

Computer Exercise 2 Answers: Determinants and Multicollinearity

```
. reg cost q q2 if _n<11, nocons
```

Source	SS	df	MS			
Model	2.45207913	2	1.22603956	Number of obs =	10	
Residual	1.00215589	8	.125269486	F(2, 8) =	9.79	
				Prob > F =	0.0071	
				R-squared =	0.7099	
				Adj R-squared =	0.6373	
Total	3.45423501	10	.345423501	Root MSE =	.35393	

costs	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
q	10.00407	3.100237	3.23	0.012	2.85491	17.15323
q2	-36.3137	18.3049	-1.98	0.083	-78.52488	5.897482

```
. corr q q2 if _n<11
(obs=10)
```

	q	q2
q	1.0000	
q2	0.9623	1.0000

```
. mkmat q q2 if e(sample), mat(X)
```

```
. matrix list X
```

```
X[10,2]
      q      q2
r1   .02   .0004
r2   .03   .0009
r3   .04   .0016
r4   .04   .0016
r5   .05   .0025
r6   .09   .0081
r7   .11   .0121
r8   .13   .0169
r9   .13   .0169
r10  .22   .0484
```

```
. matrix XpX=X'*X
```

```
. matrix list XpX
```

```
symmetric XpX[2,2]
      q      q2
q     .1094
q2    .01739 .00313814
```

```
. matrix dX=det(XpX)
```

```
. matrix list dX
```

```
symmetric dX[1,1]
      c1
r1   .0000409
```

```
. reg cost q q2 if _n<12, nocons
```

Source	SS	df	MS			
Model	3.56435923	2	1.78217962	Number of obs =	11	
Residual	1.31551179	9	.146167977	F(2, 9) =	12.19	
				Prob > F =	0.0027	
				R-squared =	0.7304	
				Adj R-squared =	0.6705	
Total	4.87987103	11	.443624639	Root MSE =	.38232	

costs	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
q	7.597686	2.917844	2.60	0.029	.9970639	14.19831
q2	-16.4953	14.41379	-1.14	0.282	-49.10156	16.11097

```
. corr q q2 if _n<12
(obs=11)
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	q	q2
q	1.0000	
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```
X[11,2]
      q      q2
r1   .02   .0004
r2   .03   .0009
r3   .04   .0016
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r5   .05   .0025
r6   .09   .0081
r7   .11   .0121
r8   .13   .0169
r9   .13   .0169
r10  .22   .0484
r11  .25   .0625
```

```
. matrix XpX=X'*X
```

```
. matrix list XpX
```

```
symmetric XpX[2,2]
      q      q2
q     .1719
q2    .033015 .00704439
```

```
. matrix dX=det(XpX)
```

```
. matrix list dX
```

```
symmetric dX[1,1]
      c1
r1   .00012094
```

```
. reg cost q q2 , nocons
```

Source	SS	df	MS	Number of obs =	145
Model	77015.686	2	38507.843	F(2, 143) =	1440.72
Residual	3822.11936	143	26.7281074	Prob > F =	0.0000
				R-squared =	0.9527
				Adj R-squared =	0.9521
Total	80837.8053	145	557.502106	Root MSE =	5.1699

costs	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
q	.4499231	.0272048	16.54	0.000	.3961475 .5036986
q2	.0019086	.000258	7.40	0.000	.0013985 .0024187

```
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```

```
. matrix XpX=X'*X
```

```
. matrix list XpX
```

```
symmetric XpX[2,2]
```

```
      q      q2  
q 189762.11  
q2 18002565 2.109e+09
```

```
. matrix dX=det(XpX)
```

```
. matrix list dX
```

```
symmetric dX[1,1]
```

```
      c1  
r1 7.618e+13
```

Now invert the $(X'X)$ matrix and compare your estimates of $(X'X)^{-1}$ from the three regressions.

What do you see?

```
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```
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```
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```

```
. matrix x1=syminv(XpX)
```

```
. matrix list x1
symmetric x1[2,2]
```

```
      q      q2
q    76.726359
q2  -425.17905  2674.7894
```

```
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```

```
. matrix list x1
symmetric x1[2,2]
```

```
      q      q2
q    58.246782
q2  -272.98567  1421.3611
```

```
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costs	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
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```
. matrix x1=syminv(XpX)
```

```
. matrix list x1
```

```
symmetric x1[2,2]
```

```
      q          q2
q      .00002769
q2    -2.363e-07  2.491e-09
```

Since the variance of the OLS estimates for variable i are formed by multiplying the ii^{th} element on the main diagonal of $(X'X)^{-1}$ by s^2 (or, in practice, the unbiased estimate $s^2 = \text{RSS}/N-k$ which is given by the value highlighted in the Stata output above)

Can see that the variance of the OLS estimates also gets smaller as the degree of multicollinearity falls