A GUIDE TO Econometrics

Fourth Edition

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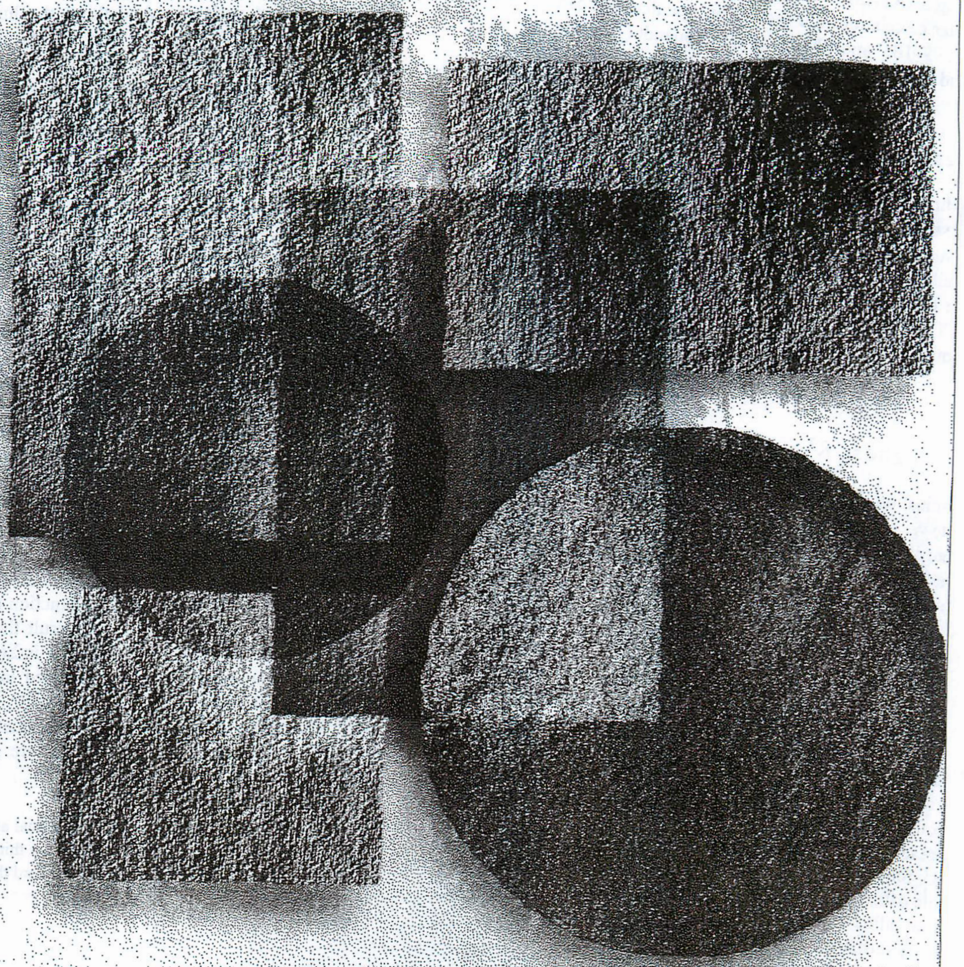

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E, RATS, SAS, SHAZAM, SORITEC, SPSS,
metrics and the *Journal of Economic Surveys*
. All these packages are very comprehensive,
techniques discussed in textbooks. For appli-
s specialized programs exist. These packages
d in econometric theory, however. Misleading
produced if these packages are used without a
s in which they are applicable, their inherent
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ng SHAZAM.
ter calculations are ignored in practice, but can
. 99–101) and Rhodes (1975). Quandt (1983) is
d methods in econometrics.

east Squares

timates tend to correspond to the average of lay-
to a scatter of data. See Mosteller et al. (1981).
sured as the vertical distances from the observa-
alternative to this vertical measure is the orthogo-
observation to the estimating line along a line
This infrequently seen alternative is discussed in
ometimes used when measurement errors plague

Highest R^2

mination. It is the square of the correlation coeffi-
te $\hat{y}$.
nt variable y about its mean, $\Sigma(y - \bar{y})^2$, is called
e "explained" variation, the sum of squared devia-
dependent variable about their mean, $\Sigma(\hat{y} - \bar{\hat{y}})^2$ is
squares); and the "unexplained" variation, the sum
E (the error sum of squares). R^2 is then given by

nerally accepted answer to this question. In dealing
^{2}s are not unusual, because of common trends. Ames
ple, that on average the R^2 of a relationship between
ts own value lagged one period is about 0.7, and that
obtained by selecting an economic time series and
other randomly selected economic time series. For
re not nearly so high.
R^2. Since the R^2 measure is used as an index of how
ple data, the OLS estimator is often called the "best-
ften called a "good fit."
a are formally identical, objections to the latter apply

to the former. The most frequently voiced of these is that searching for a good fit is likely to generate parameter estimates tailored to the particular sample at hand rather than to the underlying "real world." Further, a high R^2 is not necessary for "good" estimates; R^2 could be low because of a high variance of the disturbance terms, and our estimate of β could be "good" on other criteria, such as those discussed later in this chapter.

- The neat breakdown of the total variation into the "explained " and "unexplained" variations that allows meaningful interpretation of the R^2 statistic is valid only under three conditions. First, the estimator in question must be the OLS estimator. Second, the relationship being estimated must be linear. Thus the R^2 statistic only gives the percentage of the variation in the dependent variable explained *linearly* by variation in the independent variables. And third, the linear relationship being estimated must include a constant, or intercept, term. The formulas for R^2 can still be used to calculate an R^2 for estimators other than the OLS estimator, for nonlinear cases and for cases in which the intercept term is omitted; it can no longer have the same meaning, however, and could possibly lie outside the 0–1 interval. The zero intercept case is discussed at length in Aigner (1971, pp. 85–90). An alternative R^2 measure, in which the variations in y and $\hat{y}$ are measured as deviations from zero rather than their means, is suggested.
- Running a regression without an intercept is the most common way of obtaining an R^2 outside the 0–1 range. To see how this could happen, draw a scatter of points in (x,y) space with an estimated OLS line such that there is a substantial intercept. Now draw in the OLS line that would be estimated if it were forced to go through the origin. In both cases *SST* is identical (because the same observations are used). But in the second case the *SSE* and the *SSR* could be gigantic, because the $\hat{\varepsilon}$s and the $(\hat{y} - \bar{y})$s could be huge. Thus if R^2 is calculated as $1 - SSE/SST$, a negative number could result; if it is calculated as SSR/SST, a number greater than one could result.
- R^2 is sensitive to the range of variation of the dependent variable, so that comparisons of R^2s must be undertaken with care. The favorite example used to illustrate this is the case of the consumption function versus the savings function. If savings is defined as income less consumption, income will do exactly as well in explaining variations in consumption as in explaining variations in savings, in the sense that the sum of squared residuals, the unexplained variation, will be exactly the same for each case. But in *percentage* terms, the unexplained variation will be a higher percentage of the variation in savings than of the variation in consumption because the latter are larger numbers. Thus the R^2 in the savings function case will be lower than in the consumption function case. This reflects the result that the expected value of R^2 is approximately equal to $\beta^2 V/(\beta^2 V + \sigma^2)$ where V is $\Sigma(x - \bar{x})^2$.
- In general, econometricians are interested in obtaining "good" parameter estimates where "good" is not defined in terms of R^2. Consequently the measure R^2 is not of much importance in econometrics. Unfortunately, however, many practitioners act as though it is important, for reasons that are not entirely clear, as noted by Cramer (1987, p. 253):

> These measures of goodness of fit have a fatal attraction. Although it is generally conceded among insiders that they do not mean a thing, high values are still a source of pride and satisfaction to their authors, however hard they may try to conceal these feelings.

Because of this, the meaning and role of R^2 are discussed at some length throughout this book. Section 5.5 and its general notes extend the discussion of this section. Comments are offered in the general notes of other sections when appropriate. For example, one should be aware that R^2 from two equations with different dependent variables should not be compared, and that adding dummy variables (to capture seasonal influences, for example) can inflate R^2, and that regressing on group means overstates R^2 because the error terms have been averaged.

2.5 Unbiasedness

- In contrast to the OLS and R^2 criteria, the unbiasedness criterion (and the other criteria related to the sampling distribution) says something specific about the relationship of the estimator to β, the parameter being estimated.
- Many econometricians are not impressed with the unbiasedness criterion, as our later discussion of the mean square error criterion will attest. Savage (1954, p. 244) goes so far as to say: "A serious reason to prefer unbiased estimates seems never to have been proposed." This feeling probably stems from the fact that it is possible to have an "unlucky" sample and thus a bad estimate, with only cold comfort from the knowledge that, had all possible samples of that size been taken, the correct estimate would have been hit on average. This is especially the case whenever a crucial outcome, such as in the case of a matter of life or death, or a decision to undertake a huge capital expenditure, hinges on a single correct estimate. None the less, unbiasedness has enjoyed remarkable popularity among practitioners. Part of the reason for this may be due to the emotive content of the terminology: who can stand up in public and state that they prefer *biased* estimators?
- The main objection to the unbiasedness criterion is summarized nicely by the story of the three econometricians who go duck hunting. The first shoots about a foot in front of the duck, the second about a foot behind; the third yells, "We got him!"

2.6 Efficiency

- Often econometricians forget that although the BLUE property is attractive, its requirement that the estimator be linear can sometimes be restrictive. If the errors have been generated from a "fat-tailed" distribution, for example, so that relatively high errors occur frequently, linear unbiased estimators are inferior to several popular nonlinear unbiased estimators, called robust estimators. See chapter 19.
- Linear estimators are not suitable for all estimating problems. For example, in estimating the variance σ^2 of the disturbance term, quadratic estimators are more appropriate. The traditional formula $SSE/(T-K)$, where T is the number of observations and K is the number of explanatory variables (including a constant), is under general conditions the best quadratic unbiased estimator of σ^2. When K does not include the constant (intercept) term, this formula is written as $SSE(T-K-1)$.
- Although in many instances it is mathematically impossible to determine the best unbiased estimator (as opposed to the best *linear* unbiased estimator), this is not the case if the *specific* distribution of the error is known. In this instance a lower bound, called the *Cramer–Rao lower bound*, for the variance (or variance–covariance matrix)