

Statistical Modeling

CH.8 - Analysis of Collinear Data

SS 2021 || Prof. Dr. Buchwitz

Wir geben Impulse

1 Organizational Information

2 Multicollinearity

3 Effects of Multicollinearity

4 Detection of Collinearity

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1	Simple Linear Regression
2	Multiple Linear Regression
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4	Qualitative Variables as Predictors
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1 Organizational Information

2 Multicollinearity

3 Effects of Multicollinearity

4 Detection of Collinearity

- The interpretation of the coefficients in a multiple regression equation depend implicitly on the assumption that the predictors are **not strongly interrelated**.
- The common interpretation of regression coefficient is the change in the response when the corresponding predictor is increased by one unit and all other predictors are held constant.

This interpretation may not be valid if there are strong linear relationships among the regressors.

- When there is complete absence of linear relationships among the predictor variables, they are said to be *orthogonal*.
- In most applications the regressors are not orthogonal. However, in some situations the predictor variables are so strongly interrelated that the regression results are ambiguous.
- The condition of severe nonorthogonality is also referred to as the problem of **multicollinearity**.
- This problem is *not a specification error* and thus cannot be detected in the residuals.
- **Multicollinearity** is a condition of deficient data.

We cover the following topics:

- 1 How does collinearity affect statistical inference and forecasting?
- 2 How can collinearity be detected?
- 3 What can be done to resolve the difficulties associated with collinearity (**next Session**).

In an analysis these questions cannot be answered separately. When multicollinearity all these issues must be treated simultaneously.

1 Organizational Information

2 Multicollinearity

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4 Detection of Collinearity

Example: Effects on Inference

P236

##	ACHV	FAM	PEER	SCHOOL
## 1	-0.43148	0.60814	0.03509	0.16607
## 2	0.79969	0.79369	0.47924	0.53356
## 3	-0.92467	-0.82630	-0.61951	-0.78635
## 4	-2.19081	-1.25310	-1.21675	-1.04076
## 5	-2.84818	0.17399	-0.18517	0.14229
## 6	-0.66233	0.20246	0.12764	0.27311
## 7	2.63674	0.24184	-0.09022	0.04967
## 8	2.35847	0.59421	0.21750	0.51876
## 9	-0.91305	-0.61561	-0.48971	-0.63219
## 10	0.59445	0.99391	0.62228	0.93368
## 11	1.21073	1.21721	1.00627	1.17381
## 12	1.87164	0.41436	0.71103	0.58978
## 13	-0.10178	0.83782	0.74281	0.72154
## 14	-2.87949	-0.75512	-0.64411	-0.56986
## 15	3.92590	-0.37407	-0.13787	-0.21770
## 16	4.35084	1.40353	1.14085	1.37147
## 17	1.57922	1.64194	1.29229	1.40269
## 18	3.95689	-0.31304	-0.07980	-0.21455
## 19	1.09275	1.28525	1.22441	1.20428
## 20	-0.62389	-1.51938	-1.27565	-1.36598
## 21	-0.63654	-0.38224	-0.05353	-0.35560
## 22	-2.02659	-0.19186	-0.42605	-0.53718
## 23	-1.46692	1.27649	0.81427	0.91967
## 24	3.15078	0.52310	0.30720	0.47231
## 25	-2.18938	-1.59810	-1.01572	-1.48315
## 26	1.91715	0.77914	0.87771	0.76496

Data Description

ACHV Student achievements.

FAM Faculty credentials

PEER Influence of peer group in school.

SCHOOL School facilities.

All variables are normalized indices. Goal is to evaluate the effect of school inputs on achievements.

Example: Effects on Inference

- The goal of the analysis is to measure the effect of the school inputs on achievements to assess *Equal Education Opportunity*. The variable SCHOOL is an index and we assume that it measures those aspects of the school environment that would affect achievement (physical plant, teaching materials, special programs, etc.).
- ACHV is an index constructed based on normalized test scores.
- Before we can assess the effect of the school we need to account for other variables that may influence ACHV, like the peer group and the personal environment. We assume that those are captured in the indices for PEER and FAM.

$$ACHV = \beta_0 + \beta_1 FAM + \beta_2 PEER + \beta_3 SCHOOL + \epsilon$$

Example: Effects on Inference

- The contribution of the SCHOOL variable can be tested using the t -Test for β_3 .
- The t -Test checks whether SCHOOL is necessary in the equation, given that FAM and PEER are already included.
- This can be interpreted as checking for an effect after the ACHV index has been adjusted for FAM and PEER.

$$ACHV - \beta_1 FAM - \beta_2 PEER = \beta_0 + \beta_3 SCHOOL + \epsilon$$

Note: This model is only for the sake of interpretation the model on the previous page is sufficient for the actual analysis.

Example: Effects on Inference

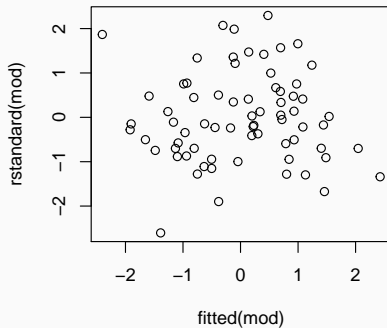
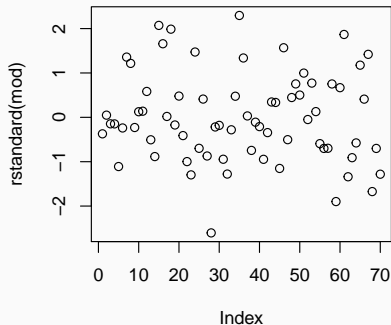
```
mod <- lm(ACHV ~ 1 + FAM + PEER + SCHOOL, data=P236)
```

```
summary(mod)
```

```
##  
## Call:  
## lm(formula = ACHV ~ 1 + FAM + PEER + SCHOOL, data = P236)  
##  
## Residuals:  
##      Min       1Q   Median       3Q      Max   
## -5.2096 -1.3934 -0.2947  1.1415  4.5881   
##  
## Coefficients:  
##              Estimate Std. Error t value Pr(>|t|)      
## (Intercept) -0.06996    0.25064  -0.279    0.781      
## FAM          1.10126    1.41056   0.781    0.438      
## PEER         2.32206    1.48129   1.568    0.122      
## SCHOOL      -2.28100    2.22045  -1.027    0.308      
##  
## Residual standard error: 2.07 on 66 degrees of freedom  
## Multiple R-squared:  0.2063, Adjusted R-squared:  0.1702   
## F-statistic: 5.717 on 3 and 66 DF,  p-value: 0.001535
```

Example: Effects on Inference

```
par(mfrow=c(1,2))  
plot(rstandard(mod))  
plot(fitted(mod), rstandard(mod))
```



Example: Effects on Inference

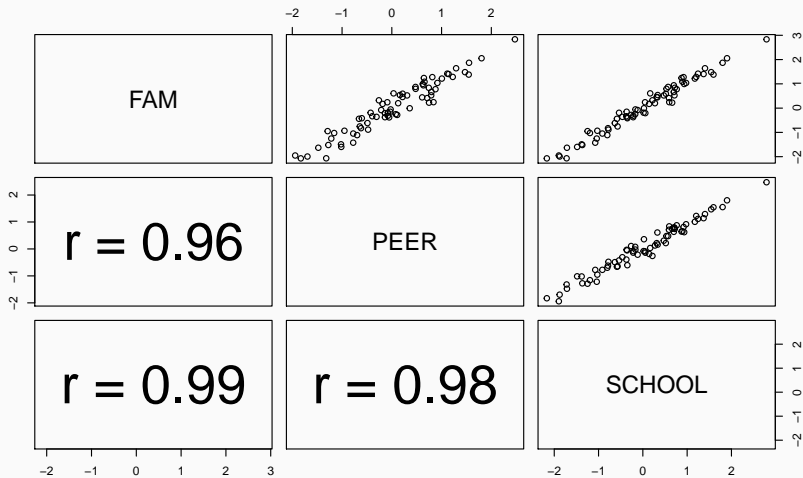
Observation:

- The regression model accounts for 20.63% of the data.
- The F -Statistic with a value of 5.7168 is significant and indicates a joint effect of the variables.
- All t -Statistics are small and indicate that none of the variables individually are significant.

Conclusion:

- The given situation is common for settings where **multicollinearity** occurs.
- The small t -values suggest that any of the variables can be dropped and the joint R^2 is affected by the relationship among the predictors.

Example: Effects on Inference



Example: Effects on Inference

Combination	FAM	PEER	SCHOOL
1	+	+	+
2	+	+	-
3	+	-	+
4	-	+	+
1	+	-	-
2	-	+	-
3	-	-	+
4	-	-	-

A "+" indicates a value above average in the data. The dataset only contains combinations 1 and 8 and is deficient so that not all partial effects can be estimated.

Example: Effects on Inference

- The dataset contains *missing combinations* which leads to the empty regions in the pairsplot. There may be two reasons for this:
 - 1) Incomplete data collection, so that collecting additional data leads to disappearing multicollinearity.
 - 2) The ground truth (population) only contains a specific set of combinations. Then it is not possible to separate effects and estimate the individual effects on achievement. A detailed investigation may lead to additional variables that are *more basic* determinants for the response.

Example: Effects on Forecasting

- We now examine the effect of multicollinearity on **forecasting**.
- The considered dataset (imports in the French economy) is index by time (variable YEAR).
- To generate **forecasts for the response**, future values of the predictor variables are plugged into the estimated regression equation.
- The future values of the predictor variables must be known or need to be forecasted themselves (not discussed in this course).
- We assume that the future values of the predictor variables are **given**, which is highly **unrealistic and only for explanatory purposes**.

Example: Effects on Forecasting

P241

##	YEAR	IMPORT	DOPROD	STOCK	CONSUM
## 1	49	15.9	149.3	4.2	108.1
## 2	50	16.4	161.2	4.1	114.8
## 3	51	19.0	171.5	3.1	123.2
## 4	52	19.1	175.5	3.1	126.9
## 5	53	18.8	180.8	1.1	132.1
## 6	54	20.4	190.7	2.2	137.7
## 7	55	22.7	202.1	2.1	146.0
## 8	56	26.5	212.4	5.6	154.1
## 9	57	28.1	226.1	5.0	162.3
## 10	58	27.6	231.9	5.1	164.3
## 11	59	26.3	239.0	0.7	167.6
## 12	60	31.1	258.0	5.6	176.8
## 13	61	33.3	269.8	3.9	186.6
## 14	62	37.0	288.4	3.1	199.7
## 15	63	43.3	304.5	4.6	213.9
## 16	64	49.0	323.4	7.0	223.8
## 17	65	50.3	336.8	1.2	232.0
## 18	66	56.6	353.9	4.5	242.9

Data Description

YEAR Year of Observation.

IMPORT Import Volume.

DOPROD Domestic Production.

STOCK Stock Formation.

CONSUM Domestic Consumption.

Variables are measured in billion French francs.

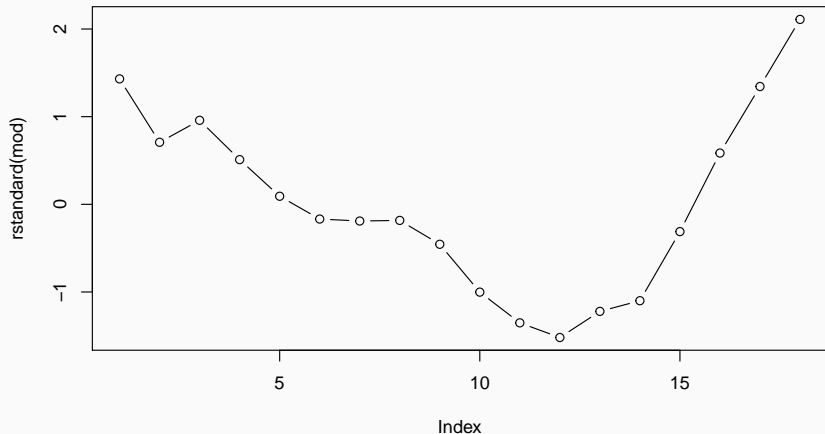
Example: Effects on Forecasting

```
mod <- lm(IMPORT ~ 1 + DOPROD + STOCK + CONSUM, data=P241)
summary(mod)

##
## Call:
## lm(formula = IMPORT ~ 1 + DOPROD + STOCK + CONSUM, data = P241)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.7208 -1.8354 -0.3479  1.2973  4.1008
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -19.7251     4.1253  -4.782 0.000293 ***
## DOPROD         0.0322     0.1869   0.172 0.865650
## STOCK         0.4142     0.3223   1.285 0.219545
## CONSUM        0.2427     0.2854   0.851 0.409268
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.258 on 14 degrees of freedom
## Multiple R-squared:  0.973, Adjusted R-squared:  0.9673
## F-statistic: 168.4 on 3 and 14 DF, p-value: 3.212e-11
```

Example: Effects on Forecasting

```
plot(rstandard(mod), type="b")
```



Example: Effects on Forecasting

$$\text{IMPORT} = \beta_0 + \beta_1 \text{DOPROD} + \beta_2 \text{STOCK} + \beta_3 \text{CONSUM} + \epsilon$$

- The index plots of the residuals suggests that the model is not well specified, even though the R^2 is high.
- The problem reflected in the data is that the European Common Market began operations in 1960, causing changes in import-export relationships.
- Our objective is to study the effect of **multicollinearity**, we decide to ignore the dynamics after 1959 and only analyze the first 11 years of data.

Example: Effects on Forecasting

```
mod <- lm(IMPORT ~ 1 + DOPROD + STOCK + CONSUM, data=head(P24, 10))
summary(mod)

##
## Call:
## lm(formula = IMPORT ~ 1 + DOPROD + STOCK + CONSUM, data = head(P24, 10))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.52367 -0.38953  0.05424  0.22644  0.78313
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -10.12799    1.21216   -8.355  6.9e-05 ***
## DOPROD         -0.05140    0.07028   -0.731  0.488344
## STOCK          0.58695    0.09462    6.203  0.000444 ***
## CONSUM         0.28685    0.10221    2.807  0.026277 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4889 on 7 degrees of freedom
## Multiple R-squared:  0.9919, Adjusted R-squared:  0.9884
## F-statistic: 285.6 on 3 and 7 DF,  p-value: 1.112e-07
```

An increase in Domestic Production should cause an increase in the imports, when STOCK and CONSUM are held constant. Contrary to the prior model and to our beliefs, the coefficient for DOPROD is not statistically significant. The residuals show no suspicious patterns.

Example: Effects on Forecasting

```
kable(round(cor(head(P241,11)),4))
```

	YEAR	IMPORT	DOPROD	STOCK	CONSUM
YEAR	1.0000	0.9476	0.9952	-0.0329	0.9952
IMPORT	0.9476	1.0000	0.9653	0.2507	0.9719
DOPROD	0.9952	0.9653	1.0000	0.0259	0.9973
STOCK	-0.0329	0.2507	0.0259	1.0000	0.0357
CONSUM	0.9952	0.9719	0.9973	0.0357	1.0000

- Investigation reveals that correlation between CONSUM and DOPROD is very high throughout the 11 year period.

Example: Effects on Forecasting

- The estimated relationship between CONSUM and DOPROD is given below.

$$\widehat{\text{CONSUM}} = 6.259 + 0.686(\text{DOPROD})$$

- Even in the presence of severe multicollinearity the regression equation *may* produce some good forecasts. The forecasting equation follows directly from the regression output.

$$\widehat{\text{IMPORT}} = -10.128 - 0.051(\text{DOPROD}) + 0.587(\text{STOCK}) + 0.287(\text{CONSUM})$$

For our purpose we must be confident that the character and strength of the overall relationship will hold into future periods (which is untrue in the given case, but ignored for convenience of explanation).

Example: Effects on Forecasting

- If we forecast the change in IMPORT next year corresponding to an increase in DROPROD of 10 units while holding STOCK and CONSUM at their current levels:

$$\text{IMPORT}_{1960} \approx \text{IMPORT}_{1959} - 0.051 \cdot 10$$

- This leads to a decrease in IMPORT by ≈ 0.51 units. However, if the relationship between DROPROD and CONSUM is kept intact, CONSUM will increase as well and the forecasted results change and yields a forecasted increase in IMPORT.

$$\text{IMPORT}_{1960} \approx \text{IMPORT}_{1959} - 0.051 \cdot 10 + 0.287 \cdot 0.686 \cdot 10$$

1 Organizational Information

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3 Effects of Multicollinearity

4 Detection of Collinearity

- In the following we review the discussed ideas and introduce additional criteria that indicate multicollinearity.
- Besides simple indicators we are going to consider the two criteria **Variance Inflation Factors (VIF)** and **Condition Indices**.
- Simple indicators of multicollinearity are usually encountered during the process of adding, deleting or transforming variables or data points while searching for a good model.

Simple Signs of Collinearity

Indications of multicollinearity that appear as instability in the estimated coefficients are as follows:

- Large changes in the estimated coefficients when a variable is added or deleted.
- Large changes in the estimated coefficients when a data point is added or deleted.

Once the residual plots indicate that the model has been satisfactorily specified, collinearity may be present if:

- The algebraic signs of estimated coefficients do not conform to prior expectations.
- Coefficients of variables that are expected to be important have large standard errors (small t -values).

Simple Signs of Collinearity

- The table shows the effect of adding an removing a variable for the French economy data. We see that the presence or absence of certain variables has a large effect on the other coefficients.
- This problem is visible in the pairwise correlation coefficients.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
(Intercept)	-6.56* (2.59)	19.61*** (3.25)	-8.01** (2.44)	-8.44*** (1.44)	-8.88* (2.85)	-9.74*** (1.06)	-10.13*** (1.21)
DOPROD	0.15*** (0.01)			0.15*** (0.01)	-0.11 (0.17)		-0.05 (0.07)
STOCK		0.69 (0.89)		0.62** (0.13)		0.60*** (0.09)	0.59*** (0.09)
CONSUM			0.21*** (0.02)		0.37 (0.24)	0.21*** (0.01)	0.29* (0.10)
R ²	0.93	0.06	0.94	0.98	0.95	0.99	0.99
Adj. R ²	0.92	-0.04	0.94	0.98	0.93	0.99	0.99
Num. obs.	11	11	11	11	11	11	11

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 4: Statistical models

Simple Signs of Collinearity

The source of multicollinearity may be more subtle than the simple relationship between two variables so that it **may not be possible to detect such a relationship with a simple correlation coefficient.**

```
kable(cor(P248)) # Advertising Data
```

	St	At	Pt	Et	At.1	Pt.1
St	1.0000000	-0.1704051	0.5401769	0.8108732	-0.3051611	-0.0520353
At	-0.1704051	1.0000000	-0.3569539	-0.1285210	-0.1397402	-0.4959912
Pt	0.5401769	-0.3569539	1.0000000	0.0625887	-0.3164655	-0.2963645
Et	0.8108732	-0.1285210	0.0625887	1.0000000	-0.1664279	0.2081124
At.1	-0.3051611	-0.1397402	-0.3164655	-0.1664279	1.0000000	-0.3577610
Pt.1	-0.0520353	-0.4959912	-0.2963645	0.2081124	-0.3577610	1.0000000

Simple Signs of Collinearity

P248

##	St	At	Pt	Et	At.1	Pt.1
## 1	20.11371	1.98786	1.0	0.30	2.01722	0.0
## 2	15.10439	1.94418	0.0	0.30	1.98786	1.0
## 3	18.68375	2.19954	0.8	0.35	1.94418	0.0
## 4	16.05173	2.00107	0.0	0.35	2.19954	0.8
## 5	21.30101	1.69292	1.3	0.30	2.00107	0.0
## 6	17.85004	1.74334	0.3	0.32	1.69292	1.3
## 7	18.87558	2.06907	1.0	0.31	1.74334	0.3
## 8	21.26599	1.01709	1.0	0.41	2.06907	1.0
## 9	20.48473	2.01906	0.9	0.45	1.01709	1.0
## 10	20.54032	1.06139	1.0	0.45	2.01906	0.9
## 11	26.18441	1.45999	1.5	0.50	1.06139	1.0
## 12	21.71606	1.87511	0.0	0.60	1.45999	1.5
## 13	28.69595	2.27109	0.8	0.65	1.87511	0.0
## 14	25.83720	1.11191	1.0	0.65	2.27109	0.8
## 15	29.31987	1.77407	1.2	0.65	1.11191	1.0
## 16	24.19041	0.95878	1.0	0.65	1.77407	1.2
## 17	26.58966	1.98930	1.0	0.62	0.95878	1.0
## 18	22.24466	1.97111	0.0	0.60	1.98930	1.0
## 19	24.79944	2.26603	0.7	0.60	1.97111	0.0
## 20	21.19105	1.98346	0.1	0.61	2.26603	0.7
## 21	26.03441	2.10054	1.0	0.60	1.98346	0.1
## 22	27.39304	1.06815	1.0	0.58	2.10054	1.0

Data Description

S_t Sales Volume.

A_t Advertising Expenditures.

P_t Promotion Expenditures.

E_t Sales Expense.

A_{t-1} and P_{t-1} are the lagged one-year variables.

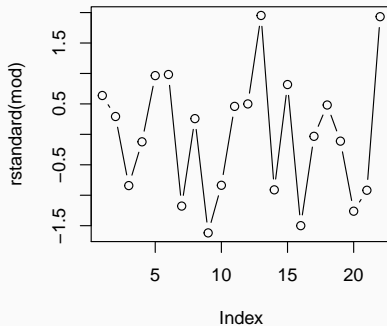
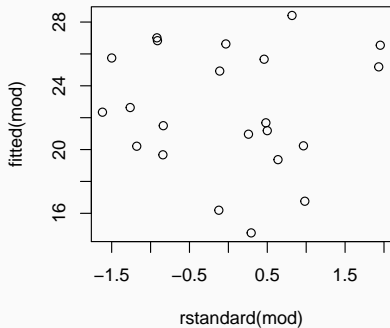
Simple Signs of Collinearity

```
mod <- lm(St ~ 1 + At + Pt + Et + At.1 + Pt.1, data=P248)
summary(mod)

##
## Call:
## lm(formula = St ~ 1 + At + Pt + Et + At.1 + Pt.1, data = P248)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.8601 -0.9848  0.1323  0.7017  2.2046
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -14.194      18.715  -0.758   0.4592
## At              5.361       4.028   1.331   0.2019
## Pt              8.372       3.586   2.334   0.0329 *
## Et             22.521       2.142  10.512 1.36e-08 ***
## At.1           3.855       3.578   1.077   0.2973
## Pt.1           4.125       3.895   1.059   0.3053
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.32 on 16 degrees of freedom
## Multiple R-squared:  0.9169, Adjusted R-squared:  0.8909
## F-statistic: 35.3 on 5 and 16 DF, p-value: 4.289e-08
```

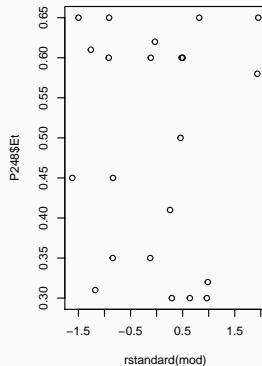
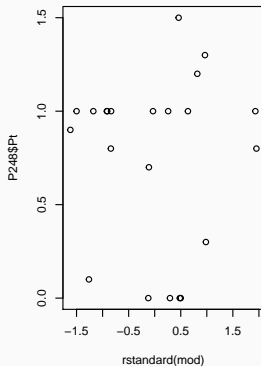
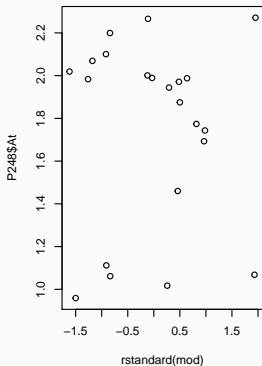
Simple Signs of Collinearity

```
par(mfrow=c(1,2))  
plot(rstandard(mod), fitted(mod))  
plot(rstandard(mod), type="b")
```



Simple Signs of Collinearity

```
par(mfrow=c(1,3))  
plot(rstandard(mod), P248$At)  
plot(rstandard(mod), P248$Pt)  
plot(rstandard(mod), P248$Et)
```



Simple Signs of Collinearity

- The residual plots do not exhibit clear signs of misspecification and the correlation between the predictors is moderate and does not indicate a problem.
- Experimentation shows that dropping the advertising variable A_t leads to severe changes in the coefficients (coefficient of P_t drops significantly, coefficients of lagged values change signs.)

```
mod.experiment <- lm(St ~ 1 + Pt + Et + At.1 + Pt.1, data=P248)
coef(mod.experiment)
```

## (Intercept)	Pt	Et	At.1	Pt.1
## 10.5093791	3.7017522	22.7941828	-0.7691882	-0.9686601

Simple Signs of Collinearity

- The reason for the multicollinearity in the previous example is a budget constraint so that the sum of A_t , A_{t-1} , P_t and P_{t-1} was held approximately constant:

$$A_t + A_{t-1} + P_t + P_{t-1} \approx 5$$

- This can be empirically confirmed by regressing A_t on A_{t-1} , P_t and P_{t-1} .

```
mod.constraint <- lm(At ~ 1 + Pt + At.1 + Pt.1, data=P248)
equatiomatic::extract_eq(mod.constraint, use_coef=T)
```

$$\hat{A}_t = 4.63 - 0.87(P_t) - 0.86(A_{t-1}) - 0.95(P_{t-1})$$

Variance Inflation Factors (VIF)

- A thorough investigation of multicollinearity will involve examining the value of R^2 that results from regression **each of the predictors against all others**.
- The resulting effects can be judged by examining a quantity called *variance inflation index (VIF)*.

$$VIF_j = \frac{1}{1 - R_j^2} \quad \text{with } j = 1, \dots, p$$

- R_j^2 denotes the multiple correlation coefficient from regression the predictor X_j on all other $p - 1$ predictor variables.
- When X_j has a strong linear relationship with the other variables, R_j^2 will be close to 1 and VIF_j will be large.

A $VIF > 10$ is often taken as indicator that the data has multicollinearity problems.

Variance Inflation Factors (VIF)

- When R_j^2 is close to zero $VIF \approx 1$. The departure from 1 indicates departure from orthogonality and tendency toward collinearity.
- The naming is derived from the fact that VIF_j measures the amount by which the variance of the j -th regression coefficient is increased due to the linear association of X_j with other predictors **relative** to the value of the variance that would result in absence of a linear relation.
- As R_j^2 approaches 1, the VIF_j for $\hat{\beta}_j$ tends to infinity.

Variance Inflation Factors (VIF)

- The precision of the OLS estimates is measured by its variance, which is proportional to the variance of the error term in the regression model σ^2 .
- The **constant of proportionality** is the VIF.
- The VIF's therefore can be used to obtain an expression for the expected squared distance of the OLS estimators from their true values. The smaller D^2 the more accurate are the estimates.

$$D^2 = \sigma^2 \sum_{j=1}^p \text{VIF}_j$$

- If the predictors were orthogonal, the VIF's would be equal to 1 and $D^2 = p\sigma^2$. It follows that the ratio $\overline{\text{VIF}}$ measures the squared error in the OLS estimators relative to the size of the error if the data were orthogonal.

$$\overline{\text{VIF}} = \frac{\sigma^2 \sum_{i=1}^p \text{VIF}_i}{p\sigma^2} = \frac{\sum_{i=1}^p \text{VIF}_i}{p}$$

- $\overline{\text{VIF}}$ can also be used as an **index for multicollinearity**.

Variance Inflation Factors (VIF)

```
# Equal Education Opportunity Data
```

```
mod.eeo <- lm(ACHV ~ 1 + FAM + PEER + SCHOOL, data=P236)
```

```
vif.eeo <- car::vif(mod.eeo)
```

```
c(vif.eeo, averageVIF = mean(vif.eeo))
```

```
##          FAM          PEER      SCHOOL averageVIF
##  37.58064   30.21166   83.15544   50.31591
```

```
# Import Data
```

```
mod.imp <- lm(IMPORT ~ 1 + DOPROD + STOCK + CONSUM, data=P241)
```

```
vif.imp <- car::vif(mod.imp)
```

```
c(vif.imp, averageVIF = mean(vif.imp))
```

```
##      DOPROD      STOCK      CONSUM averageVIF
## 469.742135   1.049877 469.371343 313.387785
```

```
# Advertising Data
```

```
mod.adv <- lm(St ~ 1 + At + Pt + Et + At.1 + Pt.1, data=P248)
```

```
vif.adv <- car::vif(mod.adv)
```

```
c(vif.adv, averageVIF = mean(vif.adv))
```

```
##          At          Pt          Et      At.1      Pt.1 averageVIF
##  36.941513  33.473514   1.075962  25.915651  43.520965  28.185521
```

Condition Indices

- Another way to detect collinearity in the data is to examine the condition indices for the *correlation matrix* of the predictor variables.
- The condition indices are based on the eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_p$ of the correlation matrix. If any $\lambda = 0$, there is perfect linear relationship, which is an extreme case of collinearity. Strong heterogeneity in the eigenvalues (one value much smaller than the others) also indicates multicollinearity.
- An empirical criterion for the presence of collinearity is given by the sum of the reciprocals of the eigenvalues of the correlation matrix. If that sum is much larger (e.g. 5 times larger) than the number of predictor variables p , collinearity is present.

$$\sum_{j=1}^p \frac{1}{\lambda_j}$$

- The condition indices measures the overall collinearity of the variables. The j -th condition index is given by

$$\kappa_j = \sqrt{\frac{\lambda_1}{\lambda_p}} \quad \text{for } j = 1, 2, \dots, p$$

- The largest condition index is called *condition number* of the matrix. If that condition number is small, then the predictor variables are not collinear. A large condition number indicates strong evidence of collinearity.
- Corrective actions should be taken, when the condition number **exceeds 15** (which means that λ_1 is more than 225 times λ_p)

Condition Indices

```
# Equal Education Opportunity Data
```

```
mod.eeo <- lm(ACHV ~ 1 + FAM + PEER + SCHOOL, data=P236)
round(olsrr::ols_eigen_cindex(mod.eeo), 4)
```

##	Eigenvalue	Condition Index	intercept	FAM	PEER	SCHOOL
## 1	2.9547	1.0000	0.0005	0.0030	0.0037	0.0014
## 2	0.9974	1.7211	0.9756	0.0000	0.0000	0.0000
## 3	0.0400	8.5996	0.0004	0.3068	0.4428	0.0008
## 4	0.0079	19.2826	0.0235	0.6903	0.5535	0.9978

```
# Import Data
```

```
mod.imp <- lm(IMPORT ~ 1 + DOPROD + STOCK + CONSUM, data=head(P241,11))
round(olsrr::ols_eigen_cindex(mod.imp), 4)
```

##	Eigenvalue	Condition Index	intercept	DOPROD	STOCK	CONSUM
## 1	3.8384	1.0000	0.0010	0.0000	0.0109	0.0000
## 2	0.1484	5.0863	0.0053	0.0001	0.9385	0.0001
## 3	0.0132	17.0732	0.7743	0.0015	0.0330	0.0011
## 4	0.0001	265.4613	0.2193	0.9984	0.0175	0.9989

```
# Advertising Data
```

```
mod.adv <- lm(St ~ 1 + At + Pt + Et + At.1 + Pt.1, data=P248)
round(olsrr::ols_eigen_cindex(mod.adv), 4)
```

##	Eigenvalue	Condition Index	intercept	At	Pt	Et	At.1	Pt.1
## 1	5.2810	1.0000	0.0000	0.0000	0.0002	0.0023	0.0001	0.0002
## 2	0.3798	3.7291	0.0000	0.0000	0.0075	0.0003	0.0000	0.0118
## 3	0.2272	4.8209	0.0000	0.0015	0.0160	0.0000	0.0011	0.0054
## 4	0.0601	9.3777	0.0000	0.0047	0.0004	0.2912	0.0160	0.0006

- Using the described techniques we can now detect multicollinearity.
- However, it is unclear how to deal with variables that cause collinearity issues. Removing those variables is often not a viable option.
- We will learn better ways of dealing with collinearity in the next chapter.