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BINGHAM McCUTCHEN LLP
DONN P. PICKETT (SBN 72257)
GEOFFREY M. HOWARD (SBN 157468)
HOLLY A. HOUSE (SBN 136045)
ZACHARY J. ALINDER (SBN 209009)
BREE HANN (SBN 215695)
Three Embarcadero Center
San Francisco, CA 94111-4067
Telephone: (415) 393-2000
Facsimile: (415) 393-2286
donn.pickett@bingham.com
geoff.howard@bingham.com
holly.house@bingham.com
zachary.alinder@bingham.com
bree.hann@bingham.com

BOIES, SCHILLER & FLEXNER LLP
DAVID BOIES (Admitted *Pro Hac Vice*)
333 Main Street
Armonk, NY 10504
Telephone: (914) 749-8200
Facsimile: (914) 749-8300
dboies@bsfllp.com
STEVEN C. HOLTZMAN (SBN 144177)
FRED NORTON (SBN 224725)
1999 Harrison St., Suite 900
Oakland, CA 94612
Telephone: (510) 874-1000
Facsimile: (510) 874-1460
sholtzman@bsfllp.com
fnorton@bsfllp.com

DORIAN DALEY (SBN 129049)
JENNIFER GLOSS (SBN 154227)
500 Oracle Parkway, M/S 5op7
Redwood City, CA 94070
Telephone: (650) 506-4846
Facsimile: (650) 506-7114
dorian.daley@oracle.com
jennifer.gloss@oracle.com

Attorneys for Plaintiffs Oracle USA, Inc., *et al.*

UNITED STATES DISTRICT COURT
NORTHERN DISTRICT OF CALIFORNIA
OAKLAND DIVISION

ORACLE USA, INC., *et al.*, Plaintiffs, v. SAP AG, *et al.*, Defendants.	CASE NO. 07-CV-01658 PJH (EDL) **EXHIBIT 4 TO THE DECLARATION OF DANIEL S. LEVY, PH.D. IN SUPPORT OF MOTION NO. 1: TO EXCLUDE TESTIMONY OF DEFENDANTS' EXPERT STEPHEN CLARKE** **FILED PURSUANT TO DKT. NO. 915**

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EXHIBIT 4

Introductory Econometrics

A Modern Approach

4e

Jeffrey M. Wooldridge
Michigan State University

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Jeffrey M. Wooldridge

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Using one-variable calculus, it can be shown that $\tilde{\beta}_1$ must solve the first order condition:

$$\sum_{i=1}^{n} x_i(y_i - \tilde{\beta}_1 x_i) = 0. \quad \textbf{2.65}$$

From this, we can solve for $\tilde{\beta}_1$:

$$\tilde{\beta}_1 = \frac{\sum_{i=1}^{n} x_i y_i}{\sum_{i=1}^{n} x_i^2}, \quad \textbf{2.66}$$

provided that not all the x_i are zero, a case we rule out.

Note how $\tilde{\beta}_1$ compares with the slope estimate when we also estimate the intercept (rather than set it equal to zero). These two estimates are the same if, and only if, $\bar{x} = 0$. [See equation (2.49) for $\hat{\beta}_1$.] Obtaining an estimate of β_1 using regression through the origin is not done very often in applied work, and for good reason: if the intercept $\beta_0 \neq 0$, then $\tilde{\beta}_1$ is a biased estimator of β_1. You will be asked to prove this in Problem 2.8.

SUMMARY

We have introduced the simple linear regression model in this chapter, and we have covered its basic properties. Given a random sample, the method of ordinary least squares is used to estimate the slope and intercept parameters in the population model. We have demonstrated the algebra of the OLS regression line, including computation of fitted values and residuals, and the obtaining of predicted changes in the dependent variable for a given change in the independent variable. In Section 2.4, we discussed two issues of practical importance: (1) the behavior of the OLS estimates when we change the units of measurement of the dependent variable or the independent variable and (2) the use of the natural log to allow for constant elasticity and constant semi-elasticity models.

In Section 2.5, we showed that, under the four Assumptions SLR.1 through SLR.4, the OLS estimators are unbiased. The key assumption is that the error term u has zero mean given any value of the independent variable x. Unfortunately, there are reasons to think this is false in many social science applications of simple regression, where the omitted factors in u are often correlated with x. When we add the assumption that the variance of the error given x is constant, we get simple formulas for the sampling variances of the OLS estimators. As we saw, the variance of the slope estimator $\hat{\beta}_1$ increases as the error variance increases, and it decreases when there is more sample variation in the independent variable. We also derived an unbiased estimator for $\sigma^2 = \text{Var}(u)$.

In Section 2.6, we briefly discussed regression through the origin, where the slope estimator is obtained under the assumption that the intercept is zero. Sometimes, this is useful, but it appears infrequently in applied work.

Much work is left to be done. For example, we still do not know how to test hypotheses about the population parameters, β_0 and β_1. Thus, although we know that OLS is unbiased for the population parameters under Assumptions SLR.1 through SLR.4, we have no way of drawing inference about the population. Other topics, such as the efficiency of OLS relative to other possible procedures, have also been omitted.

Thus, adding the average sentence variable increases R^2 from .0413 to .0422, a practically small effect. The sign of the coefficient on *avgsen* is also unexpected: it says that a longer average sentence length increases criminal activity.

Example 3.5 deserves a final word of caution. The fact that the four explanatory variables included in the second regression explain only about 4.2% of the variation in *narr86* does not necessarily mean that the equation is useless. Even though these variables collectively do not explain much of the variation in arrests, it is still possible that the OLS estimates are reliable estimates of the ceteris paribus effects of each independent variable on *narr86*. As we will see, whether this is the case does not directly depend on the size of R^2. Generally, a low R^2 indicates that it is hard to predict individual outcomes on y with much accuracy, something we study in more detail in Chapter 6. In the arrest example, the small R^2 reflects what we already suspect in the social sciences: it is generally very difficult to predict individual behavior.

Regression through the Origin

Sometimes, an economic theory or common sense suggests that β_0 should be zero, and so we should briefly mention OLS estimation when the intercept is zero. Specifically, we now seek an equation of the form

$$\tilde{y} = \tilde{\beta}_1 x_1 + \tilde{\beta}_2 x_2 + \dots + \tilde{\beta}_k x_k, \qquad \textbf{3.30}$$

where the symbol "~" over the estimates is used to distinguish them from the OLS estimates obtained along with the intercept [as in (3.11)]. In (3.30), when $x_1 = 0, x_2 = 0, \dots, x_k = 0$, the predicted value is zero. In this case, $\tilde{\beta}_1, \dots, \tilde{\beta}_k$ are said to be the OLS estimates from the regression of y on $x_1, x_2, \dots, x_k$ *through the origin*.

The OLS estimates in (3.30), as always, minimize the sum of squared residuals, but with the intercept set at zero. You should be warned that the properties of OLS that we derived earlier no longer hold for regression through the origin. In particular, the OLS residuals no longer have a zero sample average. Further, if R^2 is defined as 1 − SSR/SST, where SST is given in (3.24) and SSR is now $\sum_{i=1}^{n}(y_i - \tilde{\beta}_1 x_{i1} - \dots - \tilde{\beta}_k x_{ik})^2$, then R^2 can actually be negative. This means that the sample average, $\bar{y}$, "explains" more of the variation in the y_i than the explanatory variables. Either we should include an intercept in the regression or conclude that the explanatory variables poorly explain y. To always have a nonnegative R-squared, some economists prefer to calculate R^2 as the squared correlation coefficient between the actual and fitted values of y, as in (3.29). (In this case, the average fitted value must be computed directly since it no longer equals $\bar{y}$.) However, there is no set rule on computing R-squared for regression through the origin.

One serious drawback with regression through the origin is that, if the intercept β_0 in the population model is different from zero, then the OLS estimators of the slope parameters will be biased. The bias can be severe in some cases. The cost of estimating an intercept when β_0 is truly zero is that the variances of the OLS slope estimators are larger.