Three models for combining information from causal indicators

The `sheafcoef` and `propcnsreg` package

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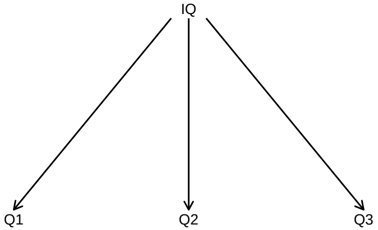
- This is a good thing! But, we need models to make the best use possible of this information.

Effect indicators and causal indicators

- Effect indicators are variables that are influenced by the latent variable.



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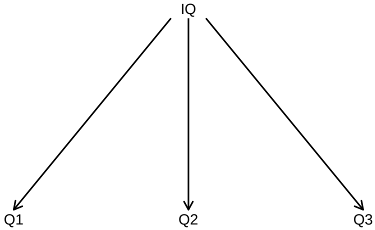

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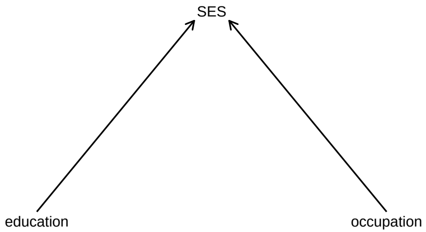

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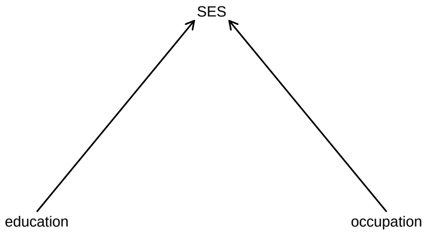
- Causal indicators are variables that influence the latent variable.
  - For example:
  - sheaf coefficients (`sheafcoef`),
  - parametrically weighted covariates, and
  - MIMIC models (`propcnsreg`).



The basic model

MIMIC

$$
\begin{aligned}
y &= \beta_0 + (\lambda_0 + \lambda_1 z_1)\eta + \varepsilon_y \\
\eta &= \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \varepsilon_\eta
\end{aligned}
$$

The basic model

parametrically weighted covariates

$$
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\end{aligned}
$$

The basic model

Sheaf coefficients

$$
\begin{aligned}
y &= \beta_0 + (\lambda_0 \qquad\qquad)\eta + \varepsilon_y \\
\eta &= \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2
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$$

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- The empirical information we use to estimate the γs and λs is that we choose the γs to optimize the effect of η on y.
- The empirical information we use to estimate the variance of ε_η in the MIMIC model is that this model assumes that the total residual variance changes along z_1 according to $var(\varepsilon_y) + (\lambda_0 + \lambda_1 z_1)^2 \times var(\varepsilon_\eta)$
- η is a latent variable, so we need to fix its origin and its unit.
  - Fix the origin by setting η to 0 when x_1 and x_2 are both 0
  - Fix the unit by setting the standard deviation of η to 1.

Data preparation

```
. sysuse nlsw88, clear
(NLSW, 1988 extract)

. gen byte occ2 = occupation
(9 missing values generated)

. recode occ2 (2=1) (3 4 11 12 = 2) (5/10= 3) (13=.)
(occ2: 1920 changes made)

. label define occ2 1 "higher services" 2 "lower services" 3 "manual"

. label value occ2 occ2

.
.
. gen byte hs = grade == 12 if grade < .
(2 missing values generated)

. gen byte sc = grade > 12 & grade < 16 if grade < .
(2 missing values generated)

. gen byte c = grade >= 16 if grade < .
(2 missing values generated)

.
. replace tenure = tenure / 10
(2180 real changes made)

. gen white = race == 1 if race < .

.
. gen ln_w = ln(wage)
```

Sheaf coefficients after a linear regression

```
. qui xi: reg ln_w i.occ2 hs sc c
. sheafcoef, latent( _I* ; hs sc c) post
```

ln_w	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
p1	.2000228	.0124272	16.10	0.000	.1756516	.224394
a1__Iocc2_2	-1.528682	.1075842	-14.21	0.000	-1.739668	-1.317696
a1__Iocc2_3	-2.600971	.0133063	-195.47	0.000	-2.627067	-2.574876
p2	.144066	.0124393	11.58	0.000	.119671	.168461
a2_hs	.9303067	.2141218	4.34	0.000	.5103867	1.350227
a2_sc	2.205349	.1904522	11.58	0.000	1.831848	2.57885
a2_c	3.031032	.133601	22.69	0.000	2.769024	3.293041
_cons	1.933329	.0378121	51.13	0.000	1.859174	2.007483

```
. test _b[p1] = _b[p2]
 ( 1)  p1 - p2 = 0
       F(  1,  2042) =     6.95
            Prob > F =    0.0084
```

Sheaf coefficients after logistic regression

```
. qui xi: logit union i.occ2 hs sc c
. sheafcoef, latent( _I* ; hs sc c) eform post
```

union	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
p1_e	1.241842	.0855004	14.52	0.000	1.074265	1.40942
a1__Iocc2_2	1.58573	.5031156	3.15	0.002	.5996415	2.571818
a1__Iocc2_3	2.585204	.1054152	24.52	0.000	2.378594	2.791814
p2_e	1.028296	.0661664	15.54	0.000	.8986119	1.15798
a2_hs	-1.15095	5.973281	-0.19	0.847	-12.85837	10.55647
a2_sc	.6553856	7.081814	0.09	0.926	-13.22471	14.53549
a2_c	1.394004	7.161541	0.19	0.846	-12.64236	15.43037
_cons_e	.2045564	.042083	4.86	0.000	.1220752	.2870376

```
(_e) indicates the variables whose coefficients have been exponentiated
. test _b[p1] = _b[p2]
 ( 1)  p1_e - p2_e = 0
           chi2(  1) =    6.02
         Prob > chi2 =    0.0142
```

Syntax of `sheafcoef`

```
sheafcoef,
latent( varlist_1 [ ; varlist_2 [; varlist_3 [...]]]  )
[ eform post iterate(#) level(#) ]
```

Parametrically weighted covariates

```
. propcnsreg ln_w white tenure, lambda(tenure white) ///
>           constrained(hs sc c) nolog
                                                Number of obs   =       2229
                                                LR chi2(8)      =     133.01
Log likelihood = -1607.2184                     Prob > chi2     =     0.0000

Constraint: sd of latent variables = 1
------------------------------------------------------------------------------
        ln_w |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
unconstrai~d |
       white |   .2176303   .0366948     5.93   0.000     .1457098    .2895508
      tenure |   .3317353   .0330047    10.05   0.000     .2670473    .3964233
       _cons |   1.252169   .0400622    31.26   0.000     1.173648    1.330689
-------------+----------------------------------------------------------------
constrained  |
          hs |   .6364459   .1429802     4.45   0.000     .3562099    .9166819
          sc |   1.931921   .1414771    13.66   0.000     1.654631    2.209211
           c |    2.75269   .0907335    30.34   0.000     2.574856    2.930525
-------------+----------------------------------------------------------------
lambda       |
      tenure |  -.0429628   .0199328    -2.16   0.031    -.0820303   -.0038952
       white |  -.0938623   .0249237    -3.77   0.000    -.1427118   -.0450128
       _cons |   .3049783   .0251357    12.13   0.000     .2557131    .3542434
-------------+----------------------------------------------------------------
sigma        |
       _cons |   .4976345   .0074532    66.77   0.000     .4830266    .5122424
------------------------------------------------------------------------------
LR test vs. unconstrained model: chi2(4) =       3.22    Prob > chi2 =     0.522

BIC(unconstrained) - BIC(constrained) =     19.91
This difference suggests very strong evidence for the constrained model
```

MIMIC model

```
. propcnsreg ln_w white tenure, lambda(tenure white) ///
>            constrained(hs sc c) mimic nolog
                                                  Number of obs   =       2229
                                                  LR chi2(8)      =     137.63
Log likelihood = -1587.8862                       Prob > chi2     =     0.0000

Constraint: sd of latent variables = 1
------------------------------------------------------------------------------
        ln_w |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
unconstrai~d |
       white |   .1154214   .0275711     4.19   0.000      .061383    .1694599
      tenure |    .354109   .0309777    11.43   0.000     .2933937    .4148243
       _cons |   1.290095   .0384749    33.53   0.000     1.214685    1.365504
-------------+----------------------------------------------------------------
constrained  |
          hs |   .7559966   .1473374     5.13   0.000     .4672207    1.044773
          sc |   2.039394   .1383171    14.74   0.000     1.768298    2.310491
           c |   2.805831   .0899889    31.18   0.000     2.629456    2.982206
-------------+----------------------------------------------------------------
lambda       |
      tenure |  -.0658272   .0182428    -3.61   0.000    -.1015825    -.030072
       white |  -.0035393   .0108898    -0.33   0.745    -.0248829    .0178044
       _cons |   .2547694   .0198169    12.86   0.000      .215929    .2936097
-------------+----------------------------------------------------------------
sigma        |
       _cons |   .3016388   .0579338     5.21   0.000     .1880907    .4151869
-------------+----------------------------------------------------------------
sigma_latent |
       _cons |   .4684396   .0384153    12.19   0.000     .3931471    .5437321
------------------------------------------------------------------------------
```

Syntax of `propcnsreg`

`propcnsreg` *depvar* [*indepvars*] [*if*] [*in*] [*weight*] ,

`constrained(`*varlist*`)` `lambda(`*varlist*`)` [

`standardized` `lcons` `unit(`*varname*`)`

`mimic`

`robust` `cluster(`*varname*`)` `level(`*#*`)`

em_maximize_options *maximize_options*]

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- Causal indicators require a different strategy to recover the latent variable than effect indicators
- Models with causal indicators recover the latent variable by scaling the observed indicators to optimize the effect of the latent variable on the dependent variable.
- A MIMIC model also recovers measurement error by making a parametric assumption on how the total residual variance changes over observed variables.

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  MIMIC model measurement error, effect of latent variable changes over observed variables

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  - MIMIC model: measurement error, effect of latent variable changes over observed variables
- The model with sheaf coefficients can be estimated using `sheafcoef`,

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  - Sheaf coefficients: no measurement error, effect of latent variable is constant
  - Parametrically weighted covariates: no measurement error, effect of latent variable changes over observed variables
  - MIMIC model: measurement error, effect of latent variable changes over observed variables
- The model with sheaf coefficients can be estimated using `sheafcoef`,
- the model with parametrically weighted covariates and the MIMIC model can be estimated using `propcnsreg`.

References

Bollen, Kenneth A.
Multiple Indicators: Internal Consistency or No Necessary Relationship.
Quality and Quantity, 18(4): 377-385, 1984.

Bollen, Kenneth A. and Richard Lennox.
Conventional Wisdom on Measurement: A Structural Equation Perspective.
Psychological Bulletin, 110(2): 305-314, 1991.

Hauser, Robert M. and Arthur S. Goldberger.
The Treatment of Unobservable Variables in Path Analysis.
Sociological Methodology 3: 81-117, 1971.

Heise, David R.
Employing nominal variables, induced variables, and block variables in path analysis.
Sociological Methods & Research 1(2): 147-173, 1972.

Yamaguchi, Kazuo.
Regression models with parametrically weighted explanatory variables.
Sociological Methodology 32: 219-245, 2002.