Three models for combining information from causal indicators

The `sheafcoef` and `propcnsreg` package

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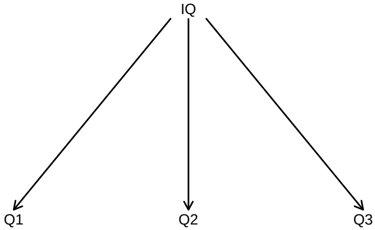
- This is a good thing! But, we need models to make the best use possible of this information.

Effect indicators and causal indicators

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



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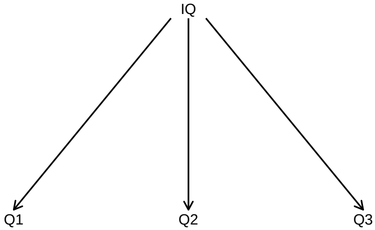

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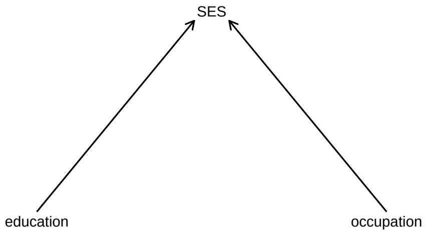

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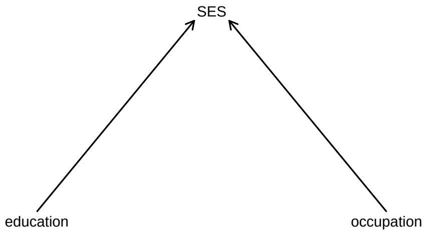
- Causal indicators are variables that influence the latent variable.
  - For example:
  - sheaf coefficients (`sheafcoef`),
  - parametrically weighted covariates, and
  - MIMIC models (`propcnsreg`).



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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$$

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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  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`.

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