

# Collinearity in Linear Structural Models of Market Power

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## Abstract

The well-known structural model used to estimate market power suffers from a severe collinearity problem if the marginal cost and demand equations are linear.

*Key Words:* collinearity, estimation, market power.

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# Collinearity in Structural Models of Market Power

A structural model due to Just and Chern (1980) has been widely used to estimate market power based on market-level data.<sup>1</sup> Bresnahan (1982) used a simple linear structural model to illustrate the method and to demonstrate that identification problems can arise. The linear model has been estimated by many competent econometricians.<sup>2</sup> Unfortunately, this linear model is fundamentally flawed due to a previously unrecognized multicollinearity problem.

We discovered this problem when we tried to estimate a simulated linear model. The simulations demonstrated that a loglinear model could be reliably estimated; however, a linear model produced completely unreliable estimates due to severe multicollinearity problems (see Hyde and Perloff, 1995 or Perloff et al., 2007).

In this paper, we demonstrate that an econometrician trying to estimate the linear model faces three very unattractive possibilities. First, if the true model is not linear, the estimates are biased (simulations in Hyde and Perloff, 1995, illustrate that equation misspecification biases in the estimates of market power may be severe). Second, if the true model is linear and the equations hold exactly, the variables are perfectly collinear so that the model cannot be estimated. Third, if the true linear model equations hold with errors, one can estimate the

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<sup>1</sup> Hundreds of studies have used this New Empirical Industrial Organization (NEIO) approach. For a partial list, see Bresnahan (1989) or Perloff et al. (2007). There are a number of alternative approaches that are widely used as well including a variant on the original NEIO approach using mixed logit to estimate demand equations, nonparametric approaches, dynamic models, and others. See Perloff et al. (2007) for a description of these alternatives.

<sup>2</sup> In these papers, a linear model is estimated, though other models may be estimated as well: Buschena and Perloff (1991), Jans and Rosenbaum (1996), Deodhar and Sheldon (1997), Kim and Knittel (2006), Roy et al. (2006), and Mérel (2008).

equations, but the estimated coefficients are likely to be highly unstable and unreliable due to nearly perfect collinearity.

## Structural Model of Market Power

In most studies based on industry-level data, the econometrician starts by assuming that the market consists of identical firms (or makes other similar assumptions), so that the “average” market power of these firms can be estimated. Typically, in this approach, the “true” model reflects the behavior of a single firm that may not be profit-maximizing.

Problems arise when both the marginal cost and demand curves are linear. Following Bresnahan (1982), suppose that the marginal cost curve is

$$MC = \eta + \alpha w + \beta r + \gamma Q + \varepsilon_c, \quad (1)$$

where  $w$  is the wage,  $r$  is the rental rate on capital,  $Q$  is market output, and  $\varepsilon_c$  is an error term.<sup>3</sup>

Also following Bresnahan, the demand curve is

$$p = \phi_0 - [\phi_1 + \phi_2 Z]Q + \phi_3 Y + \varepsilon_d, \quad (2)$$

where  $p$  is the price,  $Z$  is an exogenous variable (such as the price of a substitute, a proxy for taste changes, or income) that rotates the demand curve,  $Y$  is an additive exogenous variable (such as income), and  $\varepsilon_d$  is an error term. The slope of the demand curve is  $p' = dp/dQ = -[\phi_1 + \phi_2 Z]$ .

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<sup>3</sup> This function form was introduced by Bresnahan (1982) for expositional purposes, but has been widely used by others, even though this specification implies that the cost function is not homogeneous if  $\gamma$  is nonzero.

Following Just and Chern (1980), Bresnahan (1982), and Lau (1982), we use a parameter  $\lambda$  to nest various market structures.<sup>4</sup> Specifically, we define an “effective” marginal revenue function as

$$MR(\lambda) = p + \lambda p'Q = p - \lambda[\phi_1 + \phi_2 Z]Q.$$

If  $\lambda = 0$ , marginal revenue equals price and the market is competitive; if  $\lambda = 1$ , marginal revenue equals the marginal revenue of a monopoly; if  $\lambda$  lies between 0 and 1, the degree of market power lies between that of monopoly and competition. For example, with  $n$  identical Cournot firms,  $\lambda = 1/n$ .

The optimality or equilibrium condition is that the industry sets its effective marginal revenue equal to its marginal cost,  $MR(\lambda) = MC$ , so  $p = MC + \lambda[\phi_1 + \phi_2 Z]Q$ , or

$$p = \eta + \alpha w + \beta r + [\lambda(\phi_1 + \phi_2 Z) + \gamma]Q + \varepsilon_c. \quad (3)$$

The econometrician simultaneously estimates Equations 2 and 3 to obtain an estimate of  $\lambda$ , the measure of market power. Bresnahan (1982) and Lau (1982) show that  $\lambda$  is identified in the linear model only if  $\phi_2 \neq 0$  (the  $ZQ$  interaction term matters) or  $\gamma = 0$  (marginal cost does not vary with output, so that there are constant returns to scale).

## Perfect Collinearity

Even if the linear model is correctly specified and identified, it has a fundamental problem of multicollinearity. As we show in the appendix, the six regressors in Equation 3, the

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<sup>4</sup> Some researchers view  $\lambda$  as a conjectural variation, while others describe it as the outcome of an unknown game, where  $\lambda$  is a summary measure of the gap between  $p$  and  $MC$ . Bresnahan (1989) and Corts (1999) discuss these alternative interpretations.

constant,  $w$ ,  $r$ ,  $Y$ ,  $ZQ$ , and  $Q$ , are perfectly collinear if the equations hold exactly ( $\varepsilon_d = \varepsilon_c = 0$ ). To make this intuition clear, we consider the special case where  $Y$ ,  $w$ , and  $r$  are irrelevant ( $\phi_3 = \alpha = \beta = 0$ ) and marginal cost does not vary with output ( $\gamma = 0$ ). We can solve for the equilibrium value of  $Q$  by substituting for  $p$  from Equation 2 into Equation 3:

$$Q = \frac{\phi_0 - \eta}{(1 + \lambda)(\phi_1 + \phi_2 Z)}.$$

We now show that the right-hand-side variables in the optimality equation,  $Q$  and  $ZQ$ , are perfectly collinear by demonstrating that the weighted sum of these two variables is a constant.

Let the weight on  $Q$  be  $\lambda\phi_1$  and the weight on  $ZQ$  be  $\lambda\phi_2$ , then

$$\begin{aligned} \lambda\phi_1 Q + \lambda\phi_2 ZQ &= \lambda[\phi_1 + \phi_2 Z]Q \\ &= \lambda[\phi_1 + \phi_2 Z] \frac{\phi_0 - \eta}{(1 + \lambda)(\phi_1 + \phi_2 Z)} \\ &= \frac{\lambda}{1 + \lambda} [\phi_0 - \eta], \end{aligned}$$

where the last term is a constant.

Thus, when the demand and optimality equations hold exactly, the optimality equation suffers from perfect multicollinearity. This perfect multicollinearity creates a problem (Greene, 2012) that is more fundamental than the one Bresnahan (1982) and Lau (1982) discuss where only  $\lambda$  cannot be identified. Here, due to perfect linear dependency, none of the coefficients can be estimated.

## Nearly Perfect Collinearity

If the demand and optimality equations do not hold exactly ( $\varepsilon_d \neq 0$  and  $\varepsilon_c \neq 0$ ), one can mechanically estimate this system of equations, but the right-hand-side variables are nearly perfectly collinear, which creates the usual problems:

1. Coefficients may have large standard errors (low precision) even though they are jointly highly significant.
2. Coefficients may have the “wrong” sign or an implausible magnitude.
3. Estimates may be very sensitive to addition or deletion of a few observations or the deletion of an apparently insignificant variable.

We illustrate these multicollienarity problem using simulations. Tables 1 and 2 summarize a 1,000 replications of experiments with 50 observations each. We set  $\alpha = \beta = \gamma = \delta_1 = \delta_2 = \eta = 1$ ,  $\phi_3 = 0$ ,  $\delta_0 = 10$ , and  $\lambda = 0.5$ . Both  $\varepsilon_d \neq 0$  and  $\varepsilon_c$  are distributed  $N(0, \sigma)$ , where  $\sigma = \sigma_d = \sigma_c$ .<sup>5</sup>

If we were to set  $\sigma = \sigma_d = \sigma_c \leq 0.00001$ , the model cannot mechanically be estimated because of virtually perfect collinearity. With a slightly larger amount of noise, we can mechanically estimate the model. In the tables, we report simulations for  $\sigma$  equal to 0.001, 0.5, 1, and 2.

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<sup>5</sup> The exogenous variables are constructed as random variable where  $w \sim N(3, 1)$ ,  $r \sim N(0, 1)$ ,  $Z \sim N(10, 1)$ . Two additional instruments are created by adding an additional random variable drawn from  $N(0, 1)$  to  $w$  and to  $r$ .

We estimated the model using two-stage least square (2SLS), three-stage least squares (3SLS), and nonlinear three-stage least squares (NL3SLS). Except where otherwise noted, the tables report the 2SLS estimates. Both 3SLS and NL3SLS produce similar results.

Table 1 shows several summary statistics. Because we used 2SLS, the  $R^2$  for the demand and optimality equations may lie between  $-\infty$  and 1. When relatively little error is added to the equations ( $\sigma = 0.001$ ), the  $R^2$  for these two equations is virtually one in every experiment. As the error grows, the mean  $R^2$  measure falls, and is negative when  $\sigma$  is at least one for the optimality equation and two for the demand equation.

Although the demand equation, Equation 2, can be accurately estimated, the optimality equation, Equation 3, suffers from extreme multicollinearity (even with a large error). When  $\sigma = 0.001$ , the average condition number (the square root of the ratio of the largest to the smallest characteristic root of the regressors) is at least 1,433 in our examples and as high as  $6.4 \times 10^7$  (same order of magnitude as with the infamous Longley data).<sup>6</sup> Belsley et al. (1980) suggest that condition numbers above 20 indicate potential problems. Similarly, in an auxiliary regression where we regress one of the right-hand-side variables,  $ZQ$ , on the others ( $w$ ,  $r$ , and  $Q$ ), the average  $R^2$  is at least 0.91 (and virtually 1.0 when  $\sigma = 0.001$ ).

Table 2 shows the coefficient estimates. With 2SLS, the multicollinearity in the optimality equation does not affect the demand equation, so we are able to estimate it very well (at least when  $\sigma \leq 1$ ). For example, the true value of the coefficient on  $Q$  in the demand equation,

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<sup>6</sup> We are reporting the condition number using the actual right-hand-side variables,  $w$ ,  $r$ ,  $ZQ$ , and  $Z$ . If we replace the latter two with the instrumental estimates, the condition number rises by at least several orders of magnitude.



$\phi_1$ , is 1. As Table 2 shows, the average estimated value for  $\phi_1$  is 1.0 (with a standard deviation of 0.004) when  $\sigma = 0.001$ , 0.99 (1.98) when  $\sigma = 0.5$ , and 0.97 (3.96) when  $\sigma = 1$ . The other two demand coefficients are estimated equally well.

In contrast, we cannot accurately estimate the optimality equation coefficients due to the extreme collinearity. The true value of  $\alpha$ , the coefficient on  $w$  in the optimality equation, is 1. The average estimated value ranges from 0.46 to 0.49 with standard deviations that range between 0.88 and 1.04. The true value of the scale parameter,  $\gamma$ , is 1, but the average of the estimates range from 5.85 to 5.73 with large standard deviations (between 7.89 and 8.66). In the optimality Equation 3, the estimated standard deviations remain relatively unchanged as the size of the error terms fall (whereas the estimated standard deviations shrink in the demand equation as the error terms fall).

Typically, we are most interested in the market power coefficient,  $\lambda$ , which equals 0.5 in our experiments. With the 2SLS estimates, we obtain two estimates of  $\lambda$ .<sup>7</sup> As a practical matter, both provide nearly identical estimates in our experiments.<sup>8</sup> As the table shows, the average estimate of  $\lambda$  using 2SLS is usually negative and has a very large standard deviation. When  $\sigma > 0.001$ , the average of the 3SLS estimates is either negative or much above 1.0 (outside the plausible range). Even when  $\sigma = 0.001$  and the average, 0.46, is close to the true value, the standard deviation is gigantic (8.98).

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<sup>7</sup> First, we can divide the estimate of the coefficient on the  $Q$  term,  $\lambda\phi_1$ , in the optimality Equation 3 by the estimate of  $\phi_1$  in the demand Equation 2. Second, we can divide the estimate of the coefficient on the  $ZQ$  term in Equation 3,  $\lambda\phi_2$ , by the estimate of  $\phi_2$  from Equation 2.

## Conclusions

Studies of market power based on market-level data are commonly used. Many of these studies have employed a linear specification that avoids the problem described by Bresnahan (1982) and Lau (1982) that precludes identifying the market power parameter. However, we demonstrate that estimates based on the linear model inherently suffer from a severe multicollinearity problem that makes estimates of all the parameters in the optimality equation, including the market power parameter, unreliable.

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<sup>8</sup> Imposing the restriction that the two estimates are equal in our NL3SLS model does not improve our estimates meaningfully.

## Appendix

We demonstrate that the  $w$ ,  $r$ ,  $ZQ$ , and  $Q$  terms in Equation 3 are perfectly collinear  $\varepsilon_d = \varepsilon_c = 0$ . We show this result by demonstrating that there exist nonzero coefficients  $\chi_1, \chi_2, \chi_3, \chi_4$ , and  $\chi_5$  such that

$$QZ + \chi_1 Q + \chi_2 w + \chi_3 r + \chi_4 Y + \chi_5 = 0. \quad (\text{A1})$$

To show that Equation A1 holds, we first solve for the equilibrium output,  $Q$ , as a function of the exogenous variables and parameters:

$$Q = \frac{\phi_0 + \phi_3 Y - \eta - \alpha w - \beta r}{(\lambda + 1)(\phi_1 + \phi_2 Z) + \gamma}. \quad (\text{A2})$$

Substituting  $Q$  from Equation A2 into Equation A1 and rearranging terms, we obtain

$$\zeta_1 Z + \zeta_2 YZ + \zeta_3 wZ + \zeta_4 rZ + \zeta_5 Y + \zeta_6 w + \zeta_7 r + \zeta_8 = 0, \quad (\text{A3})$$

where  $\zeta_1 = \phi_0 - \eta + (\lambda + 1)\phi_2\chi_5$ ,  $\zeta_2 = \phi_3 + (\lambda + 1)\phi_2\chi_4$ ,  $\zeta_3 = -\alpha + (\lambda + 1)\phi_2\chi_2$ ,  $\zeta_4 = -\beta + (\lambda + 1)\phi_2\chi_3$ ,  $\zeta_5 = \phi_3 + [(\lambda + 1)\phi_1 + \gamma]\chi_4$ ,  $\zeta_6 = -\alpha\chi_1 + [(\lambda + 1)\phi_1 + \gamma]\chi_2$ ,  $\zeta_7 = -\beta\chi_1 + [(\lambda + 1)\phi_1 + \gamma]\chi_3$ ,  $\zeta_8 = [\phi_0 - \eta]\chi_1 + [(\lambda + 1)\phi_1 + \gamma]\chi_5$ . If we set  $\zeta_{ii} = 0$  for  $i = 1, \dots, 7$ , we have a seven-equation system in five unknowns, with the unique solution:

$$\chi_1 = [(\lambda + 1)\phi_1 + \gamma] / [(\lambda + 1)\phi_2],$$

$$\chi_2 = \alpha / [(\lambda + 1)\phi_2],$$

$$\chi_3 = \beta / [(\lambda + 1)\phi_2],$$

$$\chi_4 = -\phi_3 / [(\lambda + 1)\phi_2],$$

$$\chi_5 = [\phi_0 - \eta] / [(\lambda + 1)\phi_2].$$

Thus, there exist  $\chi_1, \chi_2, \chi_3, \chi_4,$  and  $\chi_5$  such that Equation 4 holds, so the linear model is perfectly collinear and cannot be estimated.

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**Table 1**  
**Linear Model Simulation Summary Statistics**

	$\sigma = 0.001$	$\sigma = 0.5$	$\sigma = 1$	$\sigma = 2$
<i>Model</i>				
R <sup>2</sup> Demand Equation	1.00 (0.3E-6)	0.76 (0.07)	0.32 (0.22)	-0.15 (0.52)
R <sup>2</sup> Optimality Equation	1.00 (0.1E-4)	0.51 (2.67)	-0.41 (8.13)	-1.85 (19.85)
<i>Multicollinearity Checks</i>				
R <sup>2</sup> Auxiliary Equation*	1.00 (0.3E-6)	0.91 (0.03)	0.91 (0.03)	0.96 (0.01)
Condition number	6.4E7 (1.8E7)	1,433.2 (483.2)	1,614.9 (575.13)	2,643.2 (1,027.1)

Note: Standard deviations in parentheses.

\* R<sup>2</sup> of the auxiliary regression of  $ZQ$  on  $w$ ,  $r$ , and  $Q$ .

**Table 2**  
**Linear Model Simulation Estimates**

	<i>True Coefficient</i>	<i>Average Estimated Coefficient (Standard Deviation)</i>			
		$\sigma = 0.001$	$\sigma = 0.5$	$\sigma = 1$	$\sigma = 2$
<i>2SLS</i>					
<i>Demand</i>					
$\phi_0$	10	10.00 (0.001)	9.96 (0.33)	9.86 (0.65)	9.46 (1.20)
$\phi_1$	1	1.00 (0.004)	0.99 (1.98)	0.97 (3.96)	0.88 (7.80)
$\phi_2$	1	1.00 (0.004)	0.99 (0.21)	0.97 (0.42)	0.87 (0.82)
<hr style="border-top: 1px dashed black;"/>					
<i>Optimality</i>					
$\alpha$	1	0.46 (0.88)	0.46 (0.91)	0.47 (0.93)	0.49 (1.04)
$\gamma$	1	5.85 (7.89)	5.85 (8.15)	5.78 (8.21)	5.73 (8.66)
$\lambda$	0.5	-0.31 (1.31)	-0.29 (1.34)	0.09 (11.48)	-1.53 (30.41)
<i>3SLS</i>					
$\lambda$	0.5	0.46 (8.98)	-0.61 (24.34)	27.28 (844.28)	1.22 (25.57)

The demand curve is  $p = \phi_0 - \phi_1 Q - \phi_2 ZQ + \varepsilon_d$ .

The optimality condition is  $p = \eta + \alpha w + \beta r + [\lambda(\phi_1 + \phi_2 Z) + \gamma]Q + \varepsilon_c$ .