

Multiple linear regression 1

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Why do we need multiple linear regression.

An example

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The general model

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The parameters.

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Checking the model

Fitted values, residuals and leverage

Extending the model

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Linear and Logistic regression - Note 2.1

Why do we need a multiple regression

The simple linear regression model only models how the dependent variable, y , depend on **one** independent variable (covariate), x_1 .

We are often interested in **how** several independent variables, x_1, x_2, \dots, x_k , influence the dependent variable, y .

Sometimes we want to **adjust** the influence of some of the information, such as age and sex, before we look at the 'effect' of other variables.

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A multiple linear regression model

We will here start by considering a **random** subsample consisting of 200 persons from the Frammingham data set used in the book.

A multiple linear regression model:

$$\ln(sbp) = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{woman} + \beta_3 \cdot \ln(bmi) + E$$

Where the **errors**, E , are assumed to be **independent** and **normal** with mean zero and standard deviation σ .

Note, that variable **woman** is a **dummy**/indicator variable, that it is

one if the person is a **woman** and
zero if it is a **man**.

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Interpretation of the coefficients 0 - the constant

$$\ln(sbp) = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{woman} + \beta_3 \cdot \ln(bmi) + E$$

The first coefficient (the constant term) is the **expected** $\ln(sbp)$ for

a **man** (that is ok!)

$\text{age}=0$??????

$\text{bmi}=1 \text{ kg/m}^2$?????? ($\ln(1)=0$).

As in the simple linear regression this not of any interest.

But again we can control the interpretation, by choosing **relevant reference** values for **age** and **bmi**. E.g.

$$\ln(sbp) = \alpha_0 + \beta_1 \cdot (\text{age} - 45) + \beta_2 \cdot \text{woman} + \beta_3 \cdot \ln\left(\frac{\text{bmi}}{25}\right) + E$$

↑
age45

lnBMI25

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Interpretation of the coefficients 1

$$\ln(sbp) = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{woman} + \beta_3 \cdot \ln(bmi) + E$$

The **expected** $\ln(sbp)$ for a **man** with $\text{bmi}=27 \text{ kg/m}^2$ is:

$$\beta_0 + \beta_1 \cdot \text{age} + \beta_3 \cdot \ln(27)$$

The **expected** $\ln(sbp)$ for another **man** with the same **bmi**, but 1.7 year older: $\beta_0 + \beta_1 \cdot (\text{age} + 1.7) + \beta_3 \cdot \ln(27)$

The difference is: $1.7\beta_1$

We see that this difference

• does not depend on the **age** of the first man.

• does not depend on the **bmi** as long as it is the same for the two men.

• would be the same if the two persons were women.

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Interpretation of the coefficients 2

$$\ln(sbp) = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{woman} + \beta_3 \cdot \ln(bmi) + E$$

The **expected** $\ln(sbp)$ for a 50 year old **man** with $\text{bmi}=27 \text{ kg/m}^2$ is: $\beta_0 + \beta_1 \cdot 50 + \beta_3 \cdot \ln(27)$

The **expected** $\ln(sbp)$ for **woman** with the same **age** and **bmi** $\beta_0 + \beta_1 \cdot 50 + \beta_2 + \beta_3 \cdot \ln(27)$

The difference is: β_2

We see that this difference

• does not depend on the **age** as long as it is the same for the two persons.

• does not depend on the **bmi** as long as it is the same for the two persons.

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Interpretation of the coefficients 3

$$\ln(\text{sbp}) = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{woman} + \beta_3 \cdot \ln(\text{bmi}) + E$$

The **expected** $\ln(\text{sbp})$ for a **woman** who is 50 year old:

$$\beta_0 + \beta_1 \cdot 50 + \beta_2 + \beta_3 \cdot \ln(\text{bmi})$$

The **expected** $\ln(\text{sbp})$ for another **woman** with the same age, but with a **bmi** which is 10% higher:

$$\beta_0 + \beta_1 \cdot 50 + \beta_2 + \beta_3 \cdot \ln(1.1 \cdot \text{bmi})$$

The difference $\beta_3 \cdot [\ln(1.1 \cdot \text{bmi}) - \ln(\text{bmi})] = \beta_3 \cdot \ln(1.1)$

We see that this difference

• **does not depend on the bmi** of the first woman.

• **does not depend on the age** as long as it is the same for the two women.

• **would be the same if the two persons were men.**

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Interpretation of the coefficients 4

$$\ln(\text{sbp}) = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{woman} + \beta_3 \cdot \ln(\text{bmi}) + E$$

$$\beta_3 \cdot [\ln(1.1 \cdot \text{bmi}) - \ln(\text{bmi})] = \beta_3 \cdot \ln(1.1)$$

As the **bmi** is introduced on the **log-scale**, then "differences" of this variable is measured **relatively**.

So comparing a pair of persons how **only differ** in **bmi**.

One having $\text{bmi}=25 \text{ kg/m}^2$ and the other $\text{bmi}=27 \text{ kg/m}^2$.

Then the expected difference in $\ln(\text{sbp})$ is:

$$\beta_3 \cdot \ln\left(\frac{27}{25}\right) = \beta_3 \cdot 0.077$$

If the **bmi**'s were 21 kg/m^2 and

23 kg/m^2 , then the expected

difference in $\ln(\text{sbp})$ would be:

$$\beta_3 \cdot \ln\left(\frac{23}{21}\right) = \beta_3 \cdot 0.091$$

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Interpretation of the coefficients 5

$$\ln(\text{sbp}) = \beta_0 + \beta_1 \cdot \text{age} + \beta_2 \cdot \text{woman} + \beta_3 \cdot \ln(\text{bmi}) + E$$

Taking the **exponential** we get:

$$\text{sbp} = \gamma_0 \cdot \gamma_1^{\text{age}} \cdot \gamma_2^{\text{woman}} \cdot \text{bmi}^{\beta_3} \cdot \exp(E)$$

where $\gamma_0 = \exp(\beta_0)$, $\gamma_1 = \exp(\beta_1)$ and $\gamma_2 = \exp(\beta_2)$

That is a non-linear model on the **sbp scale**!

The error is **multiplicative**.

As **medians** are preserved by the exponential transformation then the estimates telling of **effect on the median sbp**.

An example: The age and bmi adjusted median is a factor γ_2 higher for man than for women.

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The multiple linear regression in general

Y the **dependent variable**

(x_1, x_2, \dots, x_k) the **independent variables**.

$$Y = \beta_0 + \sum_{p=1}^k \beta_p \cdot x_p + E \quad E \sim N(0, \sigma^2)$$

This model is based on the **assumptions**:

1. The **expected** value of Y is $\beta_0 + \sum_{p=1}^k \beta_p \cdot x_p$
2. The **unexplained** random deviations are **independent**.
3. The unexplained random deviations have the **same distributions**.
4. This distribution is **normal**.

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The multiple linear regression in general

$$Y = \beta_0 + \sum_{p=1}^k \beta_p \cdot x_p + E \quad E \sim N(0, \sigma^2)$$

We see that the assumptions fall in **two parts**:

The **first concerning** the systematic part

and the three other which focus on the error, the unexplained random variation.

Before we turn to how one can check some of the assumptions we will take a closer look at the first assumption.

The **expected** value of Y is $\beta_0 + \sum_{p=1}^k \beta_p \cdot x_p$

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The assumption of linearity

The **expected** value of Y is $\beta_0 + \sum_{p=1}^k \beta_p \cdot x_p$

This is based on three (sub) assumptions:

- a. **Additivity:** The contribution from each of the independent variables are **added**.
- b. **Proportionality:** The contribution from independent variables is **proportional** to its value (with a factor β)
- c. **No effectmodification:** The contribution from one independent variables is **the same** whatever the values are for the other.

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The assumption of linearity

The **expected** value of Y is $\beta_0 + \sum_{p=1}^k \beta_p \cdot x_p$

If one consider two persons who differ with

Δx_1 in x_1 , Δx_2 in x_2 ... and Δx_k in x_k

then difference in the **expected** value of Y is :

$$\sum_{p=1}^k \beta_p \cdot \Delta x_p$$

Again we see that the **contribution** for each of the explanatory variables:

are **added**,
are **proportional to the difference**
and **does not dependent** of the differences in the other

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Estimation

It is almost impossible to find the estimates by hand, but easy if you use a computer.

In Stata: `regress lnSBP age45 woman lnBMI25`

(Note first we have to generate `lnSBP`, `age45`, `woman` and `lnBMI25`)

Source	SS	df	MS	Number of obs	= 200
Model	1.05572698	3	.351908994	F(3, 196) =	16.46
Residual	4.18969066	196	.021375973	Prob > F =	0.0000
				R-squared =	0.2013
Total	5.24541764	199	.026358883	Adj R-squared =	0.1890
				Root MSE =	.14621

lnSBP	coef.	std. Err.	t	P> t	[95% Conf. Interval]
woman	.0036329	.0208905	0.17	0.862	-.0375662 .0448319
age45	.0065384	.0012844	5.09	0.000	.0040053 .0090715
lnBMI25	.2583399	.0758295	3.41	0.001	.1087934 .4078864
_cons	4.856592	.0154266	314.82	0.000	4.826169 4.887016

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Estimation

The last part of the output: **No CI for σ !**
It can be calculated "by hand"

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lnSBP					$\hat{\sigma}$ Root MSE = .14621
woman	.0036329	.0208905	0.17	0.862	-.0375662 .0448319
age45	.0065384	.0012844	5.09	0.000	.0040053 .0090715
lnBMI25	.2583399	.0758295	3.41	0.001	.1087934 .4078864
_cons	4.856592	.0154266	314.82	0.000	4.826169 4.887016

the $\hat{\beta}$'s

the se's

The CI's

Test for $\beta_2 = 0$

The hypothesis: "no difference in $\ln(sbp)$ between men and women **adjusted** for age and bmi"

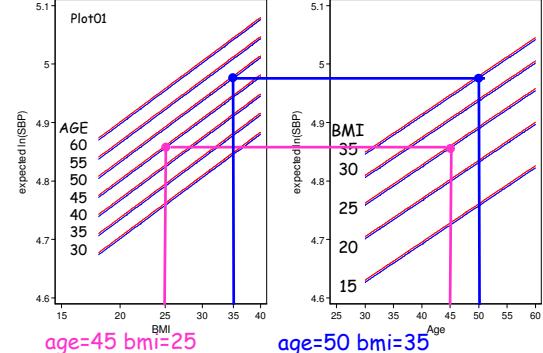
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Estimated systematic part

$$\ln(sbp) = 4.8566 + 0.0065 \cdot (age - 45) + 0.0036 \cdot woman + 0.2583 \cdot \ln\left(\frac{bmi}{25}\right)$$



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Stata special - plotting response curves

`regress lnSBP age45 woman lnBMI25`

lnSBP	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
woman	.0036329	.0208905	0.17	0.862	-.0375662 .0448319
age45	.0065384	.0012844	5.09	0.000	.0040053 .0090715
lnBMI25	.2583399	.0758295	3.41	0.001	.1087934 .4078864
_cons	4.856592	.0154266	314.82	0.000	4.826169 4.887016

After a regression command, Stata leave will several information in the memory for later use.

You can get a list by writing "ereturn list" and we have already used this feature in the calculation of the confidence interval for σ .

Another example:

```
. display %12.7f _b[woman] %12.7f _se[woman]
0.0036329 0.0208905
```

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Stata special - plotting response curves

The Stata code below will generate a "global macro" with the estimated equation and four other global macros with the estimated coefficients.

If our are going to use it, then copy-paste from today's do-file ([Stataplots.do](#)).

```
macro drop c* regvar eq freq
matrix zzzmat=e(b)
global regvar : colnames e(b)
global eq "0"
global freq "0"
local zzzn 0
foreach zzz in $regvar {
  local zzzn=$zzzn+1
  local coef=zzzmat[1, `zzzn']
  if abs(`coef')>0.00000001 {
    global c`zzz'=`coef'
    global freq="$freq" + " + #c" + "`zzz'"+ "*`zzz'"
    global eq="$eq" + "+string(`coef',"%.4f")+"*`zzz'"
  }
}
```

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Stata special - plotting response curves

After this you can see the estimated equation by:

```
display "$eq"
0 + 0.0065*age45 + 0.0036*woman + 0.2583*lnBMI25 + 4.8566*_cons
display "$eq"
0 + #cage45*age45 + #cwoman*woman + #clnBMI25*lnBMI25 +
#c_cons*_cons
```

If you write "macro list" you will get a list the "macros"

```
. macro list
eq: 0 + 0.0065*age45 + 0.0036*woman + 0.2583*lnBMI25 + 4.8566*_cons
feq: 0 + #cage45*age45 + #cwoman*woman + #clnBMI25*lnBMI25 + #c_cons*_cons
c_cons: 4.856592269392944
clnBMI25: .2583398993331005
cwoman: .0036328605876014
cage45: .0065383788673611
regvar: age45 woman lnBMI25 _cons
S_E_depvar: lnSBP
S_E_cmd: regress
....
```

The macros `c_cons`, `clnBMI25`, `cwoman` and `cage45` contains the coefficients and can be used in calculation. if you want use them you just write `$clnBMI25`.

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Stata special - plotting response curves

The expected $\ln(SBP)$ for a 30 year old man with $BMI=27$

```
display $c_cons+$cwoman*0+$cage45*(30-45)+$clnBMI25*ln(27/25)
4.7783987
```

You could also get this (with CI) using the `lincom` command:

```
display ln(27/25)
.07696104
. lincom _cons-15*age45+.07696104*lnBMI25
( 1) - 15 age45 + .076961 lnBMI25 + _cons = 0
----- lnSBP | Coef. Std. Err. t P>|t| [95% Conf. Interval]
----- (1) | 4.778399 .0266891 179.04 0.000 4.725764 4.831033
```

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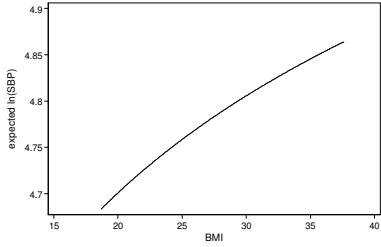
Stata special - plotting response curves

The expected $\ln(SBP)$ for a 30 year old man as a function of the **BMI** is given as:

$\$c_cons + \$cwoman*0 + \$cage45*(30-45) + \$clnBMI25*\ln(BMI/25)$

We can plot this by using the `plot` function in Stata:

```
twoway
( function y=$c_cons+$cwoman*0+$cage45*(30-45)+$clnBMI25*ln(x/25) , range(bmi) lco(blue) ) ///
( function y=$c_cons+$cwoman*1+$cage45*(50-45)+$clnBMI25*ln(x/25) , range(bmi) lco(red) ) ///
, legend(off) ytit("expected ln(SBP)") xtit("BMI") xlab( 15(5)40)
```



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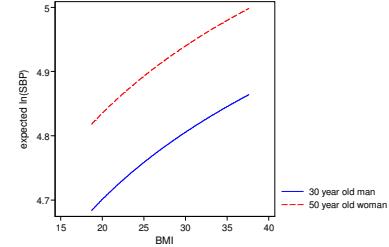
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Stata special - plotting response curves

The expected $\ln(SBP)$ for a 30 year old **man** and a 50 year old **woman** as a function of the **BMI** is given as:

```
twoway
( function y=$c_cons+$cwoman*1+$cage45*(50-45)+$clnBMI25*ln(x/25) , range(bmi) lco(blue) ) ///
( function y=$c_cons+$cwoman*1+$cage45*(50-45)+$clnBMI25*ln(x/25) , range(bmi) lco(red) ) ///
, ytit("expected ln(SBP)") xtit("BMI") xlab( 15(5)40)
legend(label(1 "30 year old man") label(2 "50 year old woman"))
```



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The distribution of the estimates

It can be shown that the **estimates of the coefficients** have **normal distributions**, with **means** equal to the **true values**.

The formulas for the standard deviation of the estimates are **complicated**, but they are estimated by the **standard errors** given in the output.

The estimated standard deviation of the errors is given by:

$$\hat{\sigma}^2 \sim \frac{\sigma^2}{n-k-1} \chi^2(n-k-1) \quad \text{The number of parameters are } k+1$$

Which gives the confidence interval:

$$95\% \text{ CI for } \sigma: \hat{\sigma} \cdot \sqrt{\frac{n-k-1}{\chi^2_{n-k-1}(0.975)}} \leq \sigma \leq \hat{\sigma} \cdot \sqrt{\frac{n-k-1}{\chi^2_{n-k-1}(0.025)}}$$

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Confidence intervals

Just like in the simple regression we get :
(except we have $n-k-1$ degrees of freedom).

Exact 95% confidence intervals, CI 's, for β_p is found from the estimates and standard errors

$$95\% \text{ CI for } \beta_p: \hat{\beta}_p \pm t_{n-k-1}^{0.975} \cdot \text{se}(\hat{\beta}_p)$$

Where $t_{n-k-1}^{0.975}$ is the upper 97.5 percentile in the t-distribution $n-k-1$ degrees of freedom.

These confidence intervals are found in the output.

Note that if $n-k-1$ is large then this percentile is close to 1.96 and one can use the **approximate confidence intervals**:

$$\text{Approx. } 95\% \text{ CI for } \beta_p: \hat{\beta}_p \pm 1.96 \cdot \text{se}(\hat{\beta}_p)$$

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The ANOVA table and the F-test

The first part of the output:

An analysis of variance table dividing the variation in y in two components: explained by the **model** (i.e. the 3 variables) and the **residual** (the rest)

Source	SS	df	MS
Model	1.05572698	3	.351908994
Residual	4.18969066	196	.021375973
Total	5.24541764	199	.026358883

Number of obs = 200
 $F(3, 196) = 16.46$
 $P > F = 0.0000$
 R-squared = 0.2013
 Adj R-squared = 0.1890
 Root MSE = .14621

A F-test testing the hypothesis: "all (except β_0) is zero."

Here the test is highly significant: The model explains a statistically significant part of the variation in y !

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The F-test and R-squared

The F-test calculated as: $F = \frac{0.35519}{0.02138} = 16.16$

Source	SS	df	MS
Model	1.05572698	3	.351908994
Residual	4.18969066	196	.021375973
Total	5.24541764	199	.026358883

Number of obs = 200
 $F(3, 196) = 16.46$
 $P > F = 0.0000$
 R-squared = 0.2013
 Adj R-squared = 0.1890
 Root MSE = .14621

And under the hypothesis it follows an F-distribution with 3 and 196 degrees of freedom.

The R-squared is the amount of the total variation explained by the model ($=1.0557/5.2454$).

As this will **increase** if we include more variables in the model one can look at the **adjusted R-squared**.

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Predicted values, residuals and leverages

$$Y = \beta_0 + \sum_{p=1}^k \beta_p \cdot x_p + E \quad E \sim N(0, \sigma^2)$$

As in the simple linear regression one can find **predicted values**, **residuals**, **leverages** and **standardized residuals**:

Predicted value: $\hat{y}_i = \hat{\beta}_0 + \sum_{p=1}^k \hat{\beta}_p \cdot x_{pi}$

Residual: $r_i = y_i - \hat{y}_i = y_i - \sum_{p=1}^k \hat{\beta}_p \cdot x_{pi}$

Leverage: $h_i = \text{a complicated formula}$

Standardized-Residual: $z_i = \frac{r_i}{\hat{\sigma} \sqrt{1 - h_i}}$

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Leverage

Although the formula for leverage is complicated, the **interpretation** of leverage is the same:

A **high leverage** indicates that the data point has **extreme** values of the explanatory variables and hence a **high influence** on the estimates.

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Checking the model 1:

As model is much more complicated than the simple linear regression checking the model is also complicated

Again **assumption no. 2: the errors should be independent**, is mainly checked by considering how the data was collected.

The **distribution of the error** is checked by the same type of plot as for the simple linear regression.

• Plots of residuals versus **fitted**

• Plots of residuals versus **each of the explanatory variables**.

• Histogram and QQ-plot of the residuals.

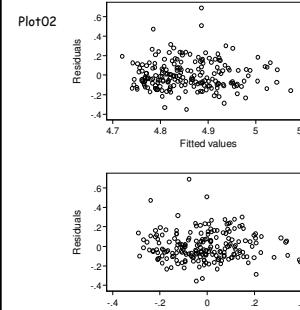
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```
rvfplot ,name(p1,replace)
rvpplot age45 ,name(p2,replace)
rvpplot lnBMI25 ,name(p3,replace)
rvpplot woman ,name(p4,replace)
graph combine p1 p2 p3 p4
```

residual versus fitted
residual versus predictor



Not informative see next page

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Diagnostic plots for categorical variables - here woman

```
predict res if e(sample),res
qnorm res if woman==0, title(woman==0) name(p1,replace)
qnorm res if woman==1, title(woman==1) name(p2,replace)
graph combine p1 p2 , row(1) name(p3,replace)
graph box res , over(woman) name(p4,replace)
graph combine p3 p4,col(1)
by woman: sum res
```

Plot03

???
Plot03

Plot03

Residuals

Residuals

sd=0.131 sd=0.157

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Diagnostic plots for continuous variables - dividing into groups

```
xtile age6=age,nq(6)
graph box res,over(age6) name(p1,replace) nodraw
dotplot res,over(age6) name(p2,replace) nodraw
graph combine p1 p2 ,col(1)
graph export Reg2_1_plot04.wmf, replace
```

Plot04

Plot04

Residuals

Residuals

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Identifying special points

leverage vs. residuals leverage vs. normed residuals squared#

Plot05

1017, 2337, 2187 have relative large residuals

#:
$$\frac{r_i^2}{\sum r_j^2}$$

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Checking the model 2: Independent errors ?

Assumption no. 2: the errors should be **independent**, is mainly checked by considering **how the data was collected**.

The assumption is **violated** if

- some of the persons are **relatives** (and some are not) and the dependent variable have some **genetic component**.
- some of the persons were **measured** using one instrument and others with another.
- in general if the persons were sampled in **clusters**.

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Checking the model 3: Extending the model

One should **also** try to check the validity of the linearity assumption that is the assumption of **additivity**, **proportionality** and **no effect modification** (no interaction).

It can be done by:

1. Introducing an the explanatory variable in a **different scale**, e.g. adding `age2` or `log(age)`
2. Introducing the explanatory variable as a **categorical** variable instead e.g. use `age` in divided into **agegroups** instead as age in years.
3. Introducing **interaction** between some of the explanatory variables.
4.

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