IHS Economics Series
Working Paper 194
September 2006

Econometric Issues in Estimating User Cost Elasticity

Huntley Schaller

Institut für Höhere Studien
Institute for Advanced Studies
Vienna

Impressum

Author(s):
Huntley Schaller

Title:
Econometric Issues in Estimating User Cost Elasticity

ISSN: Unspecified

2006 Institut für Höhere Studien - Institute for Advanced Studies (IHS)
Josefstädter Straße 39, A-1080 Wien
E-Mail: office@ihs.ac.at
Web: www.ihs.ac.at

194

Reihe Ökonomie

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Contact:

Huntley Schaller
Department of Economics
Carleton University
1125 Colonel By Drive
Ottawa ON K1S 5B6
Canada
Tel: (613) 520-3751
Fax: (613) 520-3906
Email: schaller@ccs.carleton.ca
and
Visiting Research Professor
Department of Economics
Institute for Advanced Studies (Vienna)

Abstract

The user cost elasticity is a parameter of considerable importance in economics, with implications for the effects of budget deficits, tax-based savings incentives, monetary policy, corporate taxes, and tariffs and quotas on capital goods. This paper analyzes the econometric issues that account for differences in the estimated elasticity between the two existing papers that estimate the long-run elasticity on aggregate data. The preferred estimate that results from this analysis is substantially higher than most previous estimates. The empirical evidence suggests that, when adjustment frictions are important, long-run estimates of key parameters are less biased – and the details of the econometrics matter. In particular, DOLS estimates appear less biased than the alternatives considered here. The econometric issues that are analyzed in this paper have wide-ranging implications for research areas where adjustment frictions are important, including nominal price stickiness, habit formation, and sticky information models, among others.

Keywords
User cost elasticity, capital stock, investment, adjustment frictions, cointegration and long-run econometrics

JEL Classification
E22, E44, H25

Comments
I would like to thank Heidi Portuondo for research assistance and the SSHRC for financial support.

Contents

I. Introduction

The capital stock of an economy is important because it is a key determinant of per capita output. Another key determinant is technological progress, at least some of which is embodied in new capital, especially equipment capital. In some endogenous growth models, the size of the capital stock influences the rate of economic growth.

A variety of public policy measures have the potential to influence the capital stock -- budget deficits, tax-based savings incentives, corporate taxes (including accelerated depreciation allowances and investment tax credits), tariffs and quotas on capital goods (which tend to be more of an issue in developing countries), and monetary policy. The primary parameter that determines how large an effect the interest rate, taxes, and capital goods prices have on the capital stock is the user cost elasticity.

Unfortunately, the user cost elasticity is difficult to estimate. The capital stock seems to adjust slowly to shocks. Economic theory has postulated different adjustment frictions that may account for this sluggish adjustment, including quadratic adjustment costs, fixed costs of adjusting the capital stock, and irreversibility. These adjustment frictions imply that estimates of the user cost elasticity based on high frequency movements in the data (which encompasses the great bulk of previous estimates) are subject to large biases.

There is a second problem in estimating the user cost elasticity. The elasticity is associated with the demand curve for capital. But observed combinations of user cost and quantity of capital reflect movements in both the supply and demand curves for capital. In the short run (i.e., at business cycle frequencies), fluctuations in demand are relatively important. If the supply curve for capital is upward sloping, standard techniques will tend to confound the negative demand elasticity with the positive supply elasticity. This bias may help to explain why estimates of the user cost elasticity are often small in magnitude (or sometimes positive, though seldom in published papers).

Intuitively, it should be possible to obtain less biased estimates of the user cost elasticity by using econometric techniques that emphasize low-frequency movements in the data. A sensible way to do this is by estimating the cointegrating relationship between the capital stock and user cost. Even here, there are potential pitfalls. One possible approach is to use OLS to estimate the cointegrating relationship. This is often referred to as Static OLS (SOLS). However, SOLS is biased when there are adjustment frictions. This small sample bias can be large in the case of the user cost elasticity.

Two papers estimate the user cost elasticity on aggregate data using econometric techniques that emphasize low-frequency movements in the data. Caballero (1994) is the pioneering study. Caballero obtains a preferred user cost elasticity estimate of -0.9. This is larger than the majority of previous estimates surveyed in Chirinko (1993) and Hassett and Hubbard (2002). In a more recent paper, Schaller (2005) obtains an estimate of -1.6.

The focus of this paper is accounting for the differences in user cost elasticity estimates between Caballero (1994) and Schaller (2005). Part of the difference arises from the fact that Schaller's estimates are based on a small, open economy. In a small, open economy, user cost will be largely exogenous. Equivalently, the supply curve will be flat. This reduces the simultaneity bias.

The main focus of this paper, however, is the econometric issues in estimating the user cost elasticity. Previous analytical results and Monte Carlo simulations show that ignoring the small sample bias in simple OLS can have a large effect on estimates when adjustment frictions are important. Work on actual data in this paper reinforces the importance of this point. The estimated user cost elasticity is about 50 % higher when a correction is made for small sample bias (about -1.2 versus an estimate of approximately -0.8 if no correction is made for small sample-bias). Moreover, there is evidence that the exact nature of the small sample bias correction is important. Previous Monte Carlo simulations [Caballero 1994] show that a one-sided summation procedure can be substantially biased if adjustment frictions are important. In fact, the estimated elasticity is about 25 % smaller if a one-sided procedure is used instead of Dynamic OLS (DOLS).

The combination of exogeneity of user cost implied by the flat supply of capital curve for a small, open economy and DOLS estimation yields an estimate of the long-run user cost elasticity which is about 75 % larger (in absolute value) than the best existing estimate. The best existing estimate is about -0.9 (for a large, open economy). Using the same econometric procedure applied to a small, open economy yields an estimate of about -1.2. Using data from a small, open economy and DOLS yields an estimate of about -1.6.

The paper is organized as follows. Section 2 reviews previous estimates of the user cost elasticity. Section 3 describes the data. Section 4 presents the cointegrating relationship between capital and user cost, describes the details of SOLS estimation, and reports SOLS estimates of the user cost elasticity for equipment. Section 5 explains why SOLS suffers from small sample bias and how DOLS is able to overcome this bias. In addition, Section 5 presents DOLS estimates of the user cost elasticity for equipment. Caballero's (1994) pioneering study recognizes the issue of small sample bias and addresses it with a one-sided summation procedure that is related to DOLS but not, strictly speaking, DOLS. Section 6 compares this one-sided summation procedure with DOLS. Section 7 reports user cost elasticity estimates for structures capital. Section 8 concludes.

II. Previous Estimates of the User Cost Elasticity

A. Short-Run[1]

There is considerable variation in estimates of the short-run user cost elasticity. In his survey of the literature, Chirinko (1993, p. 1906) concludes that "the response of investment to price variables tends to be small and unimportant relative to quantity variables." In a more recent survey, Hassett and Hubbard (2002) suggest that the user cost elasticity is probably between -0.5 and -1. Turning to individual studies, Cummins and Hassett (1992) estimate an elasticity of slightly more than -1, using firm-level U.S. data. (The convention in this paper will be to use "more" and "larger" to refer to user cost elasticities that are greater in absolute value.) Clark (1993) finds an estimated elasticity of -0.01 using aggregate U.S. data; the elasticity estimate is higher (about -0.2) when Clark uses only tax changes (rather than full user cost) to estimate the elasticity. Using aggregate data for Japan, Kiyotaki and West (1996) estimate a user cost elasticity of -0.05 to -0.07. Chirinko, Fazzari, and Meyer (1999) obtain a preferred elasticity of about -0.25 using firm-level U.S. investment data. Using U.S. data disaggregated by type of asset, Goolsbee (2000) finds that a 10 % investment tax credit raises investment by about 4 to 5 %. Tevlin and Whelan (2003) estimate an elasticity of –0.18 using aggregate U.S. data.

There are several possible explanations for the variation in estimates of the short-run user cost elasticity. First, in models with non-convex adjustment costs, the short-run user cost elasticity is time-varying and history dependent, as discussed by Caballero (1999). Caballero, Engel, and Haltiwanger (1995) and Caballero and Engel (1999), among others, provide evidence of the importance of time variation in the response of the capital stocks to fundamentals. Estimates of the short-run elasticity can vary depending on the time period over which they are estimated. This applies to estimates based on both aggregate and disaggregate data.

Second, a number of the more recent studies use disaggregate data. If the short-run elasticity varies depending on firm size, across industries, or based on the degree to which firms face finance constraints, elasticity estimates can vary depending on the particular sample of micro units for which the researcher has data.[2]

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[1] The term "long-run" in reference to user cost elasticity estimates is used here to refer to cointegration-based estimates; all other estimates are referred to as "short-run". This usage follows Caballero (1999, Sections 2.2.1 and 2.2.2.)

[2] As discussed elsewhere in this paper, Caballero, Engel, and Haltiwanger (1995) find considerable variation across industries, even for the long-run elasticity.

B. Long-Run

Caballero (1994) is the pioneering study that uses a cointegrating relationship between user cost and the capital stock to estimate the long-run elasticity. Caballero (1994) uses quarterly aggregate U.S. data for equipment over the period 1957:1 – 1987:4 and an econometric procedure motivated by the work of Stock and Watson (1993). He obtains an estimated elasticity of about -0.9.

Caballero, Engel, and Haltiwanger (1995) use plant-level, U.S. data for equipment over the period 1972-88 to estimate user cost elasticities for 20 two-digit SIC industries. Their estimates range from -0.01 for transportation to -2.0 for textiles. Consistent with the issues raised in the introduction to this paper, they find short-run elasticities are much smaller (around 10 % of the corresponding long-run elasticity).[3]

III. Data

As in Schaller (2005), this paper uses Canadian aggregate data for the period 1962:1 to 1999:4. In particular, the investment data is non-residential, gross, real, fixed capital formation (seasonally adjusted) for the business sector from the National Income and Expenditure Accounts. In the Canadian data, investment is divided into equipment and non-residential structures.

The capital stock is calculated by the perpetual inventory method using a depreciation rate of .13 for equipment and .06 for structures.[4]

The cost of capital is calculated as follows

$$\text{(1)} \qquad \tilde{R}_t = (i_t + \delta + \gamma - \pi_t^K)\left(\frac{1-\zeta_t - u_t}{1-\tau_t}\right)\frac{p_t^K}{p_t^Y}$$

where *i* is the nominal interest rate, δ is set at .13 for equipment and .06 for structures, γ is a fixed risk premium (set at 6 %), π^K is the rate of inflation for capital goods, ζ is the present value of depreciation allowances, *u* is the investment tax credit rate, τ is the corporate tax rate, p^K is the price of capital goods, and p^Y is the price of output.[5] For discussions and derivations of the user cost of capital, see, e.g., Hall and Jorgenson (1967),

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[3] One paper is difficult to categorize. Chirinko, Fazzari, and Meyer (2001) are sensitive to the problems with estimating the short-run elasticity but do not use a cointegrating relationship. Instead, using firm-level U.S. data, they average the key variables over several years and obtain an elasticity estimate of -0.4.

[4] The robustness of the results to depreciation rates is explored in Schaller (2005).

[5] Since δ and γ enter additively, variation in δ in Schaller (2005) can also be interpreted as variation in γ.

Auerbach (1983) or Hassett and Hubbard (2002). Although there is no time subscript on δ, we explore the issue of variable depreciation rates in Section VIII. The cost of capital is calculated for both equipment and structures.

Output is matched to the investment data, which are for the business sector, by subtracting government expenditures from GDP.

A more detailed description of the data is contained in the Data Appendix, which provides Statistics Canada series numbers and discusses details such as the calculation of the present value of depreciation allowances.

IV. Cointegration and SOLS

Suppose that

$$\begin{aligned} &k_t = \alpha_0 + \alpha_R R_t + z_t \\ &\Delta R_t = u_{2t} \end{aligned} \qquad (2)$$

where k is the log capital/output ratio, R (=ln $\tilde{R}$) is the log of user cost, and z and u_2 are stationary.[6] The variables k and R will then be cointegrated.

Cointegration between k and R is a good description of the data. First, ADF tests show unit roots in both k and R for equipment. Second, standard cointegration tests reject the null hypothesis of no cointegration between k and R.[7]

Cointegrating regressions are often estimated by Static OLS (SOLS); i.e., the estimation of an equation like (2) by OLS. Under the strong assumption of no serial correlation in either z_t or u_{2t}, the usual t and F statistics can be used to test hypotheses. Once the assumption of no serial correlation is relaxed, the SOLS t statistics must be adjusted, specifically by multiplying by s_T / λ_1^*, where

$$s_T^2 = (T-n)^{-1} \sum_{t=1}^{T} (k_t - \hat{\alpha}_0 - \hat{\alpha}_R R_t)^2 \qquad (3)$$

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[6] This relationship can be obtained by solving the firm’s problem (under the consumption of Cobb-Douglas technology) for the frictionless capital stock and relaxing the unit user cost elasticity constraint. See, e.g., Caballero (1999, p. 816-821).

[7] Using aggregate U.S. data for equipment, Clark (1993) tests whether k and R are cointegrated (imposing the assumption that $a_R = 1$) and rejects the null hypothesis of no cointegration.

is the variance of the residuals from OLS estimation (T being the sample size and n=2 being the number of estimated coefficients) and λ_1^* is constructed from a regression of the residuals $\hat{z}_t$ on q lags of the residuals:

$$(4) \qquad \hat{z}_t = \phi_1 \hat{z}_{t-1} + \phi_2 \hat{z}_{t-2} + \dots + \phi_q \hat{z}_{t-q} + e_t$$

where the order of this autoregression is chosen by selecting the value of q from the set {1, 2, …, $T^{1/3}$} so as to minimize the Bayesian information criterion (BIC). Specifically:

$$(5) \qquad \hat{\lambda}_1^* = \frac{\hat{\sigma}_1}{1 - \hat{\phi}_1 - \hat{\phi}_2 - \dots - \hat{\phi}_q}$$

where $\hat{\sigma}_1$ is the standard deviation of $\hat{e}_t$:

$$(6) \qquad \hat{\sigma}_1^2 = (T-q)^{-1} \sum_{t=q+1}^{T} \hat{e}_t^2$$

This is the procedure used to calculate all SOLS t-statistics reported in subsequent sections.

The SOLS estimate of user cost elasticity is -0.82 (with a standard error of 0.20). This is considerably larger -- about twice as big -- as the only other comparable aggregate estimate of the long-run user cost elasticity, the Caballero (1994) SOLS estimate, which is for a large economy; i.e., one which is big enough to have an effect on world prices. The larger estimate is consistent with the idea that user cost should be more exogenous in a small, open economy.

V. Small Sample Bias and DOLS

A. An Intuitive Explanation of Small Sample Bias

Asymptotically, SOLS yields consistent estimates of the coefficients in the cointegrating regression. In the presence of adjustment frictions, though, SOLS will tend to produce biased estimates in samples of the size normally available for aggregate time series estimation. Analytical results in Caballero (1994) show that SOLS could be downward biased (i.e., biased towards 0) by 50 to 60 % for a sample of 120 observations and 70 to 80 % for a sample of 50 observations, if adjustment frictions are large.

To explain the intuition for the SOLS bias, it will be helpful to ignore the constant term. Let k^* be the frictionless capital stock (measured in logs and normalized by the log of output) and let it be a linear function of user cost:

$$(7) \qquad k_t^* = \alpha_R R_t$$

Adjustment frictions (broadly defined) will cause a gap z_t between the actual capital stock k_t and the frictionless capital stock. Thus the actual capital stock will be equal to the frictionless capital stock plus z_t:

$$k_t = \alpha_R R_t + z_t \tag{8}$$

In the presence of adjustment frictions, k^* will typically fluctuate more than k, since k will respond only slowly and partially to shocks. Since k is a sum of the random variables k^* and z.

$$\text{var}(k) = \text{var}(k^*) + \text{var}(z) + 2\,\text{cov}(k^*, z) \tag{9}$$

so the variance of k can be smaller than the variance of k^* only if cov(k^*,z) is negative. However, the OLS estimates of k^* and z (i.e., $\hat{k}^* = \hat{\alpha}_R R$ and $\hat{z} = k - \hat{\alpha}_R R$) are orthogonal by construction, which implies var$(\hat{k}^*)$ is less than var(k). In order to achieve this, OLS will tend to bias the estimate of α_R toward 0.[8] Monte Carlo simulations by Caballero (1994) show that if the actual capital stock responds sluggishly to shocks, the OLS estimate can be biased downward by a factor of two or more.

B. Dynamic OLS

The necessary condition for *unbiased* SOLS estimation of α_0 and α_R is that z_t be uncorrelated with u_{2s} for all *s* and *t.* [9] This strong condition arises because it is only under this condition that R will be uncorrelated with the error term z since:

$$\begin{aligned} \mathbf{c}\text{ov}(R_t, z_t) &= \text{cov}(R_0 + \Delta R_1 + \Delta R_2 + ... + \Delta R_t, z_t) \\ &= \text{cov}(u_{21} + u_{22} + ... + u_{2t}, z_t) \end{aligned} \tag{10}$$

One solution to the problem of small sample bias in SOLS is the DOLS estimator proposed by Stock and Watson (1993). Dynamic OLS (DOLS) addresses the problem of finite sample bias by replacing the original error term z by a new error term v, which is constructed to be orthogonal to R.[10] The intuition is straightforward. OLS projects the dependent variable onto the space spanned by the right hand side variables. The remaining variation in the dependent variable is orthogonal to the right hand side variables. Suppose z were projected

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[8] This argument follows Caballero (1994, 1999).

[9] Early statements of SOLS bias, in a more general context, can be found in Bannerjee et al (1986) and Stock (1987).

[10] In addition to addressing the SOLS bias, DOLS has other attractive properties. In the most general case considered by Stock and Watson (1993), DOLS is asymptotically efficient (when interpreted semiparametrically). Perhaps more important, in Monte Carlo simulations of the most general case (Case C) considered by Stock and Watson (1993), DOLS has the lowest RMSE among a set of estimators of cointegrating regressions.

onto the space spanned by all leads and lags of ΔR (which is equivalent to the space spanned by u_2). The error term v_t from this regression will be orthogonal to R_s since:

$$\text{(11)} \qquad \operatorname{cov}(R_s, v_t) = \operatorname{cov}(R_0 + \Delta R_1 + \ldots + \Delta R_s, v_t) = 0$$

The last equality follows from the fact that v_t is orthogonal to all leads and lags of ΔR_t by construction.

As noted above, the assumptions required for SOLS estimation are unlikely to be satisfied in estimating the user cost elasticity, primarily because of the slow adjustment of the capital stock to shocks and the resulting correlation between shocks to user cost (u_2) and the gap (z) between the frictionless capital stock and the actual capital stock. The preferred estimation procedure is therefore DOLS (rather than SOLS). Specifically, the empirical specification used below is:

$$\text{(12)} \qquad k_t = \alpha_0 + \alpha_R R_t + \sum_{s=-p}^{p} \beta_s \Delta R_{t-s} + \varepsilon_t$$

Results are presented below for many possible choices of p.[11] A common way of choosing p is by minimizing the BIC, and this is the option emphasized below when we focus on a single p to highlight the key results.

Adjusted DOLS t statistics are calculated as follows:

$$\text{(13)} \qquad t \; = \; \frac{\hat{\alpha}_i}{SE(\hat{\alpha}_i)} \; \frac{s}{\hat{\lambda}_1^*}$$

where $\hat{\alpha}_i$ is the estimate of α_i, i=0 or R, $SE(\hat{\alpha}_i)$ is the standard error for $\hat{\alpha}_i$, and *s* is the standard deviation of the regression residual:

$$\text{(14)} \qquad s^2 \; = \; (T-n)^{-1} \sum_{t=1}^{T} \hat{\varepsilon}_t^2$$

[11] There are both analytical results and Monte Carlo evidence that relatively high values of p are the most effective in reducing bias in aggregate data. Among the alternative values of p he considers, the Monte Carlo evidence in Caballero (1994, p.56) suggests that bias is smallest for p=25 when T=120, where T is the sample size. In contrast, Caballero, Engel and Haltiwanger (1995) set p=5 (like Caballero using only lags, rather than both leads and lags as in DOLS estimation) and report that their results are fairly robust to variation in p (footnote 19, p.15), perhaps because the cross-sectional dimension in their panel data makes the effective sample size large.

where T is the sample size and n is the number of parameters estimated in the original equation with leads and lags of ΔR_t. Note that this formula is essentially the same as the formula for s_T above, except that, in calculating the degrees of freedom, account must be taken here of the coefficients on the lagged differences. For the DOLS estimation, n=[(2p+1)+g+1], where g is the number of estimated regression coefficients (apart from the coefficients on the lagged differences) excluding the constant (so in (11), g=1) and there is a constant.

C. DOLS Empirical Results

Table 1 presents estimates of the long-run user cost elasticity for equipment for many different values of p. At the value of p where the BIC is minimized, the DOLS estimate of the user cost elasticity is -1.64. This is about 75 % larger than the only previous comparable estimate of aggregate user cost elasticity, the Caballero (1994) estimate that accounts for small sample bias. Again, the larger estimate is consistent with the idea that user cost should be more exogenous in a small, open economy. In addition, this estimate is based on DOLS as proposed by Stock and Watson (1993) while the Caballero estimate uses a procedure which is inspired by DOLS but is not the same as the Stock and Watson (1993) DOLS estimator, a point to which we will return in the next section.

As noted above, there are analytical results and Monte Carlo evidence suggesting that large values of p may be required to correct small sample bias if adjustment frictions are large. In Table 1, estimates of the elasticity increase as p rises, reflecting the reduction in small sample bias. By about p=18 or 20, the elasticity estimate stabilizes. Interestingly, this is also consistent with previous Monte Carlo results. Caballero (1994, Table 3) shows that after the elasticity estimate gets very close to the true elasticity, adding further lagged differences of the right-hand-side variables has little effect on the estimated elasticity. If we suppose that -1.64 is the true elasticity (as suggested both by the fact that this is the estimated elasticity at the p that minimizes the BIC and that the elasticity estimate stabilizes at this value), then, for example, at p=5, the elasticity estimate is biased towards 0 by about 34 %, roughly in the range obtained by Caballero (1994) in Monte Carlo simulations of the case where adjustment frictions are large.

VI. One-Sided Summation Procedures and DOLS

DOLS can quickly use up degrees of freedom, especially if p is large. As noted above, both analytical results and Monte Carlo simulations have shown that large values of p may be necessary to overcome the SOLS small sample bias. In an effort to mitigate this problem, Caballero (1994) does not actually use DOLS estimation. Instead, he uses either lags of the first difference of user cost or leads of the first difference of user cost (i.e., one-sided summations in place of the two-sided summation in equation (12)). He conjectures that whenever adjustment costs are large, leads would not have as big an effect as lags in reducing small sample bias. In U.S. data, he found that estimates of the user cost elasticity were smaller in absolute value using leads than using lags.

As the fourth column of Table 1 shows, the one-sided summation with leads only yields elasticity estimates that are smaller in absolute value for every p than the one-sided summation with lags only, consistent with Caballero's conjecture. This paper presents the first aggregate estimates of the user cost elasticity using DOLS as proposed by Stock and Watson (1993), so it is useful to compare DOLS with the one-sided summation procedure using lags. In Monte Carlo simulations, Caballero (1994) finds that, if adjustment frictions are large, the one-sided procedure (using lags) can yield an economically significant bias even when the length of the one-sided summation is long. For example when adjustment frictions are large, the estimated elasticity is about 20 % below the true elasticity even when 25 lags are used in the one-sided summation [Caballero (1994), Table 3]. This corresponds with the results presented in Table 1. The one-sided summation with lags only yields smaller elasticity estimates than DOLS for almost every p.

Table 2 focuses on the user cost elasticity for the value of p that minimizes the BIC. Again, results are consistent with Caballero’s conjecture: the point estimate of the user cost elasticity is larger in absolute value using lags than it is using leads. The magnitude of the reduction in small sample bias that results from using the one-sided summation with leads only is comparable to that found in U.S. data by Caballero (1994). The point estimate of the user cost elasticity using a one-sided summation with leads only is about 22 % higher in absolute value than the SOLS estimate in Canadian data and about 14 % higher in U.S. data.

As Caballero (1994) found in his Monte Carlo simulations, the one-sided procedure (using lags only) appears to be biased downwards: if we assume the true elasticity is -1.64, then the one-sided procedure (using lags only) yields an estimate that is about 27 % below the true value. This suggests that, where feasible, the DOLS procedure proposed by Stock and Watson (1993) is preferable to the one-sided summation procedure, especially if there is reason to believe that adjustment frictions are large.

VII. Structures

As in the case of equipment, ADF tests show unit roots in both k and R for structures -- and cointegration tests reject the null hypothesis of no cointegration between k and R. However, the elasticity estimates for structures are markedly different than those for equipment. To begin with, the point estimate from SOLS is essentially 0 (0.02, with a standard error of 0.07). There is little evidence that this is the result of small sample bias. As shown in Table 3, the one-sided summation estimators (both lags only and leads only) yield similar elasticity estimates -- all close to 0 -- for all values of p. The DOLS estimates are also close to 0 for most values of p. For the value of p that minimizes the BIC, the DOLS point estimate of the user cost elasticity is virtually identical to the SOLS estimate (.02, with a standard error of .04). Moreover, the value of p that minimizes the BIC is 1, apparently suggesting that little bias correction is required. As Table 4 illustrates, for the value of p that minimizes the BIC , the results are essentially the same using the one-sided summation procedures.

The DOLS results for structures illustrate a point made by Caballero (1994). In his empirical work, there is a pattern of estimated user cost elasticities becoming more negative with larger values of p. Caballero pointed out that this pattern is not a mechanical artifact of the correction he uses for small sample bias nor, more generally, of the DOLS procedure proposed by Stock and Watson (1993). The results in Table 3 vividly illustrate this point: the point estimates of the user cost elasticity do not uniformly become more negative as p increases.

VIII. Conclusion

The goal of this paper is to account for the difference in the estimated user cost elasticity between the two existing papers that estimate the long-run elasticity on aggregate data -- Caballero (1994) and Schaller (2005). The sources of the difference are straightforward to describe. Schaller (2005) uses economics to address simultaneity bias and econometrics to address small sample bias. First, the economics: user cost is more exogenous in a small, open economy, leading to a reduction in simultaneity bias. Second, the econometrics: Dynamic OLS (DOLS) reduces small sample bias. Both the economics and the econometrics in Schaller (2005) increase the estimated elasticity by about one-third. Using data from a small, open economy increases the estimated elasticity from -0.9 to -1.2. Using DOLS increases the estimated elasticity from -1.2 to -1.6. In contrast, Caballero (1994): 1) uses data from a large economy (the US); and 2) uses an econometric procedure that is related to DOLS but not quite the same.

An important lesson can be drawn from the results presented here. When adjustment frictions are important, long-run estimates of key parameters are less biased -- and the details of the econometrics matter.

This paper therefore echoes the key points made by Caballero (1994) in his pioneering use of long-run econometrics in estimating the user cost elasticity. His analytical results and Monte Carlo simulations showed both the importance of small sample bias and the potential for bias even using certain long-run econometric procedures.

The points made by Caballero (1994) -- reinforced by the empirical results presented in this paper -- are of broad relevance. The careful use of long-run econometrics is likely to be helpful in any area of economics where there is slow adjustment to shocks.

Inventories are an example. Much prior empirical research has shown that the speed of adjustment of inventories is slow, with an adjustment of only about 10 % per month towards the desired inventory stock, as discussed in Blinder and Maccini (1991) and Ramey and West (1999). A long-standing puzzle is the lack of response of inventories to the real interest rate. The real interest rate represents the opportunity cost of holding inventories, so it should matter, but it has been painfully difficult to find empirical evidence of the relationship. (Again, see the surveys by Blinder and Maccini (1991) and Ramey and West (1999).) However, using DOLS estimation of the cointegrating relationship (derived from a linear-quadratic inventory model), Maccini, Moore, and Schaller (2004) find a highly significant relationship between inventories and the real interest rate.

There are many areas of economics where adjustment frictions appear to be important -- including nominal price and wage stickiness, habit formation (with potential implications for consumption and asset pricing), and sticky information models [Gabaix and Laibson (2002) and Mankiw and Reis (2002)] -- and there is therefore probably further potential to apply long-run econometrics to obtain better parameter estimates and perhaps to solve other empirical puzzles.

Data Appendix

Capital stock is calculated by the perpetual inventory method, specifically using the following formula

$$K_{t+1} = (1-\delta)K_t + I_{t+1}$$

The annual depreciation rates are set at .13 for equipment and .06 for structures.[12] (Note that since the investment data are quarterly, the depreciation rate used in the formula above is a quarterly rate.)

To construct the initial values of the capital stock, we use the current dollar measures of the capital stock (D818267 for equipment, D818265 for building construction, and D818266 for engineering construction[13]) for 1960 and deflate using the appropriate price index for investment goods produced by the System of National Accounts Division of Statistics Canada (D15605 for equipment and D15604 for structures). For example, for equipment we multiply the current dollar capital stock for 1960 by the ratio (equipment price index for 1992)/(equipment price index for 1960). The initial capital stock for structures is the sum of the building construction and engineering construction capital stocks, constructed as just described.

The investment data are business sector, non-residential, gross, real, fixed capital formation (seasonally adjusted) from the National Income and Expenditure Accounts, which is divided into non-residential structures (D14854) and equipment (D14855). Since the quarterly investment data are reported at annual rates, we divide by 4 to obtain investment in a given quarter.

The cost of capital is calculated as follows

$$\tilde{R}_t = (i_t + \delta + \gamma - \pi_t^{K})\left(\frac{1 - z_t - u_t}{1 - \tau_t}\right)\frac{p_t^{K}}{p_t^{Y}}$$

---

[12] In the specifications which are based on variable depreciation rates, we divide the capital cost allowance by the previous year's capital stock to obtain asset- and time-specific depreciation rate series. Specifically, for equipment, we divide the capital cost allowance for equipment (D834915) by the equipment capital stock (D834919). (Both the capital stock and the capital cost allowance are in constant dollars and are reported at annual frequency.) The Investment and Capital Stock Division of Statistics Canada divides structures into two categories - building construction and engineering construction. We calculate depreciation rates for building construction and engineering construction, using the respective capital cost allowances (D834913 and D834914) and capital stocks (D834917 and D834918) and then create a weighted average depreciation rate for structures using the proportions of capital each year (as measured by series D834917 and D834918) for the two categories as the weights.

[13] Statistics Canada divides structures into "building construction" and "engineering construction."

where *i* is the nominal interest rate, δ is set at .13 for equipment, .06 for structures, γ is a fixed risk premium (set at 6 %), π^K is the rate of inflation for investment goods, *z* is the present value of depreciation allowances, *u* is the investment tax credit rate, τ is the corporate tax rate, p^K is the price of investment goods, and p^Y is the price of output. $\tilde{R}$ is expressed as a annual rate, so i_t, δ, γ, and π_t^K are all expressed as annual rates. The corporate tax rate is the combined federal and Ontario (provincial) tax rate on income other than small business or manufacturing income.

The nominal interest is a three month T-bill rate (B14060). The interest rate data is monthly and starts in 1962. In order to transform it into quarterly data we took the corresponding three-month average for each of the quarters. For example, 1962:1 = (Jan/62 + Feb/62 + Mar/62)/3, where the dates refer to the interest rate for that date. The following points were missing from the original series: February 1970, November 1970, February 1971, April 1973. In these cases we constructed the quarterly data by obtaining the average of the interest rates for the two months that were available for each of those quarters. For example, the interest rate for 1970:1 = (Jan/70 + Mar/70)/2.

The corporate tax and investment tax credit rates are drawn from *Finances of the Nation* (previously *The National Finances*), published by the Canadian Tax Foundation, various issues, supplemented for the period since 1996 by personal communication with the Department of Finance.[14] Because the investment tax credit applies only to equipment, *u*=0 for structures.

The present value of depreciation allowances (per dollar of investment) is calculated as follows [Hayashi 1982, p. 221-222]:

$$z_t = \tau_t \sum_{n=1}^{T_t} D(n,t)(1+i_t)^{-n}$$

where *D*(*n,t*) is the depreciation allowance at time *t* for an asset at age *n* and *T* is the asset life for tax purposes. In general, depreciation allowances in Canada are based on the declining balance method.[15] Essentially, the Canadian declining-balance method sets D(n,t) equal to the depreciation rate for that class of assets divided by two times the purchase cost in the first year (with the idea that, on average, assets are purchased half-way through the year) and the depreciation rate times the remaining undepreciated value of the asset in subsequent years. Thus,

[14] The ITC was in place from 1962 to 1985 with two exceptions (October 10, 1966 to March 9, 1967 and April 19, 1969 to August 15, 1971). We assign the ITC rate based on the rate that prevailed for the majority of a given quarter (e.g., setting the ITC rate to zero for the last quarter of 1966 and the first quarter of 1967).

[15] A detailed discussion of the basic structure and historical information on rates is available in Buckwold (1990), p. 93-105. The rates were verified by direct personal contact with the Department of Finance.

$$D(1,t) = .5\delta_t^T$$

$$D(n,t) = (1-.5\delta_t^T)(1-\delta_t^T)^{n-2}\delta_t^T, n \geq 2$$

where δ^T is the depreciation rate for tax purposes. The present value of depreciation allowances will therefore be:

$$\begin{aligned} z_t &= \frac{\tau_t\delta_t^T}{2} + (1-.5\delta_t^T)\tau_t\delta_t^T(1+i_t)^{-1} + (1-.5\delta_t^T)\tau_t\delta_t^T\frac{1-\delta_t^T}{1+i_t}(1+i_t)^{-1} + \ldots \\ &= \frac{\tau_t\delta_t^T}{2} + (1-.5\delta_t^T)\tau_t\delta_t^T(1+i_t)^{-1}\sum_{s=0}^{\infty}\left(\frac{1-\delta_t^T}{1+i_t}\right)^s \\ &= \frac{\tau_t\delta_t^T}{2} + \frac{(1-.5\delta_t^T)\tau_t\delta_t^T}{i_t+\delta_t^T} \end{aligned}$$

For asset class 29 (the primary category for equipment between May 8, 1972 and 1987, inclusive), three-year straight-line depreciation at rates 25 % / 50 % / 25 % was applied, so the present value of depreciation allowances was:

$$z_t = .25\tau_t + \frac{.5\tau_t}{1+i_t} + \frac{.25\tau_t}{(1+i_t)^2}$$

For structures, the rate was 5 % before 1988 and has been 4 % since then. The standard rate for equipment was 20 % before 1972, 40 % from 1988 to 1989 inclusive, 30 % for 1990, 25 % from 1991 until February 26, 1992, and 30 % from February 26, 1992 on.

The price indexes for business sector structures and equipment and software investment are D15604 and D15605, respectively. The price index for output is the GDP deflator at market prices (D15612).

We attempt to match output as closely as possible to the investment data, which are for the business sector. To do this, we subtract government expenditures – net government current expenditure on goods and services (D14848), government gross fixed capital formation (D14849), and government inventories (D14850) – from GDP (D14872).

References

Auerbach, Alan J., 1983, “Taxation, Corporate Financial Policy and the Cost of Capital,” *Journal of Economic Literature*, 21, 905-940.

Bannerjee et al., 1986, “Exploring Equilibrium Relationships in Econometrics through Static Models: Some Monte Carlo Evidence,” *Oxford Bulletin of Economics and Statistics*, 48, 253-277.

Blinder, Alan S. and Maccini, Louis J. “Taking Stock: A Critical Assessment of Recent Research on Inventories.” *Journal of Economic Perspectives*, 1991, 5(1), 73-96.

Buckwold, W.J., 1990, Canadian Income Taxation: A Management Approach. (Toronto: McGraw-Hill Ryerson, 1990).

Caballero, R.J., 1994, “Small Sample Bias and Adjustment Costs,” *Review of Economics and Statistics*, 76, 52-58.

Caballero, R.J., 1999, “Aggregate Investment,” in John B. Taylor and Michael Woodford (eds.), *Handbook Of Macroeconomics*, Volume 1B (Amsterdam: Elsevier North-Holland), 813-862.

Caballero, R.J., and E. Engel, 1999, “Explaining Investment Dynamics in U.S. Manufacturing: A Generalized (S,s) Approach,” *Econometrica*, 67, 783-826.

Caballero, R.J., Engel, Eduardo M.R.A., and Haltiwanger, John C., 1995, “Plant-Level Adjustment and Aggregate Investment Dynamics,” *Brookings Papers on Economic* Activity (1995:2), 1-54.

Chirinko, Robert, 1993, “Business Fixed Investment Spending: Modeling Strategies, Empirical Results, and Policy Implications,” *Journal of Economic Literature*, 31, 1875-1911.

Chirinko, Robert, Steven M. Fazzari, and Andrew P. Meyer, 1999, “How Responsive is Business Capital Formation to its User Cost? An Exploration with Micro Data,” *Journal of Public Economics*, 74, 53-80.

Chirinko, Robert S., Fazzari, Steven M., and Meyer, Andrew P., 2001, “That Elusive Elasticity: A Long-Panel Approach to Estimating the Price Sensitivity of Business Capital”, unpublished.

Clark, Peter K., 1993, “Tax Incentives and Equipment Investment,” *Brookings Papers on Economic Activity*, 1, 317-347.

Cummins, J.G., and Hassett, K.A., 1992. “The Effects of Taxation on Investment: New Evidence from Firm Level Panel Data,” *National Tax Journal*, 45, 243-251.

Gabaix, Xavier and Laibson, David, 2002, “The 6D Bias and the Equity Premium Puzzle,” *NBER Macroeconomics Annual*, MIT Press, Ben Bernanke and Ken Rogoff, ed., 257-312.

Goolsbee, A., 2000, “The Importance of Measurement Error in the Cost of Capital,” *National Tax Journal*, 53, 215-228.

Hall, Robert, and Dale Jorgensen, 1967, “Tax Policy and Investment Behaviour,” *American Economic Review*, 57, 391-414.

Hassett, Kevin A., and Hubbard, R. Glenn, 2002, “Tax Policy and Business Investment,” *Handbook of Public Economics*, 3, 1293-1343.

Hayashi, Fumio, 1982, "Tobin's Marginal q and Average q: A Neoclassical Interpretation," *Econometrica*, 50, 213-224.

Kiyotaki, N., and West, Kenneth D., 1996, “Business Fixed Investment and the Recent Business Cycle in Japan,” *Macroeconomics Annual*, 277-323.

Manccini, Louis J., Moore, Bartholomew J., and Schaller, Huntley, 2004, “The Interest Rate, Learning, and Inventory Investment”, *American Economic Review,* 94(5), 1303-1327.

Mankiw, N. Gregory, and Reis, Ricardo, 2002. "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *Quarterly Journal of Economics*, 117(4), 1295-1328.

Ramey, Valerie A., and West, Kenneth D., 1999, “Inventories,” in John B. Taylor and Michael Woodford, eds., Handbook of Macroeconomics. Vol.1B, Amsterdam: North-Holland, 863-923.

Schaller, Huntley, 2006, “Estimating the Long-Run User Cost Elasticity,” *Journal of Monetary Economics*, 53, 725–736.

Stock, J., 1987, “Asymptotic Properties of Least Squares Estimators of Cointegrating Vectors,” *Econometric*, 55, 1035-1056.

Stock, J., and M. Watson, 1993, “A Simple Estimator of Cointegrating Vectors in Higher Order Integrated Systems,” *Econometrica,* 61, 783-820.

Tevlin, Stacey and Karl Whelan, 2003, “Explaining the Investment Boom of the 1990s,” *Journal of Money, Credit and Banking*, 35(1), 1-22.

Tables

Table 1

Estimates of User Cost Elasticity: Equipment

p	DOLS	Lags Only	Leads Only
1	-0.737 (0.362) [-2.634]	-0.852 (0.227) [-2.889]	-0.697 (2.327) [-2.938]
2	-0.832 (0.569) [-2.604]	-0.868 (0.311) [-2.885]	-0.729 (1.339) [-2.951]
3	-0.915 (0.377) [-2.575]	-0.890 (0.332) [-2.885]	-0.749 (1.511) [-2.964]
4	-0.974 (0.433) [-2.540]	-0.901 (0.306) [-2.866]	-0.777 (2.435) [-2.992]
5	-1.045 (0.406) [-2.529]	-0.914 (0.401) [-2.859]	-0.786 (2.462) [-3.007]
6	-1.124 (0.340) [-2.529]	-0.921 (0.373) [-2.839]	-0.805 (2.452) [-3.026]
7	-1.154 (0.307) [-2.542]	-0.928 (0.381) [-2.815]	-0.812 (2.394) [-3.044]
8	-1.192 (0.317) [-2.538]]	-.0936 (0.374) [-2.790]	-0.822 (2.709) [-3.056]
9	-1.243 (0.229) [-2.605]	-0.943 (0.358) [-2.762]	-0.830 (2.617) [-3.070]
10	-1.293 (0.253) [-2.681]	-0.957 (0.359) [-2.745]	-0.836 (2.770) [-3.075]
11	-1.347 (0.227) [-2.741]	-0.969 (0.337) [-2.732]	-0.848 (2.750) [-3.078]
12	-1.392 (0.250) [-2.820]	-0.980 (0.324) [-2.717]	-0.859 (2.610) [-3.087]
13	-1.428 (0.221) [-2.871]	-0.992 (0.321) [-2.710]	-0.870 (2.524) [-3.093]
14	-1.463 (0.230) [-2.910]	-1.006 (0.315) [-2.709]	-0.882 (2.369) [-3.108]
15	-1.495 (0.189) [-2.951]	-1.017 (0.282) [-2.699]	-0.899 (2.555) [-3.120]
16	-1.541 (0.193)	-1.024 (0.269)	-0.910 (2.759)

	[-3.047]	[-2.676]	[-3.125]
17	-1.574 (0.187) [-3.108]	-1.046 (0.248) [-2.698]	-0.915 (2.699) [-3.121]
18	-1.607 (0.182) [-3.192]	-1.074 (0.216) [-2.736]	-0.923 (2.405) [-3.123]
19	-1.615 (0.219) [-3.197]	-1.103 (0.210) [-2.790]	-0.930 (2.123) [-3.129]
20	-1.625 (0.264) [-3.183]	-1.127 (0.191) [-2.815]	-0.937 (1.986) [-3.135]
21	-1.637 (0.285) [-3.160]	-1.145 (0.185) [-2.822]	-0.946 (1.938) [-3.143]
22	-1.641 (0.144) [-3.120]	-1.170 (0.194) [-2.859]	-0.951 (1.723) [-3.147]
23	-1.644 (0.161) [-3.106]	-1.200 (0.172) [-2.894]	-0.964 (1.545) [-3.165]
24	-1.650 (0.094) [-3.252]	-1.207 (0.169) [-2.867]	-0.979 (1.710) [-3.200]
25	-1.667 (0.081) [-3.503]	-1.234 (0.169) [-2.888]	-0.983 (1.805) [-3.204]
26	-1.665 (0.076) [-3.785]	-1.249 (0.154) [-2.887]	-0.987 (1.667) [-3.212]
27	-1.659 (0.079) [-3.962]	-1.263 (0.147) [-2.876]	-0.990 (1.564) [-3.223]
28	-1.644 (0.079) [-4.076]	-1.276 (0.139) [-2.872]	-0.995 (1.580) [-3.227]
29	-1.632 (0.082) [-4.100]	-1.290 (0.131) [-2.866]	-0.997 (1.395) [-3.229]
30	-1.635 (0.082) [-4.102]	-1.308 (0.127) [-2.870]	-1.002 (1.383) [-3.233]

Standard errors are in parentheses. Estimation is by DOLS. See equation (12) for the precise specification. p is the number of leads and lags of first differences of the right hand side variable (user cost) used in DOLS estimation. BIC is the Bayesian Information Criterion.

Table 2

A Comparison of Bias Corrections

Equipment

Estimator	Parameter Estimates (Standard Errors)
SOLS	-.82 (.20)
One-Sided Summation (Lags only)	-1.20 (.17)
One-Sided Summation (Leads only)	-1.00 (1.38)
DOLS	-1.64 (.08)

Standard errors are in parentheses. The estimation technique is shown on the left. "One-Sided Summation (Lags only)" refers to an estimator in which the two-sided summation in equation (12) is replaced by a one-sided summation in which s runs from 0 to p. "One-Sided Summation (Leads only)" refers to an estimator in which the two-sided summation in equation (12) is replaced by a one-sided summation in which s runs from –p to 0. Elasticities are reported for the value of p that minimizes the BIC.

Table 3

Estimates of User Cost Elasticity: Structures

p	DOLS	Lags Only	Leads Only
1	0.025 (0.036) [-5.904]	0.028 (0.038) [-5.640]	0.011 (0.574) [-4.879]
2	0.028 (0.035) [-5.818]	0.030 (0.041) [-5.608]	0.010 (0.593) [-4.840]
3	0.030 (0.037) [-5.731]	0.036 (0.075) [-5.589]	0.008 (0.612) [-4.801]
4	0.031 (0.052) [-5.659]	0.037 (0.078) [-5.556]	0.006 (0.638) [-4.765]
5	0.031 (0.028) [-5.623]	0.041 (0.143) [-5.536]	0.002 (0.645) [-4.736]
6	0.030 (0.030) [-5.548]	0.043 (0.134) [-5.502]	-0.001 (0.647) [-4.702]
7	0.028 (0.030) [-5.470]	0.045 (0.142) [-5.467]	-0.005 (0.608) [-4.673]
8	0.026 (0.026) [-5.419]	0.045 (0.143) [-5.428]	-0.011 (0.662) [-4.654]
9	0.023 (0.028) [-5.364]	0.045 (0.143) [-5.388]	-0.015 (0.693) [-4.626]
10	0.021 (0.036) [-5.304]	0.046 (0.140) [-5.349]	-0.019 (0.675) [-4.604]
11	0.019 (0.028) [-5.237]	0.046 (0.147) [-5.310]	-0.023 (0.718) [-4.575]
12	0.016 (0.038) [-5.185]	0.046 (0.150) [-5.271]	-0.027 (0.727) [-4.548]
13	0.014 (0.033) [-5.138]	0.047 (0.149) [-5.232]	-0.032 (0.703) [-4.520]
14	0.012 (0.033) [-5.091]	0.047 (0.151) [-5.192]	-0.036 (0.718) [-4.493]
15	0.010 (0.039) [-5.034]	0.047 (0.150) [-5.153]	-0.040 (0.752) [-4.465]
16	0.010 (0.033) [-4.954]	0.047 (0.151) [-5.113]	-0.042 (0.757) [-4.429]
17	0.010 (0.038)	0.048 (0.148)	-0.045 (0.713)

	[-4.870]	[-5.074]	[-4.394]
18	0.009 (0.040) [-4.782]	0.049 (0.149) [-5.035]	-0.048 (0.719) [-4.361]
19	0.010 (0.041) [-4.695]	0.049 (0.151) [-4.997]	-0.051 (0.798) [-4.327]
20	0.008 (0.040) [-4.598]	0.049 (0.147) [-4.959]	-0.053 (0.794) [-4.291]
21	0.013 (0.033) [-4.501]	0.047 (0.155) [-4.923]	-0.056 (0.769) [-4.257]
22	0.024 (0.025) [-4.431]	0.046 (0.072) [-4.886]	-0.059 (0.723) [-4.225]
23	0.039 (0.034) [-4.367]	0.045 (0.074) [-4.847]	-0.064 (0.727) [-4.200]
24	0.057 (0.033) [-4.329]	0.044 (0.168) [-4.811]	-0.070 (0.744) [-4.183]
25	0.071 (0.031) [-4.294]	0.042 (0.157) [-4.779]	-0.076 (0.757) [-4.169]
26	0.091 (0.029) [-4.296]	0.041 (0.059) [-4.749]	-0.081 (0.759) [-4.147]
27	0.113 (0.027) [-4.362]	0.038 (0.082) [-4.729]	-0.086 (0.742) [-4.125]
28	0.125 (0.025) [-4.440]	0.034 (0.123) [-4.721]	-0.090 (0.766) [-4.102]
29	0.137 (0.027) [-4.573]	0.030 (0.109) [-4.751]	-0.094 (0.775) [-4.075]
30	0.147 (0.020) [-4.764]	0.023 (0.127) [-4.764]	-0.099 (0.748) [-4.054]

Standard errors are in parentheses. Estimation is by DOLS. See equation (12) for the precise specification. p is the number of leads and lags of first differences of the right hand side variable (user cost) used in DOLS estimation. BIC is the Bayesian Information Criterion.

Table 4

A Comparison of Bias Corrections:

Structures

Estimator	Parameter Estimates (Standard Errors)
SOLS	.02 (.07)
One-Sided Summation (Lags only)	.03 (.04)
One-Sided Summation (Leads only)	.01 (.57)
DOLS	.02(.04)

Standard errors are in parentheses. The estimation technique is shown on the left. "One-Sided Summation (Lags only)" refers to an estimator in which the two-sided summation in equation (12) is replaced by a one-sided summation in which s runs from 0 to p. "One-Sided Summation (Leads only)" refers to an estimator in which the two-sided summation in equation (12) is replaced by a one-sided summation in which s runs from –p to 0. Elasticities are reported for the value of p that minimizes the BIC.

Author: Econometric Issues in Estimating User Cost Elasticity

Title: Huntley Schaller

Reihe Ökonomie / Economics Series 194

ISSN: 1605-7996

Stumpergasse 56, A-1060 Vienna • ☎ +43 1 59991-0 • Fax +43 1 59991-555 • http://www.ihs.ac.at

ISSN: 1605-7996