APPENDIX A: Proof of the unbiasness of the r_s^2 estimate for a two population structured sample when loci are unlinked.

Let *S* denote the random Bernoulli variable which equals 1 if the sampled individual comes from the first population and 0 otherwise. Let *t* denote the probability of S = 1 then,

$$Esp(S) = t \tag{A1}$$

$$Var(S) = Esp(S) - (Esp(S))^{2} = t(1-t)$$
 (A2)

Let X^{l} denote the dummy random variable equaling 1 when an individual carries the A allele at locus l and 0 otherwise, then

$$Esp(X^{l}) = Esp(S = 0)Esp(X^{l} | S = 0) + Esp(S = 1)Esp(X^{l} | S = 1)$$

= (1-t)Esp(X^{l} | S = 0) + tEsp(X^{l} | S = 1) (A3)

Using equations (A1) and (A3), we get

$$Cov(X^{'}, S) = Esp(X^{'}S) - Esp(X^{'})Esp(S)$$

= $Esp(S = 1)Esp(X^{'} | S = 1) - t(1 - t)Esp(X^{'} | S = 0) - t^{2}Esp(X^{'} | S = 1)$ (A4)
= $t(1 - t)(Esp(X^{'} | S = 0) - Esp(X^{'} | S = 1))$

Using equations (A2) and (A4) we obtain

$$Cov(X^{'}, S)Var(S)Cov(S, X^{''}) = t(1-t)(Esp(X^{'} | S = 0) - Esp(X^{'} | S = 1))$$

$$(Esp(X^{''} | S = 0) - Esp(X^{''} | S = 1))$$
(A5)

On an other hand, theoretical developments of $Cov(X^{l}, X^{m})$ give

$$Cov(X^{l}, X^{m}) = Esp(X^{l}X^{m}) - Esp(X^{l})Esp(X^{m})$$

$$= (1-t)Esp(X^{l}X^{m} | S = 0) + tEsp(X^{l}X^{m} | S = 1) - Esp(X^{l})Esp(X^{m})$$

$$= (1-t)Cov(X^{l}, X^{m} | S = 0) + tCov(X^{l}, X^{m} | S = 1) - Esp(X^{l})Esp(X^{m})$$

$$+ (1-t)Esp(X^{l} | S = 0)Esp(X^{m} | S = 0) + tEsp(X^{l} | S = 1)Esp(X^{m} | S = 1)$$

$$= (1-t)Cov(X^{l}, X^{m} | S = 0) + tCov(X^{l}, X^{m} | S = 1)$$

$$+ t(1-t)(Esp(X^{l} | S = 0) - Esp(X^{l} | S = 1))(Esp(X^{m} | S = 0) - Esp(X^{m} | S = 1))$$

(A6)

Thus, using equations (A5) and (A6) we obtain that

$$Cov(X^{l} | S, X^{m} | S) = Cov(X^{l}, X^{m}) - Cov(X^{l}, S)Var(S)Cov(S, X^{m})$$

= (1-t)Cov(X^l, X^m | S = 0) + tCov(X^l, X^m | S = 1)

which equals 0 when the loci are unlinked.

APPENDIX B: Proof that the r_s^2 measure is the proportional factor to apply to sample size in order to achieve the same power of structure corrected association test at a SNP locus in linkage disequilibrium with the causal locus, as at the causal locus itself.

Let a trait, observed on a sample of size ${\it N}$, be explained by a causal locus l in the following linear model

$$Y = 11_{N} \mu + S\beta + X^{l}\theta^{l} + \varepsilon$$

where $Y = (y_1, ..., y_i, ..., y_N)^T$ is the vector of observed trait values, ε is the residual vector that is assumed to have expectation 0 and variance σ^2 , and (μ, β, θ^I) are the parameters for the mean, the structure effect and the causal locus effect, respectively.

The association t-test is equal to

$$t^{l} = \frac{\hat{\theta}^{l}}{\sqrt{\operatorname{Var}(\hat{\theta}^{l})}}$$

with

$$\operatorname{Var}(\hat{\theta}^{l}) = \hat{\sigma}^{2}([\tilde{\mathbf{S}}, \tilde{\mathbf{X}}^{l}]^{T}[\tilde{\mathbf{S}}, \tilde{\mathbf{X}}^{l}])_{2,2}^{-1}$$

where $\hat{\sigma}^2$ is the estimate of σ^2 , \tilde{S} and \tilde{X}^l are the centered S and X^l matrices, respectively, and $_{2,2}$ denotes the second diagonal block of the matrix.

By definition of the sample variance-covariance matrix, we get

$$[\tilde{\mathbf{S}}, \tilde{\mathbf{X}}^{l}]^{T}[\tilde{\mathbf{S}}, \tilde{\mathbf{X}}^{l}] = (N-1) \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^{l}} \\ \Sigma_{x^{l},s} & \Sigma_{x^{l},x^{l}} \end{pmatrix}$$

The inversion of the block matrix gives

$$\begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^{l}} \\ \Sigma_{x^{l},s} & \Sigma_{x^{l},x^{l}} \end{pmatrix}_{2,2}^{-1} = \frac{1}{(N-1)(\Sigma_{x^{l},x^{l}} - \Sigma_{x^{l},s} \Sigma_{s,s}^{-1} \Sigma_{s,x^{l}})}$$

So, asymptotically we get that t^l is Gaussian with variance 1 and expectation equal to $\sqrt{(N-1)(\Sigma_{x^l,x^l} - \Sigma_{x^l,s}\Sigma_{s,x^l}^1)} \theta^l / \sigma$.

The t-test at the SNP locus
$$m$$
 is $t^m = \frac{\hat{\theta}^m}{\sqrt{\operatorname{Var}(\hat{\theta}^m)}}$ with $\operatorname{Var}(\hat{\theta}^m) = \hat{\sigma}^2([\tilde{S}, \tilde{X}^m]^T[\tilde{S}, \tilde{X}^m])_{2,2}^{-1}$.

To find the expectation of t^m under the causal model, which is the correct one for the expectation of the data Y, it is necessary to calculate the second block of

$$([\tilde{\mathbf{S}}, \tilde{\mathbf{X}}^m]^T)^{-1}[\tilde{\mathbf{S}}, \tilde{\mathbf{X}}^m][\tilde{\mathbf{S}}, \tilde{\mathbf{X}}^m]^T Esp(Y) = \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^m} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^m} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_{x^m,x^l} \end{pmatrix}^{-1} \begin{pmatrix} \Sigma_{s,s} & \Sigma_{s,x^l} \\ \Sigma_{x^m,s} & \Sigma_$$

This second block is equal to $(\Sigma_{x^m,x^m} - \Sigma_{x^m,s} \Sigma_{s,s}^{-1} \Sigma_{s,x^m})^{-1} (\Sigma_{x^m,x^l} - \Sigma_{x^m,s} \Sigma_{s,s}^{-1} \Sigma_{s,x^l}) \theta^l$

We find, asymptotically,

$$Esp(t^{m}) \simeq \sqrt{N-1} \frac{\sum_{x^{m}, x^{l}} - \sum_{x^{m}, s} \sum_{s, s}^{-1} \sum_{s, x^{l}}}{\sqrt{\sum_{x^{m}, x^{m}} - \sum_{x^{m}, s} \sum_{s, s}^{-1} \sum_{s, x^{m}}}} \theta^{l} / \sigma = \sqrt{\hat{r}_{s}^{2}(l, m)} Esp(t^{l})$$

Thus, t^m is asymptotically Gaussian with variance 1 and expectation equal to $\sqrt{\hat{r}_s^2(l,m)}Esp(t^l)$. This finishes the first part of the proof showing that $\hat{r}_s^2(l,m)$ is the reducing power factor between the causal locus and a SNP locus in linkage disequilibrium.

Now, let us suppose that we get a N^m sample at the SNP locus and a N^l sample at the causal locus. Using that asymptotically $\hat{r}_s^2(l,m) \approx r_s^2(l,m)$ and that $\Sigma_{x^l,x^l} - \Sigma_{x^l,s} \Sigma_{s,x^l}^1 \approx Var(X^l | S)$, we get

$$Esp(t^{m}) \approx \sqrt{r_{s}^{2}(l,m)} \sqrt{(N^{m}-1)Var(X^{l} | S)} \theta^{l} / \sigma = \sqrt{r_{s}^{2}(l,m)} \sqrt{\frac{N^{m}-1}{N^{l}-1}} Esp(t^{l})$$

Then, we obtain that the sample size has to be increased by a factor equal to $1/r_s^2(l,m)$ to achieve the same power at the SNP locus, compared to the power at the causal locus.