

STA431S 23 Assignment 7

(1)

(a)

	w_1	v_1	w_2	v_2
w_1	$\Phi_x + \Omega_{11}$	$\Phi_x \beta^T + \Omega_{12}$	Φ_x	$\Phi_x \beta^T$
v_1		$\beta \Phi_x \beta^T + \Psi + \Omega_{22}$	$\beta \Phi_x$	$\beta \Phi_x \beta^T + \Psi$
w_2			$\Phi_x + \Omega_{33}$	$\Phi_x \beta^T + \Omega_{34}$
v_2				$\beta \Phi_x \beta^T + \Psi + \Omega_{44}$

$$\begin{aligned} \text{cov}(w_1, v_1) &= \text{cov}(x + e_1, y + e_2) = \text{cov}(x, y) + \text{cov}(e_1, e_2) \\ &= \text{cov}(x, \beta x + \varepsilon) + \Omega_{12} = \Phi_x \beta^T + \Omega_{12} \end{aligned}$$

$$\text{cov}(w_1, v_2) = \text{cov}(x + e_1, y + e_4) = \text{cov}(x, y) + 0 = \Phi_x \beta^T$$

$$\text{cov}(v_1, v_1) = \text{cov}(y + e_2, y + e_2) = \text{cov}(y) + 4\text{cov}(e_2) = \beta \Phi_x \beta^T + \Omega_{22}$$

$$\text{cov}(v_1, v_2) = \text{cov}(y + e_2, y + e_4) = \text{cov}(y) + 0 = \beta \Phi_x \beta^T + \Psi$$

$$\text{cov}(v_1, w_2) = \text{cov}(y + e_1, x + e_3) = \text{cov}(y, x) = \beta \Phi_x$$

$$\text{cov}(w_2) = \text{cov}(x + e_3) = \Phi_x + \Omega_{33}$$

$$(1b) \Theta = (\underbrace{\Phi_x}_{\substack{\uparrow \\ \text{unique elements of}}} \quad \Omega_{11} \quad \beta \quad \Omega_{12} \quad \Omega_{22} \quad \psi \quad \Omega_{33} \quad \Omega_{34} \quad \Omega_{44})$$

$$\Phi_x = \Sigma_{13}$$

$$\Omega_{11} = \Sigma_{11} - \Phi_x$$

$$\beta = \Sigma_{23} \Phi_x^{-1}$$

$$\Omega_{12} = \Sigma_{12} - \Phi_x \beta^T$$

$$\psi = \Sigma_{24} - \beta \Phi_x \beta^T$$

$$\Omega_{22} = \Sigma_{22} - \beta \Phi_x \beta^T - \psi$$

$$\Omega_{33} = \Sigma_{33} - \Phi_x$$

$$\Omega_{34} = \Sigma_{34} - \Phi_x \beta^T$$

$$\Omega_{44} = \Sigma_{44} - \beta \Phi_x \beta^T - \psi$$

$$(c) \tilde{\Phi}_x = \frac{1}{2} (\hat{\Sigma}_{13} + \hat{\Sigma}_{13}^T) \text{ to make it symmetric}$$

$$(d) \tilde{\beta}_n = \frac{1}{2} (\hat{\Sigma}_{23} + \hat{\Sigma}_{14}^T) \tilde{\Phi}_x^{-1} = (\hat{\Sigma}_{23} + \hat{\Sigma}_{14}^T) (\hat{\Sigma}_{13} + \hat{\Sigma}_{13}^T)^{-1}$$

$$\xrightarrow{p} (\Sigma_{23} + \Sigma_{14}^T) (\Sigma_{13} + \Sigma_{13}^T)^{-1} \text{ by } \hat{\Sigma} \xrightarrow{p} \Sigma \text{ and continuous mapping}$$

$$\begin{aligned} & (\beta \Phi_x + \beta \Phi_x) (\Phi_x + \Phi_x)^{-1} = 2\beta \Phi_x (2\Phi_x)^{-1} = 2\beta \Phi_x \cdot \frac{1}{2} \Phi_x^{-1} \\ & = \beta \Phi_x \Phi_x^{-1} = \beta \end{aligned}$$

(2) (a) Σ_{11} is $P \times P$: $P(P+1)/2$

Σ_{11} is $P \times P$: $P(P+1)/2$

β is $g \times P$: Pg

Σ_{12} is $P \times g$: Pg

Σ_{22} is $g \times g$: $g(g+1)/2$

γ is $g \times g$: $g(g+1)/2$

Σ_{33} is $P \times P$: $P(P+1)/2$

Σ_{34} is $P \times g$: Pg

Σ_{44} is $g \times g$: $g(g+1)/2$

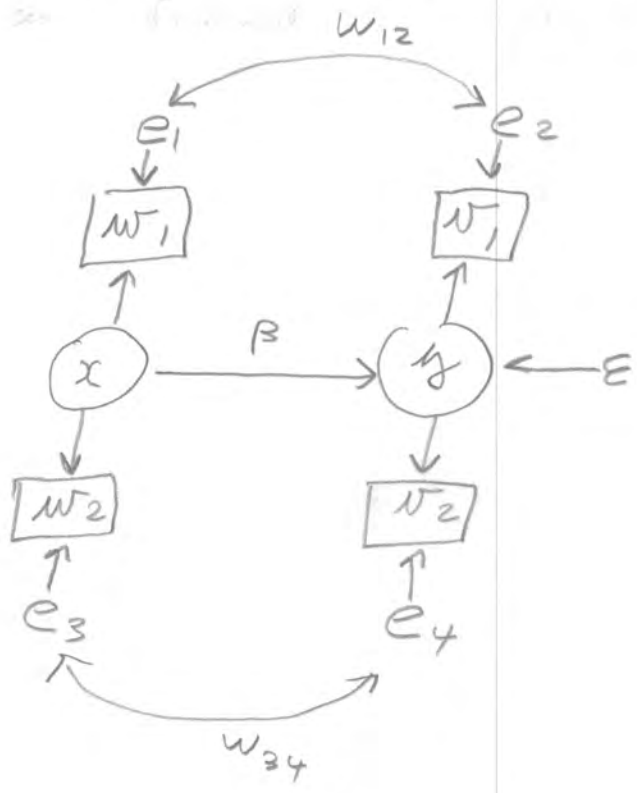
$3(P(P+1)/2 + g(g+1)/2 + Pg)$

(b) Σ is $2(P+g)$ by $2(P+g)$, so number of unique elements is $2(P+g)(2P+2g+1)/2 = (P+g)(2P+2g+1)$

(c) Looking at two answers to (1a), $\Sigma_{14} = \Sigma_{23}^T$, so that's Pg . Also Σ_{13} is symmetric, so that's $P(P-1)/2$ more. Σ_{24} is symmetric, for $g(g-1)/2$ more. Total number of constraints is $Pg + P(P-1)/2 + g(g-1)/2$

(d) Number of covariance structure equations minus number of parameters is $(P+g)(2P+2g+1) - \frac{3}{2}(P(P+1) + g(g+1) + 2Pg)$
 $= 2P^2 + 2Pg + P + 2Pg + 2g^2 + g - \frac{3}{2}P^2 - \frac{3}{2}P - \frac{3}{2}g^2 - \frac{3}{2}g - 3Pg$
 $= P^2(2 - \frac{3}{2}) + Pg + (P+g)(1 - \frac{3}{2}) + g^2(2 - \frac{3}{2})$
 $= \frac{1}{2}P^2 + \frac{1}{2}g^2 - \frac{1}{2}(P+g) + Pg = \frac{1}{2}(P^2 - P) + \frac{1}{2}(g^2 - g) + Pg$
 $= Pg + P(P-1)/2 + g(g-1)/2 = \text{Number of constraints!}$

(a) and (b) are on the printout
 (c)



$w_1 = n$ breeders @ 1
 $v_1 = n$ give births @ 1
 $w_2 = n$ breeders @ 2
 $v_2 = n$ give births @ 2
 $x =$ Number of breeders
 $y =$ Number giving births

(d) Independently for $i = 1, \dots, n$

$$y_i = \beta x_i + \epsilon_i$$

$$w_{i1} = x_i + e_{i1}$$

$$v_{i1} = y_i + e_{i2}$$

$$w_{i2} = x_i + e_{i3}$$

$$v_{i2} = y_i + e_{i4}$$

where all expected values are zero (optional)

$$\text{Var}(x_i) = \sigma \quad \text{Var}(\epsilon_i) = \psi$$

$$\text{Var}(e_{i1}) = w_{11} \quad \text{Var}(e_{i2}) = w_{22} \quad \text{Cov}(e_{i1}, e_{i2}) = w_{12}$$

$$\text{Var}(e_{i3}) = w_{33} \quad \text{Var}(e_{i4}) = w_{44} \quad \text{Cov}(e_{i3}, e_{i4}) = w_{34}$$

And all other covariances are zero.

(3e) On the printout.

(f) Yes. $G^2 = 0.087$, $df=1$, $P=0.768$

The df agrees with question 2. With $p=q=1$,

$$df = pq + p(p-1)/2 + q(q-1)/2 = 1 + 0 + 0 = 1$$

(g) $\hat{\beta} = 0.757$

(h) See printout. $\tilde{\beta} = 0.764$ is pretty close to $\hat{\beta}$.

(i) See printout: $(0.651, 0.862)$

(j) See $rel1$ and $rel2$ on printout

(k) See printout

(l) Yes. See z -tests for $w_{12} \neq w_{34}$

(m) (i) $H_0: w_{11} = w_{33}$ and $w_{33} = w_{44}$

(ii) $W_n = 23.93$, $df=2$, $P=0.00000635$

(iii) Measurement of number of sows giving birth appears to be more accurate for Questionnaire 2. See printout.

Assignment 7, Question 3

```

> # a.
> pigs = read.table("http://www.utstat.toronto.edu/brunner/openSEM/data/openpigs2.data.txt")
> head(pigs); dim(pigs)
  nbreedersQ1 ngivebirthQ1 nbreedersQ2 ngivebirthQ2
1           69           45           89           67
2           52           24           85           41
3           48           33           68           34
4            7            4           30           30
5           41           37           54           35
6           35           23           57           48
[1] 114  4
>
> # b.
> S = var(pigs); S
      nbreedersQ1 ngivebirthQ1 nbreedersQ2 ngivebirthQ2
nbreedersQ1  691.3607   581.6943   348.5299   272.6710
ngivebirthQ1  581.6943   562.6853   260.0286   239.2279
nbreedersQ2   348.5299   260.0286   770.9685   370.8930
ngivebirthQ2  272.6710   239.2279   370.8930   334.1683
> # c. and d. are handwritten.
>
> # e.
>
> # install.packages("lavaan", dependencies = TRUE) # Only need to do this once
> library(lavaan)
This is lavaan 0.6-11
lavaan is FREE software! Please report any bugs.
>
> pigmod =
+ #####
+ # Latent variable model
+ # -----
+ Lbirth ~ beta*Lbreeders
+ #
+ # Measurement model
+ # -----
+ Lbreeders =~ 1*nbreedersQ1 + 1*nbreedersQ2
+ Lbirth    =~ 1*ngivebirthQ1 + 1*ngivebirthQ2
+ #
+ # Variances
+ # -----
+ Lbreeders =~ phi*Lbreeders          # Var(Lbreeders) = phi
+ Lbirth    =~ psi*Lbirth             # Var(epsilon) = psi
+ nbreedersQ1 =~ omega1*nbreedersQ1 # Var(e1) = omega1
+ ngivebirthQ1 =~ omega2*ngivebirthQ1 # Var(e2) = omega2
+ nbreedersQ2 =~ omega3*nbreedersQ2 # Var(e3) = omega3
+ ngivebirthQ2 =~ omega4*ngivebirthQ2 # Var(e4) = omega4
+ #
+ # Covariances (between error terms)
+ # -----
+ nbreedersQ1 =~ omega12*ngivebirthQ1 # Cov(e1,e2) = omega12
+ nbreedersQ2 =~ omega34*ngivebirthQ2 # Cov(e3,e4) = omega34
+ # Reliabilities of number of breeding sows for the two questionnaires
+ # -----
+ rel1 := omega1/(phi+omega1)
+ rel2 := omega3/(phi+omega3)
+ ' ##### End of pigmod #####
>
> fit1 = lavaan(pigmod, data=pigs)
> summary(fit1)

```


lavaan 0.6-11 ended normally after 120 iterations

Estimator	ML
Optimization method	NLMINB
Number of model parameters	9
Number of observations	114

Model Test User Model:

Test statistic	0.087
Degrees of freedom	1
P-value (Chi-square)	0.768

Parameter Estimates:

Standard errors	Standard
Information	Expected
Information saturated (h1) model	Structured

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
Lbreeders =~				
nbreedersQ1	1.000			
nbreedersQ2	1.000			
Lbirth =~				
ngivebirthQ1	1.000			
ngivebirthQ2	1.000			

Regressions:

	Estimate	Std.Err	z-value	P(> z)
Lbirth ~				
Lbredrs (beta)	0.757	0.054	14.047	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
.nbreedersQ1 ~~				
.ngvbrQ1 (om12)	308.539	57.249	5.389	0.000
.nbreedersQ2 ~~				
.ngvbrQ2 (om34)	101.406	45.513	2.228	0.026

Variances:

	Estimate	Std.Err	z-value	P(> z)
Lbredrs (phi)	357.145	64.936	5.500	0.000
.Lbirth (psi)	33.634	10.861	3.097	0.002
.nbrdrQ1 (omg1)	330.683	67.114	4.927	0.000
.ngvbrQ1 (omg2)	321.255	54.160	5.932	0.000
.nbrdrQ2 (omg3)	416.335	80.763	5.155	0.000
.ngvbrQ2 (omg4)	93.000	35.566	2.615	0.009

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)
rel1	0.481	0.070	6.877	0.000
rel2	0.538	0.070	7.706	0.000

```

>
> # h.
>
> # MOM of beta: Really need to calculate Sigma to see this.
> 0.5*(S[1,4]+S[2,3])/S[1,3]
[1] 0.7642093

```

```

>
> # i.
> parameterEstimates(fit1)
      lhs op          rhs  label    est    se      z  pvalue  ci.lower  ci.upper
1    Lbirth ~      Lbreeders  beta  0.757  0.054 14.047  0.000    0.651    0.862
2    Lbreeders =~  nbreedersQ1    1.000  0.000    NA     NA    1.000    1.000
3    Lbreeders =~  nbreedersQ2    1.000  0.000    NA     NA    1.000    1.000
4    Lbirth =~    ngivebirthQ1  1.000  0.000    NA     NA    1.000    1.000
5    Lbirth =~    ngivebirthQ2  1.000  0.000    NA     NA    1.000    1.000
6    Lbreeders ~~      Lbreeders   phi 357.145 64.936  5.500  0.000 229.873 484.417
7    Lbirth  ~~      Lbirth     psi  33.634 10.861  3.097  0.002  12.348  54.920
8    nbreedersQ1 ~~  nbreedersQ1  omega1 330.683 67.114  4.927  0.000 199.143 462.224
9    ngivebirthQ1 ~~  ngivebirthQ1  omega2 321.255 54.160  5.932  0.000 215.103 427.407
10   nbreedersQ2 ~~  nbreedersQ2  omega3 416.335 80.763  5.155  0.000 258.042 574.628
11   ngivebirthQ2 ~~  ngivebirthQ2  omega4  93.000 35.566  2.615  0.009  23.291 162.709
12   nbreedersQ1 ~~  ngivebirthQ1  omega12 308.539 57.249  5.389  0.000 196.334 420.744
13   nbreedersQ2 ~~  ngivebirthQ2  omega34 101.406 45.513  2.228  0.026  12.201 190.610
14     rel1 := omega1/(phi+omega1)  rel1  0.481  0.070  6.877  0.000   0.344   0.618
15     rel2 := omega3/(phi+omega3)  rel2  0.538  0.070  7.706  0.000   0.401   0.675

```

```

> # j. k. and L. See above.
>
> # m. Compare precision of measurement.
> # H0: omega1=omega3 and omega2=omega4
> # For Wald tests: Wtest = function(L,Tn,Vn,h=0) # H0: L theta = h
> source("http://www.utstat.utoronto.ca/~brunner/Rfunctions/Wtest.txt")
>
> # Fit model with bootstrap SEs
> fit2 = lavaan(pigmod, data=pigs, se = "bootstrap")
> summary(fit2) # I didn't ask for this explicitly, so no questions on it.
lavaan 0.6-11 ended normally after 120 iterations

```

```

Estimator          ML
Optimization method NLMINB
Number of model parameters 9

```

```

Number of observations 114

```

Model Test User Model:

```

Test statistic          0.087
Degrees of freedom      1
P-value (Chi-square)    0.768

```

Parameter Estimates:

```

Standard errors          Bootstrap
Number of requested bootstrap draws 1000
Number of successful bootstrap draws 1000

```

Latent Variables:

```

      Estimate Std.Err z-value P(>|z|)
Lbreeders =~
  nbreedersQ1    1.000
  nbreedersQ2    1.000
Lbirth =~
  ngivebirthQ1   1.000
  ngivebirthQ2   1.000

```


Regressions:

	Estimate	Std.Err	z-value	P(> z)
Lbirth ~ Lbredrs (beta)	0.757	0.071	10.721	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
.nbreedersQ1 ~ .ngvbrQ1 (om12)	308.539	54.937	5.616	0.000
.nbreedersQ2 ~ .ngvbrQ2 (om34)	101.406	37.255	2.722	0.006

Variances:

	Estimate	Std.Err	z-value	P(> z)
Lbredrs (phi)	357.145	81.988	4.356	0.000
.Lbirth (psi)	33.634	11.319	2.972	0.003
.nbrdrQ1 (omg1)	330.683	60.901	5.430	0.000
.ngvbrQ1 (omg2)	321.255	52.548	6.114	0.000
.nbrdrQ2 (omg3)	416.335	86.653	4.805	0.000
.ngvbrQ2 (omg4)	93.000	30.053	3.095	0.002

Defined Parameters:

	Estimate	Std.Err	z-value	P(> z)
rel1	0.481	0.085	5.686	0.000
rel2	0.538	0.082	6.537	0.000

```

>
> # Wald test of H0: omegal=omega3 and omega2=omega4
> That = coef(fit2); That
  beta   phi   psi omegal  omega2  omega3  omega4  omegal2  omega34
0.757 357.145 33.634 330.683 321.255 416.335 93.000 308.539 101.406
> VV = vcov(fit2)
> LL = rbind(c(0, 0, 0, 1, 0,-1, 0, 0, 0),
+           c(0, 0, 0, 0, 1, 0,-1, 0, 0))
> Wtest(LL,That,VV)
      W      df      p-value
2.393441e+01 2.000000e+00 6.349046e-06
>
> # Follow-up
> # omegal vs. omega3
> L13 = rbind(c(0, 0, 0, 1, 0,-1, 0, 0, 0))
> Wtest(L13,That,VV)
      W      df      p-value
0.7262899 1.0000000 0.3940884
> # omega2 vs. omega4
> L24 = rbind(c(0, 0, 0, 0, 1, 0,-1, 0, 0))
> Wtest(L24,That,VV)
      W      df      p-value
1.338262e+01 1.000000e+00 2.539661e-04
>

```

(4) (a) C_{23} is $g \times p$

(b) i. C has $p+g+p+g = 2p+2g$ rows & columns, so number of unique elements is $2(p+g)(2p+2g+1)/2 = (p+g)(2p+2g+1)$

ii. Φ_z has $p(p+1)/2$ unique elements

iii. K has p^2 elements

(c) Σ is $(2p+g) \times (2p+g)$, so there are $(2p+g)(2p+g+1)/2$ unique elements.

(d) No way. There are fewer covariance structure equations than elements of C .

(e) Under the naive model $v = \beta w + \epsilon$

$$\Sigma = \text{cov} \begin{pmatrix} z \\ w \\ v \end{pmatrix} = \begin{bmatrix} \Phi_z & K & K\beta^T \\ & \Phi_w & \Phi_w\beta^T \\ & & \beta\Phi_w\beta^T + \Psi \end{bmatrix}$$

$$\begin{aligned} \text{cov}(z, v) &= \text{cov}(z, \beta w + \epsilon) = \text{cov}(z, \beta(x + \epsilon) + \epsilon) \\ &= \text{cov}(z, \beta x) + 0 = K\beta^T \end{aligned}$$

$$\text{cov}(w, v) = \text{cov}(w, \beta w + \epsilon) = \Phi_w \beta^T$$

$$\text{cov}(v) = \text{cov}(\beta w + \epsilon, \beta w + \epsilon) = \beta \Phi_w \beta^T + \Psi$$

$$\text{So } \beta^T = \Sigma_{22}^{-1} \Sigma_{23}, \text{ and } \hat{\beta}_{\text{bad}} = \hat{\Sigma}_{23}^+ \hat{\Sigma}_{22}^{-1} = \hat{\Sigma}_{32} \hat{\Sigma}_{22}^{-1}$$

$$(4f) \hat{\beta}_{\text{bad}} = \sum_{3,2} \sum_{2,2}^{-1} \xrightarrow{P} \sum_{3,2} \sum_{2,2}^{-1} \quad \boxed{11}$$

$$= \text{cov}(w, w) \text{cov}(w)^{-1}$$

Under the true model,

$$\begin{aligned} \text{cov}(w, w) &= \text{cov}(y_2 + e_2, x + e_1) = \text{cov}(\beta x + \varepsilon + e_2, x + e_1) \\ &= \beta \text{cov}(x) + \beta \text{cov}(x, e_1) + \text{cov}(\varepsilon, x) + \text{cov}(\varepsilon, e_1) + \text{cov}(e_2, x) + \text{cov}(e_2, e_1) \\ &= \beta \Phi_x + \beta C_{13} + C_{12}^T + C_{23} + C_{14}^T + C_{34}^T \\ &= \beta \Phi_x + \beta C_{13} + C_{21} + C_{23} + C_{41} + C_{43} \end{aligned}$$

And

$$\begin{aligned} \text{cov}(w) &= \text{cov}(x + e_1, x + e_1) = \text{cov}(x, x) + \text{cov}(x, e_1) + \text{cov}(e_1, x) \\ &\quad + \text{cov}(e_1, e_1) \\ &= \Phi_x + C_{13} + C_{31} + \Omega_1 \end{aligned}$$

So $\hat{\beta}_{\text{bad}} \xrightarrow{P} (\beta \Phi_x + \beta C_{13} + C_{21} + C_{23} + C_{41} + C_{43}) (\Phi_x + C_{13} + C_{31} + \Omega_1)^{-1}$

(g) How about $\hat{\beta}_{\text{good}} = \sum_{3,1} \sum_{2,1}^{-1} \xrightarrow{P} \sum_{3,1} \sum_{2,1}^{-1}$

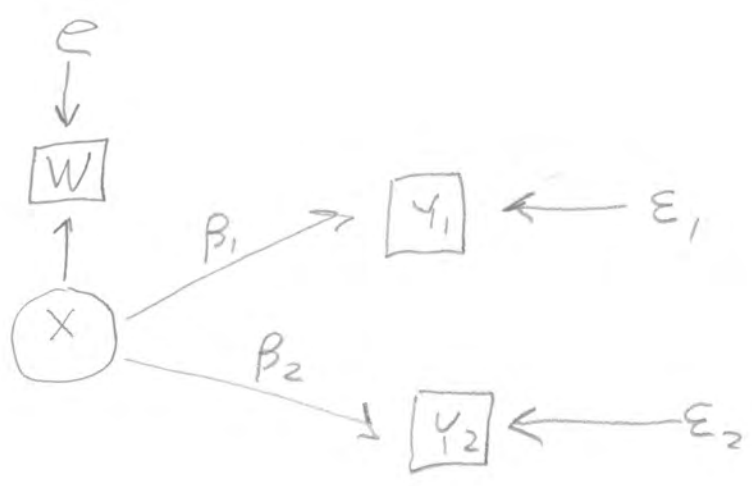
$$\begin{aligned} &= \text{cov}(w, z) \text{cov}(w, z)^{-1} = \text{cov}(y_2 + e_2, z) \text{cov}(x + e_1, z)^{-1} \\ &= \text{cov}(\beta x + \varepsilon + e_2, z) \text{cov}(x, z)^{-1} \\ &= \beta \text{cov}(x, z) \text{cov}(x, z)^{-1} = \beta \end{aligned}$$

only fails if K^{-1} does not exist.

(h) Because if not identifiable, convergence in probability is impossible. The set of parameter values where the columns of K are linearly dependent is of lower dimension, so it's a set of volume zero.

5

a



b) Unknown parameters are $(\beta_1, \beta_2, \sigma_x, \sigma_e, \sigma_{\epsilon_1}, \sigma_{\epsilon_2})$

c) $\Theta = (\beta_1, \beta_2, \sigma, \omega, \psi_1, \psi_2)$

d) Yes. There are $3(3+1)/2 = 6$ equations in 6 unknown parameters.

e)

	W	Y ₁	Y ₂
W	$\sigma + \omega$	$\beta_1 \sigma$	$\beta_2 \sigma$
Y ₁		$\beta_1^2 \sigma + \psi_1$	$\beta_1 \beta_2 \sigma$
Y ₂			$\beta_2^2 \sigma + \psi_2$

$cov(W, Y_1) = cov(X + e, \beta_1 X + \epsilon_1) = \beta_1 \sigma$

$cov(Y_1, Y_2) = cov(\beta_1 X + \epsilon_1, \beta_2 X + \epsilon_2) = \beta_1 \beta_2 \sigma$

f) β_1 is identifiable when $\beta_1 \neq 0$, because $\sigma_{12} = 0$ if and only if $\beta_1 = 0$

(5g) No, because if $\beta_1 = 0$, $\sigma_{12} = 0$ and $\sigma_{23} = 0$.

That means ϕ can't be identified and we can't get w from σ_{11} by subtraction.

(h) If $\beta_1 \neq 0$ and $\beta_2 = 0$,

$$\Sigma = \begin{pmatrix} \phi + w & \beta_1 \phi & 0 \\ \beta_1^2 \phi + \psi_1 & & 0 \\ & & \psi_2 \end{pmatrix}$$

	β_1	β_2	ϕ	w	ψ_1	ψ_2
Θ_1	1/2	0	4	1	4	1
Θ_2	2	0	1	4	1	1

Both yield

$$\Sigma = \begin{pmatrix} 5 & 2 & 0 \\ & 5 & 0 \\ & & 1 \end{pmatrix}$$

There are infinitely many other correct answers

(i) $\beta_2 = 0$ iff $\sigma_{13} = 0$, so β_2 is identifiable if equal to zero.

(5j) If $\beta_1 \neq 0$ and $\beta_2 \neq 0$,

$$\phi = \sigma_{12} \sigma_{13} / \sigma_{23}$$

$$\beta_1 = \sigma_{12} / \phi$$

$$\beta_2 = \sigma_{13} / \phi$$

$$w = \sigma_{11} - \phi$$

$$\psi_1 = \sigma_{22} - \beta_1^2 \phi$$

$$\psi_2 = \sigma_{33} - \beta_2^2 \phi$$

(k) Since $\beta_1 = \sigma_{12} / \phi = \frac{\sigma_{12}}{\sigma_{12} \sigma_{13} / \sigma_{23}}$

$$= \frac{\cancel{\sigma_{12}} \sigma_{23}}{\cancel{\sigma_{12}} \sigma_{13}} = \frac{\sigma_{23}}{\sigma_{13}}, \text{ let } \hat{\beta}_1 = \frac{\hat{\sigma}_{23}}{\hat{\sigma}_{13}}$$

(l) Because β_1 is not identifiable at points where $\beta_2 = 0$, we can't get convergence in probability there, and consistency means convergence to the true parameter values at every point in the parameter space.

(5m) $\hat{\beta}_1 \xrightarrow{p} \beta_1$ for all points with $\beta_2 \neq 0$.

(n) Same number of equations as unknowns, and parameters are identifiable so the mapping $\Sigma = g(\theta)$ is 1-1. Invariant means $\hat{\theta} = g^{-1}(\hat{\Sigma})$. Note that even if $\beta_2 = 0$, $\Pr(\hat{\beta}_2 = 0) = 0$, so with probability one, $\hat{\theta}$ lands in that part of the parameter space where θ is identifiable.

(o) If $\beta_1 = 0$, then β_1 is identifiable, but $\sigma_{12} = 0$ and $\sigma_{23} = 0$. This leaves 4 equations in the other 5 parameters, and the parameter count rule says they can't be identified except possibly on a restricted set of volume zero in \mathbb{R}^5 . This means the MLE $\hat{\theta}_0$ will not be unique, and estimation will fail.

(p) If $\beta_2 \neq 0$, then $\beta_1 = 0$ if and only if $\sigma_{12} = 0$ and $\sigma_{23} = 0$. This is unexpected because $H_0: \beta_1 = 0$ has only one = sign, and we expect a one df test.

(q) Because $\phi = \frac{\sigma_{12} \sigma_{13}}{\sigma_{23}}$ is a variance, $\frac{\sigma_{12} \sigma_{13}}{\sigma_{23}} > 0$

$\Leftrightarrow \sigma_{12} \sigma_{13} > 0$ which is unexpected.

(b) (a) Parameter count rule: Now there are 6 equations in 7 unknowns.

(b) $\Sigma = \text{Cov} \begin{pmatrix} W \\ Y_1 \\ Y_2 \end{pmatrix} =$

	W	Y ₁	Y ₂
W ₁	$\sigma + w$	$\beta_1 \sigma$	$\beta_2 \sigma + c$
Y ₁		$\beta_1^2 \sigma + \psi_1$	$\beta_1 (\beta_2 \sigma + c)$
Y ₂			$\beta_2^2 \sigma + 2\beta_2 c + \psi_2$

$w = x + e$
 $Y_1 = \beta_1 x + \epsilon_1$
 $Y_2 = \beta_2 x + \epsilon_2$

$\text{Cov}(Y_1, Y_2) = \text{Cov}(\beta_1 x + \epsilon_1, \beta_2 x + \epsilon_2)$
 $= \beta_1 \beta_2 \sigma + \beta_1 c$

$\text{Cov}(Y_2) = \text{Cov}(\beta_2 x + \epsilon_2, \beta_2 x + \epsilon_2)$
 $= \beta_2^2 \sigma + \beta_2 c + \beta_2 c + \psi_2$

It's the same covariance matrix except for the third column.

(c) $\hat{\beta}_1 = \frac{\hat{\sigma}_{23}}{\hat{\sigma}_{13}}$, same as (5).

(d) Need $\beta_2 \neq 0$ or $c \neq 0$, or both.

(e) $H_0: \sigma_{13} = \sigma_{23} = 0$

(f) i. $H_0: \sigma_{12} = \sigma_{23} = 0$

ii. Yes. Test $H_0: \sigma_{12} = 0$

iii. Yes. Look at the sign of σ_{12} .