	*All*	*Most*	*Some*	*Only a few*	*None*	*Do not know*
c	Your village	*All*	*Most*	*Some*	*Only a few*	*None*	*Do not know*
d	People from outside the village	*All*	*Most*	*Some*	*Only a few*	*None*	*Do not know*
e	People of same ethnic group	*All*	*Most*	*Some*	*Only a few*	*None*	*Do not know*
f	People from outside ethnic group	*All*	*Most*	*Some*	*Only a few*	*None*	*Do not know*
g	People from same church/mosque	*All*	*Most*	*Some*	*Only a few*	*None*	*Do not know*
h	People *not* from same church/mosque	*All*	*Most*	*Some*	*Only a few*	*None*	*Do not know*

Trust in Malawi: descriptive

Descriptive Statistics

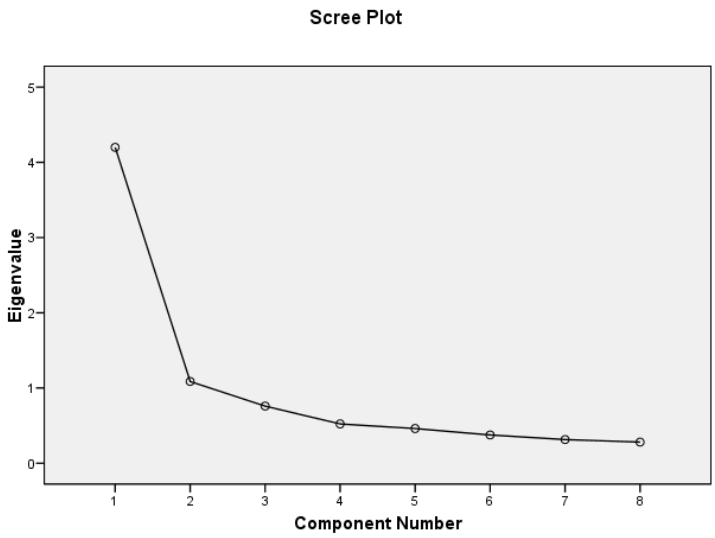
	Mean	Std. Deviation	Analysis N
M3.a. Trust in family members	1.60	.935	266
M3.b. Trust in relatives	2.12	1.136	266
M3.c. Trust in people in own village	2.69	1.090	266
M3.d. Trust in people outside the village	3.28	1.118	266
M3.e. Trust in people of same ethnic group	2.90	1.082	266
M3.f. Trust in people outside ethnic group	3.26	1.098	266
M3.g. Trust in people from same church/mosque	2.39	1.062	266
M3.h. Trust in people not from same church/mosque	3.02	1.197	266

Trust in Malawi: correlation of variables

Correlation Matrix

	M3.a. Trust in family members	M3.b. Trus in relatives	M3.c. Trust in people in own village	M3.d. Trust in people outside the village	M3.e. Trust in people of same ethnic group	M3.f. Trust i people outside ethnic group	M3.g. Trust in people from same church/mosque	M3.h. Trust in people no from same church/mosque
M3.a. Trust in family members	1.000	.500	.416	.236	.370	.316	.422	.305
M3.b. Trust in relatives	.500	1.000	.496	.315	.363	.353	.424	.292
M3.c. Trust in people in own village	.416	.496	1.000	.482	.588	.573	.465	.430
M3.d. Trust in people outside the village	.236	.315	.482	1.000	.526	.610	.233	.469
M3.e. Trust in people o same ethnic group	.370	.363	.588	.526	1.000	.702	.504	.643
M3.f. Trust in people outside ethnic group	.316	.353	.573	.610	.702	1.000	.430	.618
M3.g. Trust in people fr same church/mosque	.422	.424	.465	.233	.504	.430	1.000	.536
M3.h. Trust in people n from same church/mosque	.305	.292	.430	.469	.643	.618	.536	1.000

Trust in Malawi: number of factors



Trust in Malawi: factor/ component matrix

Component Matrix [a]

	Component	
	1	2
M3.a. Trust in family members	.588	.586
M3.b. Trust in relatives	.624	.532
M3.c. Trust in people in own village	.776	.080
M3.d. Trust in people outside the village	.675	-.398
M3.e. Trust in people of same ethnic group	.832	-.221
M3.f. Trust in people outside ethnic group	.816	-.330
M3.g. Trust in people from same church/mosque	.690	.265
M3.h. Trust in people not from same church/mosque	.757	-.262

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

Trust in Malawi: orthogonal factors

Rotated component matrix	Unrotated components		Orthogonal varimax	
Variables	**F1**	**F2**	**F1**	**F2**
M3.a. Trust in family members	.588	.586	.117	.821
M3.b. Trust in relatives	.624	.532	.178	.800
M3.c. Trust in people in own village	.776	.080	.572	.531
M3.d. Trust in people outside the village	.675	-.398	.779	.089
M3.e. Trust in people of same ethnic group	.832	-.221	.798	.324
M3.f. Trust in people outside ethnic group	.816	-.330	.850	.228
M3.g. Trust in people from same church/mosque	.690	.265	.391	.627
M3.h. Trust in people not from same church/mosque	.757	-.262	.762	.246

Trust in Malawi: communalities

Communalities

	Extraction
M3.a. Trust in family members	.689
M3.b. Trust in relatives	.671
M3.c. Trust in people in own village	.609
M3.d. Trust in people outside the village	.614
M3.e. Trust in people of same ethnic group	.741
M3.f. Trust in people outside ethnic group	.774
M3.g. Trust in people from same church/mosque	.546
M3.h. Trust in people not from same church/mosque	.641

Extraction Method: Principal Component Analysis.

Trust in Malawi: explained variance

Total Variance Explained

Component	Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.199	52.487	52.487	3.071	38.387	38.387
2	1.087	13.582	66.069	2.215	27.681	66.069

Extraction Method: Principal Component Analysis.

Trust in Malawi: oblique factors pattern matrix

Rotated component matrix	**varimax (orthogonal)**		**oblimin**		**promax**	
Variables	**F1**	**F2**	**F1**	**F2**	**F1**	**F2**
M3.a. Trust in family members	.117	**.821**	-.087	**.868**	-.145	**.901**
M3.b. Trust in relatives	.178	**.800**	-.014	**.826**	-.067	**.855**
M3.c. Trust in people in own village	**.572**	**.531**	**.493**	**.414**	**.476**	**.409**
M3.d. Trust in people outside the village	**.779**	.089	**.838**	-.133	**.864**	-.170
M3.e. Trust in people of same ethnic group	**.798**	.324	**.797**	.120	**.806**	.093
M3.f. Trust in people outside ethnic group	**.850**	.228	**.881**	-.001	**.899**	-.036
M3.g. Trust in people from same church/mosque	.391	**.627**	.268	**.573**	.237	**.582**
M3.h. Trust in people not from same church/mosque	**.762**	.246	**.779**	.045	**.792**	.016

Trust in Malawi: oblique factors structure matrix

Rotated component matrix	varimax		oblimin		promax	
Variables	F1	F2	F1	F2	F1	F2
M3.a. Trust in family members	.117	.821	.327	.826	.351	.821
M3.b. Trust in relatives	.178	.800	.380	.819	.403	.817
M3.c. Trust in people in own village	.572	.531	.690	.649	.702	.671
M3.d. Trust in people outside the village	.779	.089	.775	.267	.771	.306
M3.e. Trust in people of same ethnic group	.798	.324	.854	.500	.857	.537
M3.f. Trust in people outside ethnic group	.850	.228	.880	.419	.880	.460
M3.g. Trust in people from same church/mosque	.391	.627	.541	.700	.557	.712
M3.h. Trust in people not from same church/mosque	.762	.246	.800	.416	.801	.452

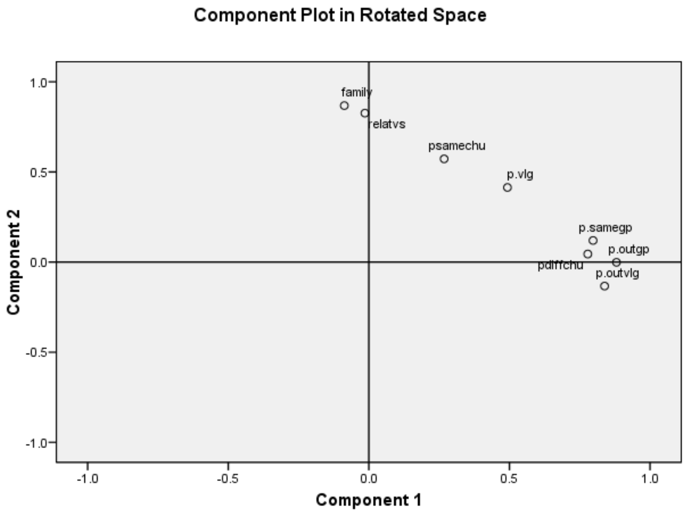
Trust in Malawi: correlation of components

Component Correlation Matrix

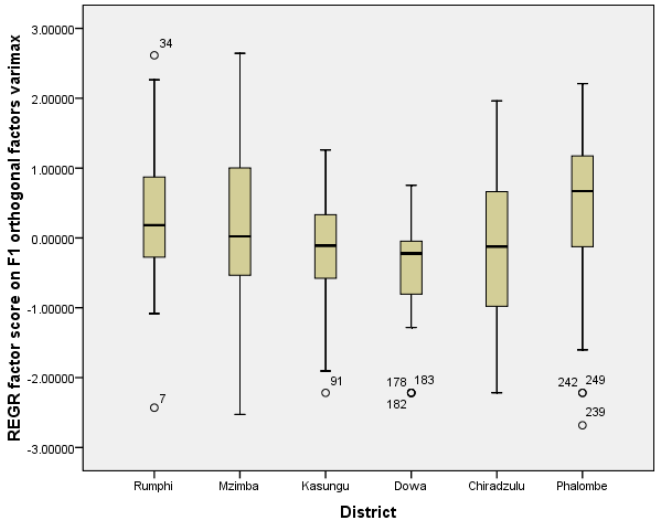
Component	1	2
1	1.000	.477
2	.477	1.000

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

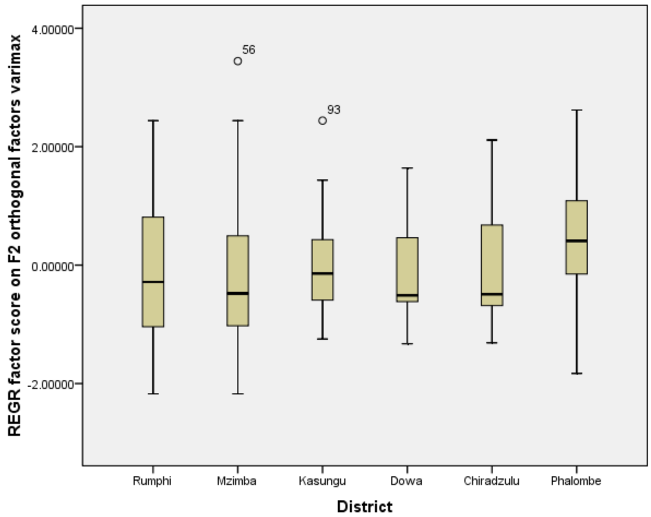
Trust in Malawi: variables in component plot



Trust in Malawi: Orthogonal Factor 1 by district



Trust in Malawi: Orthogonal Factor 2 by district



Trust in Malawi: Orthogonal factors by district

Case Processing Summary

	District	Valid N	Valid Percent	Missing N	Missing Percent	Total N	Total Percent
REGR factor score on F1 orthogonal factors varimax	Rumphi	43	95.6%	2	4.4%	45	100.0%
	Mzimba	37	82.2%	8	17.8%	45	100.0%
	Kasungu	47	95.9%	2	4.1%	49	100.0%
	Dowa	49	98.0%	1	2.0%	50	100.0%
	Chiradzulu	46	93.9%	3	6.1%	49	100.0%
	Phalombe	44	97.8%	1	2.2%	45	100.0%

Case Processing Summary

	District	Valid N	Valid Percent	Missing N	Missing Percent	Total N	Total Percent
REGR factor score on F2 orthogonal factors varimax	Rumphi	43	95.6%	2	4.4%	45	100.0%
	Mzimba	37	82.2%	8	17.8%	45	100.0%
	Kasungu	47	95.9%	2	4.1%	49	100.0%
	Dowa	49	98.0%	1	2.0%	50	100.0%
	Chiradzulu	46	93.9%	3	6.1%	49	100.0%
	Phalombe	44	97.8%	1	2.2%	45	100.0%