To calculate the variance components we need to extract the standard deviations of the random effects from the model summary, square them to get the variances, then express each as a percentage of the total:

```
sds<-c(1.150604,1.131932,1.489864,1.923191,3.917264,0.9245321)
vars<-sds^2
100*vars/sum(vars)
```

```
[1]  5.354840  5.182453  8.978173  14.960274  62.066948  3.457313
```

This indicates that the gender effect (62%) is much the most important component of overall variance. Next most important is variation from family to family (15%).

For comparison, here is the layout of the output for the same analysis using lmer:

```
library(lme4)
model1<-lmer(subject~1+(1|town/district/street/family/gender))
summary(model1)
```

```
Linear mixed-effects model fit by REML
Formula: subject ~ 1 + (1 | town/district/street/family/gender)
 AIC    BIC   logLik  MLdeviance  REMLdeviance
3349   3377   -1669         3338          3337

Random effects:
  Groups                                         Name         Variance  Std.Dev.
  gender:(family:(street:(district:town)))  (Intercept)   15.3387   3.91647
  family:(street:(district:town))           (Intercept)    3.7008   1.92375
  street:(district:town)                    (Intercept)    2.2283   1.49274
  district:town                             (Intercept)    1.2796   1.13121
  town                                      (Intercept)    1.3238   1.15056
  Residual                                                 0.8548   0.92456

number of obs: 720, groups: gender:(family:(street:(district:town))),
360; family:(street:(district:town)), 180; street:(district:town), 60;
district:town, 15; town, 5

Fixed effects:
              Estimate   Std. Error   t value
(Intercept)     8.011        0.672     11.92
```

You will see that the variance components are given in the penultimate column. Fixed effects in this model are discussed on p. 656.

Model Simplification in Hierarchical Sampling

We need to know whether all of the random effects are required in the model. The key point to grasp here is that you will need to recode the factor levels if you want to leave out a random effect from a larger spatial scale. Suppose we want to test the effect of leaving out the identity of the towns. Because the districts were originally coded with the same names within each town,

```
levels(district)
```

```
[1]  "d1"  "d2"  "d3"
```