

607

## Generalized Distance, Quadratic Forms, and the GLS principle

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### ► Readings!?!

- There are no readings for this brief note.
- But you might want to look at Mahalanobis (1936) as mentioned at the end.

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### ► Quadratic forms, distance, units, etc.

- Suppose  $\phi$  is a  $(K \times 1)$  real-valued vector
- $\phi$  defines a point in  $\mathcal{R}^K$
- And the Euclidean distance between the origin and  $\phi$  is  $D^{1/2}$  where

$$D = (\phi' \phi)$$

### ► Coordinate systems

- Take any full rank matrix  $L$  and define

$$\tilde{\phi} = L\phi$$

- We can think of  $\tilde{\phi}$  as picking out the same point as before in a new coordinate system.
- This system has the same origin as the original, but the axes that are moved around in some way.
- And we may have proportionally stretched or shrunken the units on the axes.

E.g., for  $L = \kappa I$  we have stretched/shrunk the units on every axis proportionally.

- In our new units, the distance to the origin is  $\tilde{D}^{1/2}$  where

$$\tilde{D} = \tilde{\phi}'\tilde{\phi} = \phi' L' L \phi$$

Or defining  $W = L' L$ ,

$$\tilde{\phi}'\tilde{\phi} = \phi' W \phi$$

- $W = L' L$  is obviously positive definite (since  $L$  is full rank).
- Thus, we can think of  $\phi' W \phi$  where  $W$  varies across all the positive definite matrices, as giving the distance to the origin in all coordinate systems of this type.

### ► Statistics

- If  $\phi$  is drawn from some joint distribution with mean zero elements,  $D^{1/2}$  is a measure of how far this draw is from the mean.
- With symmetric, single peaked, iid distributions,  $\phi$ s farther from the mean are less likely to be observed.
- Thus,  $D$  forms a natural measure of how unlikely  $\phi$  is to be observed.

bigger  $D$  implies less likely

- Of course, we can always ask ‘unlikely relative to what?’
- And this is essentially a matter of units
- If the elements of  $\phi$  are mean zero with variance-covariance matrix  $I\sigma^2$  we have one natural metric: the variance (or standard deviation).
- $K^{-1}E\phi'\phi = K^{-1}E[D] = \sigma^2$
- Thus, it is often useful to talk in standard deviation units. How many standard deviations away from the origin does  $\phi$  fall.
- This is given by  $(D/E[D])^{1/2}$ .

### ► Heterogeneity

- If the  $\phi$ s are heterogeneously distributed (but still mean zero), then it is not necessarily the case that larger  $D$  means less likely.

### ► Aside:: Should be obvious, but...

- Take the case with  $K = 2$  and  $E[\phi_i^2] = \sigma_i^2$ ,  $i = 1, 2$  and  $\sigma_1^2$  much larger than  $\sigma_2^2$ .
- In this case  $\phi = (2, 1)'$  (for which  $D = 5$ ) may be more likely to be observed than  $\phi = (1, 1.5)'$ , for which  $D = 3.25$ .

- Thus, with heterogeneous variances, relative  $D$ s are not a good indicator of relative likelihoods of being observed.

► **But generalized distance, however,...**

- But we could shift units to some give a metric for which  $D$  has the nice properties it does when the  $\phi$ s are mutually uncorrelated and homoskedastic.
- As you probably know, if  $E\phi\phi' = \Sigma$ , then the distance metric we want is  $\phi'W\phi$  where  $W = \Sigma^{-1}$ .
- In particular, pick  $L$  such that,

$$W \equiv L'L = \Sigma^{-1}$$

- Now measure distance in terms of  $\tilde{\phi} = L\phi$
- We have that

$$\begin{aligned} E\tilde{\phi}\tilde{\phi}' &= EL\phi\phi'L \\ &= L\Sigma L \\ &= L(L'L)^{-1}L \\ &= I \end{aligned}$$

- That is, the  $\tilde{\phi}$ s are orthonormal

(mutually orthogonal with unit variance)

- In these new units, a larger value of  $\tilde{D}$  unambiguously means that such  $\tilde{\phi}$ s are less likely to be observed when the underlying distributions are single-peaked, symmetric distributions, and differ only up to scale.

► **The GLS principle**

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- GLS principle: When you see a stochastic expression such as  $\phi'\phi$ , you should consider a more general expression,  $\phi'W\phi$ , and, in particular, to consider  $W = \Sigma^{-1}$  where  $\Sigma$  is the variance-covariance matrix of  $\phi$ .
- Perhaps better called the GLS rule of thumb, but that doesn't have the gravitas of a principle.

► **Examples: OLS and GLS**

- Consider OLS in the case with fixed regressors.

$$Y = X\beta + \varepsilon$$

- OLS is defined by minimizing  $\hat{\varepsilon}'\hat{\varepsilon}$ .

$$\hat{\varepsilon} = Y - X\hat{\beta}$$

- Of course, OLS is not efficient when  $E\varepsilon\varepsilon' = \Sigma \neq I\sigma_\varepsilon^2$

But GLS, is efficient

- GLS chooses  $\hat{\beta}$  to minimize

$$\hat{\varepsilon}'\Sigma^{-1}\hat{\varepsilon}$$

- This is the first application of the GLS principle that we usually see in econometrics and it is from this result I take the name.

► **Aside:: GLS and changed units**

- GLS can be viewed as OLS on the system

$$\tilde{Y} = \tilde{X}\beta + \tilde{\varepsilon}$$

where in each case, the tilde version of the term involves premultiplying the original by  $L$  where  $L'L = \Sigma^{-1}$ .

► **Wald test statistics**

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- As you may recall, the conventional Wald test statistic is precisely a generalized distance measure
- We estimate an unrestricted model and then take a generalized distance between the estimate,  $\hat{\beta}$  and the value hypothesized under the null,  $\beta_0$ .
- That is, the Wald statistic is:

$$(\hat{\beta} - \beta_0)'V^{-1}(\hat{\beta} - \beta_0)$$

where  $V$  is (a consistent estimator for) the variance-covariance matrix of  $\hat{\beta} - \beta$ .

► **Efficient GMM**

- We'll see below that efficient GMM essentially arises from picking the GMM weight matrix to satisfy the GLS principle.

► **Generalized distance and  $\chi^2$  distributions**

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- If  $\phi \sim N(0, \Sigma)$ , then  $\tilde{\phi} = L\phi$  where  $L'L = \Sigma^{-1}$  satisfies

$$\tilde{\phi} \sim N(0, I)$$

is

- Thus,  $\tilde{\phi}'\tilde{\phi} = \phi'\Sigma^{-1}\phi \sim \chi^2_{(p)}$
- This is where  $\chi^2$  distributions arise in testing.

► **Asymptotics**

- The results just given all follow as asymptotic results when  $\phi$  is asymptotically  $N(0, \Sigma)$ .

► **Much econometrics**

- As we are seeing, much of our advanced econometrics involves quadratic approximations and asymptotically normal random variables.
- Thus the general perspective reviewed here, and the GLS principle, in particular, will get a lot of play.

► **To nurture your scholarly nature**

- Prasanta Mahalanobis wrote a nice article entitled, ‘On the generalised distance in statistics’ in 1936.

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- What I’ve discussed as a generalized distance measure is sometimes called the Mahalandobis distance.
- There now, don’t you feel your roots in statistics growing down and reaching out?