That Elusive Elasticity:

A Long-Panel Approach To Estimating

The Price Sensitivity Of Business Capital

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(Abstract)

The sensitivity of business capital formation to its user cost plays a key role in the analysis of many economic issues. Although this elasticity has been the subject of an enormous number of studies, a consensus remains elusive. We develop an estimation strategy that exploits panel data in an original way and avoids several pitfalls -- difficult-to-specify dynamics, transitory time-series variation, and positively sloped supply schedules -- inherent in investment equations that can bias the estimated elasticity. Results are based on an extensive panel containing 1,860 manufacturing and non-manufacturing firms. Our model generates a precisely estimated user cost elasticity of approximately 0.40. The method developed here may prove useful in estimating other structural parameters from panel datasets.

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Understanding the links between capital formation and price incentives has been a prominent topic on the quantitative research agenda for decades. Policymakers frequently alter price incentives to correct market failures and enhance economic performance. Although the vast majority of academic research on capital formation utilizes the user cost of capital as the central price variable, elasticity estimates vary widely.

The range of elasticity estimates corresponds to an equally wide range of policy implications from simulation models. In a simplified version of the Ballard, Fullerton, Shoven, and Whalley (1985) computational general equilibrium (CGE) model, the change in welfare from equalizing capital tax rates across industries is 70 percent larger when the user cost elasticity rises from 0.50 to 1.00. Similarly, Engen, Gravelle, and Smetters (1997, Table 5) show that¸ when the income tax is replaced by a consumption tax, the increase in steady-state net output is 79 percent higher when the elasticity of 0.50 is replaced by a value of unity. Results from the two-country model of Roeger, Veld, and Woehrmann (2000) are also sensitive to whether the elasticity is 0.50 or 1.00; a one percentage point cut in one country's corporate tax rate leads to a 70 percent larger increase in combined consumption with the larger elasticity. Fox and Fullerton (1991) find that, in CGE models, estimated welfare gains from tax initiatives depend much more on this elasticity than on the complex features and detailed disaggregation found in many simulation models. Starting with the seminal analysis of Harberger (1959, 1962), the user cost elasticity, equivalent to the substitution elasticity between capital and other inputs, is central to assessing policy impacts.[1]

Despite the substantial research energies devoted to estimating the user cost elasticity, a consensus value remains elusive.[2] For example, in the Joint Committee On Taxation's (1997, Table 6) study of nine different tax models, user cost elasticities range from 0.20 to 1.00. The wide range of estimated elasticities reported in the literature may be attributed to a common source. Most econometric studies rely on quarterly or annual time-series variation in investment data to identify the user cost elasticity. Three biases may result that weigh more or less heavily in different studies. First, the specification of an investment equation requires assumptions about dynamics. While economic theory is highly informative about the determinants of the demand for the stock of capital, it is relatively silent about the demand for the flow of investment. Misspecified dynamics can bias estimates of the user cost elasticity (Summers, 1988). Of particular importance are the nature of adjustment costs and the role of financing constraints, which have received a great deal of attention in recent years and whose effects on investment spending remain controversial.[3] Second, coefficient estimates from investment regressions may be biased if much of the variation in the

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[1] This elasticity also plays a key role in the analysis of long-run growth. In the Solow growth model, Klump and Preissler (2000) show that the user cost elasticity is positively related to the steady-state capital/labor ratio and negatively related to the speed of convergence toward the steady-state (in dynamically inefficient economies). Furthermore, in the original article introducing the CES production function, Arrow, Chenery, Minhas, and Solow (1961) note that the impact of factor endowments on international trade and the variation of relative income shares depend on the value of this elasticity.

[2] See Chirinko (1993), Hassett and Hubbard (1997), and Mairesse, Hall, and Mulkay (1999) for surveys of the empirical literature.

[3] Regarding adjustment costs, see the surveys by Hamermesh and Pfann (1996) and Caballero (1999). Regarding financing constraints, see the survey by Hubbard (1998) and the controversy in Kaplan and Zingales (1997, 2000) and the reply by Fazzari, Hubbard, and Petersen (2000). Chirinko, Fazzari, and Meyer (1999) show that excluding cash flow (a variable typically included to capture financing constraints) from an investment equation using annual data biases upward the estimated user cost elasticity.

data reflects transitory rather than permanent changes. From an econometric perspective, a benefit of analyzing investment spending patterns is the substantial time-series variation in these data. If this time-series variation at quarterly or annual frequencies, however, largely reflects adjustments to transitory shocks and firms respond less to transitory than permanent variation because of adjustment costs, an elasticity estimated with time-series data at these frequencies will tend to be lower than the "true" long-run elasticity.[4] Third, if the supply curve of investment is upward sloping, as is more likely in the short to medium-run, studies incorrectly maintaining a perfectly elastic supply schedule will tend to understate demand elasticities (Goolsbee, 1998).[5] While the misspecification of dynamics has an indeterminate effect, the estimated user cost elasticity will be biased toward zero by transitory time-series variation and positively sloped supply schedules.

These potential problems all stem from a common source -- the use of investment data as the measure of capital formation. We avoid these problems by developing an approach that relies directly on capital stock data and exploits in an original way the substantial information available from panel data. We focus on the first-order condition relating the long-run desired capital stock (K^*) to the long-run desired values of output (Y^*) and the user cost (C^*). This specification underlies virtually all investment studies since Jorgenson's (1963) path-breaking work on the neoclassical model of capital accumulation, and can be represented as follows:

$$(1) \quad K^* = G[\underset{+}{Y^*}, \underset{-}{C^*}].$$

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[4] This point has been noted by, among others, Eisner (1967), Lucas (1969). Berndt (1976), Shapiro (1986b), and Kiyotaki and West (1996).

[5] This conclusion has been challenged by Hassett and Hubbard (1998) and Whelan (1999).

The difficulty with estimating (1) is that the desired values are not readily observable. We use panel data, long in the time dimension, to estimate the variables in (1) as time-averages within firms. With empirical counterparts to K*, Y*, and C* defined, it is straightforward to estimate G[.] directly across firms. This relatively simple yet fully rigorous approach estimates technology parameters immune to the three biases discussed above.

Our study proceeds as follows. Section I introduces the estimation strategy. The econometric equation is derived from the firm's profit-maximization problem, and long-run values of the variables entering the regression equation are defined as time-averages. Our estimation strategy accounts for a variety of productivity shocks, omitted variables, and firm fixed effects, and uses panel data in a way that differs substantially from prior panel studies. Section II discusses the panel dataset with 1860 firms for the period 1972 to 1991 and the construction of the variables. Section III presents our OLS and IV results. Both techniques yield similar estimates of the user cost elasticity of approximately 0.40. This estimate is higher than the elasticity of 0.25 reported by Chirinko, Fazzari, and Meyer (1999) based on the same dataset but using an investment model. Thus, the three problems affecting investment equations -- difficult-to-specify dynamics, transitory time-series variation, and positively sloped supply schedules -- impart a discernible bias toward zero. Nonetheless, the user cost elasticity remains far from unity, the value defining the frequently used Cobb-Douglas production function and determining the cut-off at which tax incentives become cost effective (in a static sense). Section IV assesses the importance of measurement error, examines the sensitivity of the estimates to various subsets of the sample, and compares our approach to related work with panel data. Section V offers a summary and conclusions.

I. Estimation Strategy

Our econometric model follows directly from the behavior of a firm that maximizes its discounted flow of profits over an infinite horizon. We analyze the firm's choices in long-run equilibrium, thus eliminating the need to model adjustment costs, delivery lags, and vintage effects. Under these assumptions, the firm always produces its long-run desired level of output with its long-run desired mix of inputs. The critical consequence is that the firm's dynamic optimization problem is transformed into a static problem. To determine the firm's demand for capital, we need only calculate the marginal product of capital evaluated at the long-run levels of inputs and output.

We assume that production possibilities are described by the following CES technology,

$$(2) \qquad Y^*_{f,t} = \{\omega(K^{*\,[(\sigma-1)/\sigma]}_{f,t}) + (1-\omega)(X^{*\,[(\sigma-1)/\sigma]}_{f,t})\}^{[\eta\sigma/(\sigma-1)]}\, U_{f,t}\,,$$

where $Y^*_{f,t}$ is long-run desired real output for firm f at time t, $K^*_{f,t}$ is the long-run desired real capital stock, $X^*_{f,t}$ is the long-run desired level of all other factors of production, and $U_{f,t}$ represents a stochastic productivity shock.[6] An attractive feature of the CES technology is that it depends on only three parameters characterizing returns to scale (η), the distribution of factor returns (ω) and, of particular importance for this study, substitution possibilities between the factors of production (σ). The CES function is strongly separable, and can be expanded to include many additional factors of production without affecting the estimating equation derived below. This feature gives the CES specification an important

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[6] The limiting value of (2) as $\sigma \to 1$ is the Cobb-Douglas production function under the additional assumption that η=1.

advantage relative to other technologies that allow for a more general pattern of substitution possibilities (e.g., the translog, minflex-Laurent). Our approach does not require price and quantity data on the other factors of production (whose availability and reliability are limited at the firm level) to recover the key parameter of interest.

Differentiating (2) with respect to capital, we obtain the following relation for the marginal product of capital ($MY^*_{f,t} / MK^*_{f,t}$),

$$(3) \qquad MY^*_{f,t} / MK^*_{f,t} = (\eta\omega)\, Y^{*\,[1+(1-\sigma)/\sigma\eta]}_{f,t}\, K^{*\,-[1/\sigma]}_{f,t}\, U_{f,t}^{[(\sigma-1)/\sigma\eta]} .$$

As is well-known in the study of capital accumulation, profit-maximization implies that this marginal product of capital equals the Jorgensonian user cost of capital ($C^*_{f,t}$), which combines interest, depreciation, and tax rates with relative prices (an exact specification of the user cost is deferred to section II). Setting $MY^*_{f,t} / MK^*_{f,t}$ equal to $C^*_{f,t}$ and rearranging (3), we obtain the following expression for the long-run desired capital stock,

$$(4) \qquad K^*_{f,t} = \Psi\, C^{*\,[\alpha]}_{f,t}\, Y^{*\,[\beta]}_{f,t}\, U_{f,t}^{[\zeta]} ,$$

$$\begin{aligned} \Psi &= (\eta\omega)^{\sigma}, \\ \alpha &= -\sigma, \\ \beta &= (\sigma\eta+1-\sigma) / \eta, \\ \zeta &= (\sigma-1)/\eta. \end{aligned}$$

Note that, with a CES production function, the user cost elasticity of capital is equivalent to the substitution elasticity between capital and other inputs (multiplied by minus one).

The central difficulty with estimating (4) is the that the long-run values are not observed. Most previous research addresses this problem by differencing the log of (4) to obtain an equation for investment. As discussed in the introduction, however, this approach relies on investment data, and may therefore generate biased estimates. To avoid these potential problems, we measure the capital stock directly, and then estimate the long-run desired levels of capital, output, and the user cost as time averages over several years. We refer to the years over which an average is computed as an interval. As shown in Figure 1 for a representative variable $W_{f,t}$ ($W_{f,t} = \{K_{f,t}, Y_{f,t}, C_{f,t}\}$), we divide our sample into three intervals indexed by a τ subscript, $\tau = 0,1,2$. The intervals are 1974-1980 (τ=0), 1981-1986 (τ=1), and 1987-1992 (τ=2). We assume that $W^*_{f,t}$ equals $W_{f,\tau}$, where the latter is estimated as the mean of $W_{f,t}$ over an interval. As we will discuss below, the τ=1 and τ=2 intervals are used for parameter estimation; the τ=0 interval is used only to form instruments and define classifications that split the sample.

With the variables in (4) defined in terms of the τ=1 and τ=2 intervals, we take logs, and obtain the following equation,

$$(5) \quad k_{f,\tau} = \alpha\, c_{f,\tau} + \beta\, y_{f,\tau} + \psi - u_{f,\tau}, \qquad \tau = 1,2.$$

$$\begin{aligned} k_{f,\tau} &= \ln[K_{f,\tau}] = \ln[K^*_{f,t}], \\ c_{f,\tau} &= \ln[C_{f,\tau}] = \ln[C^*_{f,t}], \\ y_{f,\tau} &= \ln[Y_{f,\tau}] = \ln[Y^*_{f,t}], \\ \psi &= \ln[\Psi], \end{aligned}$$

where $u_{f,\tau}$ is an error term that follows directly from the technology and represents productivity shocks. We model productivity shocks as follows,

$$(6) \quad u_{f,\tau} = \zeta\, [v_f + v_i + w_\tau + w_{i,\tau} + w_{f,\tau}].$$

The productivity shock is decomposed into firm-specific (v_f) and industry-specific

(v_i) components, as well as components that vary over the intervals, w_τ, $w_{i,\tau}$ and $w_{f,\tau}$. With this error structure, estimates can be obtained by differencing (5) and (6) between the τ intervals,

$$(7) \quad \Delta k_{f,\tau} = \alpha \, \Delta c_{f,\tau} + \beta \, \Delta y_{f,\tau} + \Delta\psi - \Delta u_{f,\tau},$$

$$\Delta k_f = -\sigma \, \Delta c_f + \beta \, \Delta y_f - \gamma - \lambda_i - \Delta w_f.$$

$$\gamma = \zeta \, \Delta w_\tau,$$
$$\lambda_i = \zeta \, \Delta w_{i,\tau},$$
$$\eta = (1-\sigma) / (\beta-\sigma),$$
$$\sigma = -\alpha.$$

Since there are only two intervals, first-differencing eliminates the temporal dimension to the model, and τ subscripts have been omitted in the final equation. Consequently, the parameters are estimated in a cross-section regression.

Equation (7) is our estimating equation relating growth in the capital stock to growth in the user cost and output. Fixed firm and industry effects are eliminated by differencing, and fixed interval effects are captured by the constant (γ). Industry effects that vary across intervals are captured by industry dummies (λ_i). This framework allows us to estimate the parameter of central interest in this study, the elasticity of the capital stock with respect to its user costs (σ) Additionally, we can recover the returns to scale elasticity, η, as a non-linear combination of the estimated σ and β parameters.

Our estimation strategy exploits panel data in a way that differs substantially from prior panel studies. By taking interval averages, we use low-frequency variation to estimate the long-run values of the regression variables. This approach avoids the difficult specification problems that necessarily arise with investment regressions based on data at quarterly or annual frequencies. Differencing equation

(7) across intervals controls for firm fixed effects, as well as productivity shocks and omitted variables that vary across intervals. The remaining cross-section variation provides ample degrees of freedom for estimation.

Consistency of the OLS parameter estimates depends on the relation between the stochastic element, Δw_f, and the regressors, especially Δy_f. This correlation is not likely to be a problem for two reasons. First, Δw_f is that part of the productivity shock that remains after accounting for all fixed and industry effects. Major technological changes (e.g. telecommunications, computing, the internet) are likely to have their largest effects on all firms in an industry (captured by λ_i) with only a small residual impact that is firm specific. Second, only part of the productivity shock enters the error term. As noted by Shapiro (1986a), including output in a factor demand equation can completely absorb the productivity shock. When the elasticity of substitution is unity, ζ equals zero, and $u_{f\tau}$ vanishes (cf. equation (6)). When σ deviates from unity, the impact of the productivity shock is nonetheless diminished by ζ. Despite these arguments that OLS estimates will not be appreciably affected by Δw_f, we present two alternative estimates that are robust to simultaneity. First, we impose constant returns to scale ($\eta=1$ implying $\beta=1$). Thus, Δy_f, the variable most likely to be correlated with Δw_f no longer appears as a regressor. Second, we present IV estimates and Hausman tests using the variables in the $\tau=0$ interval as instruments.

This econometric model is robust to four potentially important distortions. First, the parameter estimates are robust to trending variables. See Appendix A for formal consideration of this issue and the role played by differencing in eliminating firm-specific trends. Second, the estimates are unlikely to be influenced by additional factors that may affect the specification of the production function or the first-order conditions. For example, the estimating equation is robust to including additional factors of production. Markups that vary across firms are captured by a firm-specific fixed effect eliminated by differencing. Moreover, the information processing revolution may have led to biased technical change over the past 20 years. In terms of the CES technology, biased technical change is represented by temporal variation in ω and, like w_τ, will be reflected in the constant. Third, studies implementing the Jorgensonian framework have often been criticized for failing to distinguish between desired output and actual output (e.g., Coen, 1969; Hall, 1995). By using time-averages in the econometric equation, we recognize this important distinction. Fourth, the estimates are unlikely to be affected by measurement error in the capital stock. Classic measurement error will be part of the error term, and hence innocuous. A plausible situation where measurement error may be systematic arises when an increase in the pace of technological change effectively increases the depreciation of fixed capital through obsolescence, an effect not captured in our fixed depreciation rate assumption. However, an increase in depreciation rates would lead to a systematic overstatement of capital in τ=2, and would be captured by the constant. If omitted variables or measurement error are both firm-specific and interval-varying, consistent estimation becomes an issue. In this case, the IV estimates provide a useful safeguard to check the parameter estimates.

In sum, the estimation strategy developed here collapses the time dimension of firm panel data by defining three intervals and then time-averaging the data within an interval. The first interval is used to form instruments or sort variables into contrasting classes. The second and third intervals are used for estimation. A variety of productivity shocks, omitted variables, and fixed firm effects are accounted for by estimated parameters or differencing. Production function parameters are thus estimated in a cross-section of time-averaged, differenced firm data. This econometric model does not *solve* the estimation problems inherent with investment models -- difficult-to-specify dynamics, transitory time-series variation, and positively sloped supply schedules -- that may bias estimates of the user cost elasticity. Instead, our approach *avoids* these problems by exploiting panel data and estimating directly the first-order condition for capital.

II. The Panel Dataset

Our estimation method requires a panel dataset that is long in both the cross-section and time-series dimensions and that contains cross-section variation in the user cost. We link data sources from the Compustat Industrial Database maintained by Standard and Poors (containing financial statement data) and Data Resources, Inc. (DRI, containing user cost and industry data). In this section, we discuss the construction of the variables used for regression estimates of equation (7), for instruments, and for sorting firms into contrasting classes.

The user costs (C) are constructed from industry-level information. We have data for 26 different capital assets (24 types of equipment and two types of structures). The basis for these user costs, from Hall and Jorgenson (1967) and modified by DRI, is:

$$(8) \qquad C_{i,j,t} = [p^{I}_{j,t} / p^{Y}_{i,t}] \, [(1 - m_{j,t} - z_{j,t}) / (1 - tx_{t})] \, [r_{t} + \delta_{j}]$$

where $p^{I}_{j,t}$ is the asset-specific purchase price for asset j at time t, $p^{Y}_{i,t}$ is the industry i output price at time t, δ_j is the asset-specific economic depreciation rate, and tx_t is the income tax rate. The investment tax credit ($m_{j,t}$) and the discounted value of tax depreciation allowances ($z_{j,t}$) also vary across assets. The financial cost of capital (r_t) is a weighted average of the cost of equity (the dividend-price ratio for Standard & Poor’s Composite Stock Price Index plus an expected long-run growth rate of 2.4 percent, with a weight of 0.67) and the cost of debt (average yield on new issues of high-grade corporate bonds adjusted to a AAA basis, with a weight of 0.33). The nominal cost of debt is reduced by its tax deductibility and the expected inflation rate, defined as a weighted average of past GDP deflator growth rates. Industry-specific user costs are a weighted average of the asset user costs. The weights are the proportion of total capital in an industry accounted for by each of the 26 assets.[7] This industry information is then merged with the firm-level Compustat data using each firm's S.I.C. code.[8]

Measurement of the capital stock (K) is critical to our study. Compustat does not provide an acceptable measure of the capital stock because book values of net plant and equipment likely understate current replacement values in periods of inflation. In addition, accounting depreciation rules may not accurately reflect economic depreciation.

We measure the current replacement value of capital with a three-step, iterative algorithm.[9] First, choose a seed value. We use the book value of net plant and equipment from the firm's first observation in Compustat. The nominal seed value is deflated by a weighted average of investment goods price deflators, where the weights are determined by the specific capital asset mix of each industry.[10]

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[7] Note that these weights are from the Bureau of Economic Analysis capital flow tables and reflect asset usage by establishment. The Compustat data reflect ownership by company. The combination of industry aggregate data for the user cost and firm data for investment and other items may induce measurement error because some firms operate in a variety of industries. To the extent that such measurement error is constant within firms, however, it will be captured in firm fixed effects.

[8] We average the quarterly DRI user cost data at the firm level to obtain an annual user cost that corresponds to the Compustat data. The averages account for differences in firms' fiscal years, and therefore introduces some firm-level heterogeneity into the user cost data.

[9] This conceptual approach has been used for firm-level panel data at least since Salinger and Summers (1983).

[10] Because the book value of net plant will usually be less than the replacement cost when there is inflation, the use of net plant as a seed in 1974 distorts the measurement of the replacement cost of capital. This distortion, however, is unlikely to affect the estimated parameters for three reasons. First, the distortion will disappear as new investment is added to the capital stock at current replacement value and old capital is depreciated. The early part (τ=0) of our sample is used only for instruments. The effect of the seed value on the regression data, therefore, is attenuated because the capital series consist largely of new investment expenditures by the τ=1 and τ=2 periods. Based on the average depreciation rate of 14.8 percent, only 32.6 percent of the 1974 seed value will remain at the beginning of the estimation period in 1981. Second, a proportionate distortion of the seed value relative to the "true" replacement cost across firms is eliminated by our econometric procedure that takes logs and then first differences the capital stock data that enter the regressions. Third, any remaining random measurement error in the capital stock affects the dependent variable only and, therefore, it does not bias coefficient

These are the same weights employed in the user cost computation described above. Second, subtract capital lost to (geometric) depreciation. The firm's depreciation rate is the weighted average of the rates for individual assets from DRI, again using industry-asset proportions as weights. Thus, there is a consistency between the depreciation rates used in constructing the capital stock and user cost data. Third, add in new investment. In most cases, this step simply adds the deflated value of the Compustat capital expenditures variable. The deflator is the weighted average of each industry's investment goods price deflators. At the micro level, however, we must take into account that a firm's capital stock may rise or decline due to acquisitions or divestitures that are not included in the capital expenditure variable. If the data indicate a significant acquisition or divestiture, we use accounting identities to calculate the impact of this activity on the capital stock. Details of the capital stock calculation appear in appendix B.

Output (Y) is gross sales during the year reduced by cash discounts, trade discounts, and returned sales or allowances to customers. Sales will differ from output by the change in finished goods inventories. While this difference may be non-trivial in the short-run, it will have very little impact on the long-run averages used in our estimation. Nominal sales figures from Compustat are deflated by industry-specific output price indexes from DRI.

For some of the results that follow, we sort the data into contrasting sub-samples depending on whether a classifying variable averaged over the τ=0 pre-estimation period (1974-1980) is above or below its median. Three variables are used as classifiers: the cash flow-capital ratio (CF/K), the size of the capital stock (K), and the Brainard-Tobin Q. Cash flow is income after taxes plus non-cash expenses, primarily depreciation and amortization. The numerator of Q is the

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estimates, although it would raise standard errors.

market value of equity plus the book value of debt less the book value of inventories. The denominator is the replacement value of the capital stock measure discussed above.

To protect against results driven by a small number of extreme observations, we exclude observations in the one-percent upper and lower tails from the distributions of the firm-specific variables.[11] Firms included in the data set must have some observations for each variable in all three of the τ intervals. Our final data set contains 1,860 firms from all sectors of the economy.

Table 1 presents summary statistics for the firms in our final data set. The mean firm size is \$320.8 million in the τ=0 period and grows to \$529.2 million by τ=2 (in 1987 dollars). This growth corresponds to a 3.5 percent annualized growth rate from the midpoint of τ=0 to the midpoint of τ=2. Mean real output grows at an annualized rate of 2.7 percent. The firm data are highly skewed rightward; mean capital and output both far exceed the median values. The faster growth rate for capital than for output implies a growing capital-output ratio, which is consistent with the declining value of the user cost in the sample. The primary reason for the decline in the user cost is the declining relative price of capital goods to industry output (the first bracketed term in equation (8) above) which falls, on average, 16 percent between τ=0 and τ=2.[12]

Statistics for the growth in firm variables between the τ=1 and τ=2 intervals are presented in the final three columns of table 1. These growth rates enter

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[11] We checked the robustness of our results when we deleted both the one-half-percent and two-percent tails. The effect on the results was negligible. Because the user cost is computed from stable industry and aggregate data, we did not delete data in the tails of the user cost variable distribution.

[12] Because the base year for the price deflators is 1987, the relative price term is substantially greater than one early in the sample. The tax term is also larger than unity, averaging 1.15 over the sample. Because of these components, the mean and median values of the user cost are well above the sum of the depreciation rate (which averages 14.8 percent) and the real financial cost

directly into the econometric model, and hence are key for estimating the model parameters. It is important to contrast change-heterogeneity -- variation across firms in growth between intervals -- from level-heterogeneity -- variation across firms in levels over the entire sample -- discussed in most panel studies. These two types of heterogeneity are fundamentally different. For example, assume that level-heterogeneity is important and the data for a given variable is widely dispersed across firms within an interval. It might nonetheless be the case that this variable moves together across intervals based on aggregate factors. In this case, change-heterogeneity would be completely absent. The standard deviations in the final column of table 1, however, strongly indicate that this case does not apply to our data. There is considerable change-heterogeneity in the growth of capital, output, and user cost with coefficients of variation of 2.25, 2.41, and 2.71, respectively. This is the variation that we exploit in our estimates of equation (7). While this equation is estimated as a cross-section of firms, the value of each firm observation is based on temporal variation between intervals.

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of capital (which averages 4.1 percent).

III. Empirical Results

A. OLS Estimates

Ordinary least squares estimates of the structural parameters from equation (7) appear in table 2. The focus of our study is on the user cost elasticity of capital, σ, which is also the substitution elasticity between capital and other factors of production. In column 1, our benchmark estimate of σ is 0.367 with a standard error of 0.067. The null hypothesis that the user cost elasticity is zero can be strongly rejected at any conventional level of significance. It is also clear, however, that our estimate of σ is much smaller than unity, the value implied by the Cobb-Douglas production function and often assumed in applied work.

As shown by equation (7), the estimated returns to scale elasticity (η) is a function of the regression coefficients on the growth in both output (β) and the user cost ($-\sigma$). The OLS estimate of the returns to scale elasticity, η, is 1.135 also with a small standard error.[13] With our estimated parameter values, the primary reason that the estimated returns to scale elasticity modestly exceeds one is that the coefficient of output growth in our capital growth regression is somewhat less than unity (β=0.925). As shown in equation (7), an estimated β in the neighborhood of unity generates results for η close to constant returns for any admissible value of σ. It is interesting to note that the effect of output is much stronger here than in panel data studies using investment data (cf. Chirinko, Fazzari, and Meyer, 1999). We believe the reason for these more plausible results is that, unlike typical investment equations, our estimation method captures long-run, permanent changes in output,

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[13] The returns to scale elasticity is recovered from the estimated coefficients with the following formula: $\eta = (1-\sigma) / (\beta-\sigma)$ when $\beta > \sigma$. The variance of η depends in a complicated way on the variances and covariances of the estimated σ and β. We use an approximate formula based on a second-order Taylor series expansion of η about the estimated values of σ and β: $V[\eta] = \{V[\sigma]\,(1-\beta)^2 + V[\beta]\,(1-\sigma)^2 - 2\,C[\sigma,\beta]\,(1-\beta)\,(1-\sigma)\} / (\beta-\sigma)^4$, where V[.] and C[.] are the variance and covariance operators, respectively.

and is not affected by the transitory variation that may unduly influence investment regressions with annual or quarterly data.

The second column of table 2 presents results from including two-digit industry dummies in the benchmark regression (the λ_i terms in equation 7). These dummies control for industry-level productivity shocks between intervals τ=1 and τ=2 or, more generally, any industry-specific effects. The structural parameter estimates do not change much when the dummies are included. The σ estimate rises from 0.367 to 0.440, and η is virtually identical. The standard error of σ, however, rises by a factor of more than four. With the two-digit dummies in the model, σ is estimated very imprecisely. The structure of our user cost data accounts for this increase in the standard error of σ. While there is some firm-specific variation in the user cost within industries, the most important differences in the user cost occur across industries. The σ estimate is therefore much less precise with industry dummies in the model. For this reason and given the modest change in σ, the remaining regressions in table 2 exclude the industry dummies.

As discussed in section I, the most likely source of correlation between the error term and the independent variables in these OLS regressions comes from the correlation between firm-specific productivity shocks embedded in the error term and firm output growth. This potential simultaneity problem can be avoided by imposing constant returns to scale (η=1 which implies β=1), an assumption that removes output growth as a regressor. The third column of table 2 presents a regression with the output growth coefficient constrained to unity. The σ estimate changes only trivially when constant returns to scale are imposed (from 0.367 to 0.372).[14] These result supports our contention that the user cost elasticity is

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[14] While the R^2 decreases trivially from 0.564 (column 1) to 0.560 (column 3), the constraint of constant returns to scale is rejected at the 1 percent level, a result driven by the large number of observations used in estimation.

consistently estimated by OLS in our framework.

The final column of table 2 presents estimates based on the assumption of a Cobb-Douglas production function, which is defined by a unitary elasticity of substitution (σ=1) and constant returns to scale (η=1). Not surprisingly given the prior results for σ and η, the restrictions associated with the Cobb-Douglas are easily rejected at the 1 percent level relative to the unconstrained model in column 1.

B. Measurement Error

What role might measurement error play in biasing the estimated σ downward and away from a unitary elasticity (as emphasized recently for investment models by Goolsbee, 2000)? Measurement error introduced in the construction of the capital stock will have a modest effect on the estimates because the capital stock enters as the dependent variable. In situations where measurement error takes the classic form or is fixed for a given firm, industry, or interval, the elasticity estimates will be unaffected.

Measurement error in the regressors may arise for other reasons, and can have direct and indirect effects on the estimated σ. To assess the direct effects, assume that the true value of this elasticity is unity. If the OLS estimate is inconsistent because Δc_f is afflicted with classic measurement error, the variance of this measurement error would have to account for at least 60 percent of the variance in the observed Δc_f.[15] This seems highly implausible, especially since the estimator accounts for measurement error arising from fixed firm, industry, and interval effects by differencing. An indirect effect could result from measurement

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[15] The asymptotic bias on the estimated σ is given by the following formula: $(\sigma^{\#}-\sigma')$ = $(VAR[\xi_f]/VAR[\Delta c_f])\ \sigma^{\#}$, where σ' and $\sigma\#$ are the estimated and true values of σ, respectively, and ξ_f is the measurement error. If $\sigma^{\#}=1$, then the variance ratio must be at least equal to 0.60

error in the other independent variable. If Δy_f is measured with error, we can use the formula

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given an OLS estimate of $\sigma'=0.40$.

proposed by Rao (1973) and an auxiliary regression of Δy_f on Δc_f to assess the extent of bias on the user cost elasticity. Making the rather extreme assumption that one-half of the variance of Δy_f is measurement error, we obtain the somewhat surprising result that the estimated σ is biased upward toward unity. However, the bias is a trivial 0.043.[16] Measurement error can adversely affect the reported results but, with this estimation strategy, it does not appear to play a large role.

C. IV Estimates

The OLS estimates of equation (7) are consistent under the assumption that the error term is independent of both output and user cost growth. As discussed in section I and suggested by the constant returns model in section II.A, these are reasonable assumptions with our estimation method. Nonetheless, we present instrumental variables estimates in table 3 to explore the robustness of our OLS results. The instruments are constructed from data in the τ=0 interval. Effectively, we employ data from 1974-1980 to predict growth in the user cost and output between the 1981-1986 and the 1987-1992 intervals. The instrument list includes the user cost ($C_{i,\tau=0}$), capital stock ($K_{i,\tau=0}$), the output-capital ratio ($(Y/K)_{i,\tau=0}$), and the cash flow-capital ratio ($(CF/K)_{i,\tau=0}$). In addition, we included the annualized growth rates of capital, output, cash flow, accounts receivable, and cash and cash equivalents defined over the τ=0 interval.

The benchmark IV estimate of σ in the first column of table 3, 0.390 is

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[16] The bias on the estimated σ is given by the following formula, $(\sigma^{\#}-\sigma') = -((\beta\, b_{\Delta y,\Delta c})/(1-R^2_{\Delta y,\Delta c}))$ $(VAR[\xi_f]/VAR[\Delta y_f])$, where σ' and $\sigma\#$ are the estimated and true values of σ, respectively, β is from equation (7), $b_{\Delta y,\Delta c}$ is the coefficient on Δc_f and R^2 the correlation coefficient from the auxiliary regression of Δy_f on Δc_f and a constant, and ξ_f is the measurement error. We assume that one-half of the variance in the output variable is measurement error; hence, $VAR[\xi_f]/VAR[\Delta y_f] = 0.50$. We further assume that β equals its estimated value under IV of 1.402. From the auxiliary regression, $b_{\Delta y,\Delta c} = 0.061$ and $R^2_{\Delta y,\Delta c} = 0.0003$; hence, $(\sigma^{\#}-\sigma') = -$

almost identical to the benchmark OLS estimate from table 2 of 0.367. Not surprisingly, the standard error rises with IV, but we can still strongly reject both the hypotheses that σ equals zero or σ equals unity. Unfortunately, the IV estimates of η are not as reasonable. Because of the large coefficient on output growth (β), the point estimate of the returns to scale elasticity (η) is 0.603. The standard error of η is much larger with IV than with OLS, but the IV estimate still rejects constant returns to scale in favor of decreasing returns. However, we do not consider this result reliable because of our inability to find good instruments for output growth. Firm data in the τ=0 interval are not too useful in predicting firm output growth between the τ=1 and the τ=2 intervals.

The partial R^2 statistic developed by Shea (1997) provides quantitative confirmation of this interpretation. This statistic measures the relevance of instruments for each estimated coefficient after removing the explanatory power used in instrumenting other regressors. The partial R^2 for β is 0.040, dramatically lower than the partial R^2 of 0.515 for σ.[17]

To pursue this issue one step further, we re-estimate the model with IV imposing constant returns to scale (η=1). Under this assumption, β=1, and we no longer need to instrument output growth. The results appear in the third column of table 2. The IV estimate of σ is only modestly affected by imposing constant returns. The user cost elasticity estimate rises to 0.434 from 0.390 a change well less than one standard error. This result demonstrates that, even if the IV estimate of returns to scale is unreliable due to the lack of relevant instruments for output growth, this difficulty does not "contaminate" conclusions about σ, which is the primary focus of our study.

0.043.

[17] The partial R^2 statistic is preferable to the more commonly used first-stage R^2 for reasons discussed by Shea (1997).

The second column of table 3 presents IV estimates with two-digit industry dummies. This specification accounts for industry-level productivity shocks between the τ=1 and τ=2 periods (cf. equation (7)). The point estimate of σ hardly changes from the benchmark value (0.373 versus 0.390). As was the case for the OLS estimates with industry dummies, however, the standard error of σ rises dramatically, almost by a factor of three; we cannot reject the hypothesis that σ equals zero in this regression. The problem here is again that most of the variation in the user cost is across industries, with much less firm heterogeneity within industries. The resulting collinearity between the industry dummies and user cost growth compromises the precision of the estimated σ.[18]

As a final test of the validity of the OLS estimates, we performed Hausman tests on the σ parameters. The Hausman statistics are asymptotically distributed $\chi^2(1)$ under the null hypothesis that the OLS estimates are consistent. For the benchmark model, the test statistic is 0.07 and for the constant returns to scale model it is 0.92.[19] Both test statistics are far below the 90 percent critical value for the $\chi^2(1)$ distribution of 2.71. These tests support the validity of the OLS estimates of σ. Taken together, the unconstrained OLS and IV estimates strongly suggest that σ is approximately 0.40.

D. Sub-Sample Estimates

Table 4 explores our results further by considering how the structural parameter estimates change in several sub-samples chosen to address issues that have arisen with empirical investment models. All estimates are with the benchmark model.

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[18] Because of collinearity, it was not useful to include industry dummies in the model as both regressors and instruments. In the second column of table 2, the instrument set for output and user cost growth is the same as for the other IV regressions; the industry dummies are instrumented by themselves.

[19] The Hausman test is not defined for the model that includes industry dummies because the

The first panel presents results with the sample split by the ratio of cash flow to the capital stock. In investment regressions using annual data, Chirinko, Fazzari, and Meyer (1999) found that including cash flow had a significant effect on the estimated σ. We interpreted that finding in the context of the extensive literature on financial constraints and firms' investment spending. The approach here, however, emphasizes the *long-run* impact of the user cost on the capital stock. We therefore expect financial constraints to be less important. The first panel of table 3 presents results from data split according to the pre-sample median cash flow-capital ratio. If financial constraints were important at the horizon relevant for our estimation, we would expect the estimated σ to be significantly different for high and low cash flow firms that differ by their inadequate access to finance. There is little evidence of such an effect in our data. The OLS point estimate of σ is somewhat larger for the high cash flow firms than for low cash flow firms, but the difference is less than two standard errors. Similar results hold for the IV regressions except that σ is relatively larger for the low cash flow firms. The formal test statistics (θ's) have p-values that are greater than 0.35, easily sustaining the null hypothesis of equal σ's.[20]

Our second sort is by size, defined by the median average capital stock in the pre-sample period (τ=0). The technologies utilized by firms may vary systematically by size, and the technology parameters estimated here may change accordingly. Moreover, size is frequently used to identify firms that may be

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standard error of the IV estimate is slightly smaller than the standard error of the OLS estimate.

[20] The null hypothesis that $\sigma' = \sigma''$ (where the ' and " refer to estimates based on the low and high sub-samples, respectively) is evaluated by θ in the following auxiliary equation based on equation (7): $\Delta k_f = -\sigma \Delta c_f - \theta \Delta c_f * I_f + \beta' \Delta y_f * I_f + \beta'' \Delta y_f * (1-I_f) - \gamma' * I_f - \gamma'' * (1-I_f) - \Delta w_f$., where I_f is an indicator variable equal to 1 for the low sub-sample and 0 for the high sub-sample and θ = $\sigma' - \sigma''$ and is distributed asymptotic t under the null hypothesis that $\sigma' = \sigma''$. In the IV regressions, each individual instrument, z_f, appears twice in the instrument list as follows, $z_f * I_f$

finance constrained. External finance may be relatively costly for smaller firms because they are not be able to bear the substantial fixed costs of obtaining external funding or they lack visibility in external capital markets. Relative to the results in table 2, the OLS point estimates of σ are higher for small firms and lower for large firms. With IV, the point estimates have the reverse pattern, and both are lower than the comparable estimate of 0.390 based on the full sample (table 3). None of these differences are statistically significant. The results for returns to scale are also largely consistent with our findings from the full-sample estimation.

Finally, we split the data at the median value of the Brainard-Tobin Q variable. Firms with high values of Q are presumably further from their long-run equilibrium capital stock. Therefore, if our estimation method did not adequately account for investment dynamics, we might expect a difference in the estimated σ's across the high-Q and low-Q sub-samples. In table 4, the user cost elasticities are virtually identical in the OLS results across the Q sub-samples. The low-Q firms have a modestly higher user cost elasticity than the high-Q firms in the IV regression, but the difference is not statistically significant. This result provides additional support for the way our estimation method addresses the problems with complicated investment dynamics, avoiding these difficult specification issues by focusing directly on the long-run growth of the capital stock.

E. Comparison To Related Approaches

Prior studies estimating the user cost elasticity can be set into three categories. Most prior research has been based on time-series data at the aggregate or industry levels. A prominent example of this work is the exchanges between Hall and Jorgenson (1967, 1969, 1971) and Eisner and Nadiri (1968, 1970), Eisner (1969, 1970), and Coen (1969). Hall and Jorgenson's initial work was based on a

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and $z_f * (1-I_f)$.

Cobb-Douglas production function, and hence σ equals 1.00 by assumption. Eisner and Nadiri estimated σ freely, and reported that the responsiveness of capital to its user cost was 0.16. This gap has not been closed by subsequent research. Several important concerns, however, have been raised about elasticities estimated from aggregate data suggesting that such estimates may be biased downward due to problems with firm heterogeneity, simultaneity, measurement error, and capital market frictions.

These issues were difficult to address with aggregate data because of the limited amount of variation, and a more recent set of studies has exploited the substantial information in panel data. While some of these concerns can be addressed, these studies usually remove firm effects by differencing; thus, transitory time-series variation heavily influences the estimated user cost elasticity. A recent example is Chirinko, Fazzari, and Meyer (1999), who find a user cost elasticity of 0.25 for a panel of firms. A similar elasticity is reported by Goolsbee (2000), who analyzes a panel of equipment assets. Cummins and Hassett (1992) and Cummins, Hassett, and Hubbard (1994, 1996) develop a novel approach, focusing on those years in which there are sizeable tax policy changes to mitigate concerns about endogeneity and measurement error. In these studies, cross-section variation is key. Nonetheless, based on some auxiliary assumptions, the implied user cost elasticity for U.S. firm data in Cummins, Hassett, and Hubbard (1994) is somewhat lower than that obtained by Chirinko, Fazzari, and Meyer.[21] These studies use investment data, and the biases associated with investment models mentioned above may be important.

A third class of studies focuses on long-run relations between the capital stock and its determinants. To mitigate the distorting effects of complex dynamics, Caballero (1994) exploits the innovative idea that the user costs elasticity can be estimated in a cointegrating equation that includes the capital/output ratio and the user cost. Because cointegration is an asymptotic property, this estimate can be biased downward in finite samples. Using aggregate quarterly data for equipment spending and the Stock-Watson (1993) correction to adjust the estimates for the effects of transitory variation, Caballero obtains a range of elasticity estimates, from 0.40 to 0.93, depending on the number of lags used in the correction. Also exploiting cointegration properties, Mairesse, Hall, and Mulkay (1999) and Harhoff and Ramb (2000) estimate error correction models (ECM) containing the long-run relation between the capital stock and its determinants and the percentage changes in these variables to capture short-run dynamics. Firm-level data and fixed effects are used in both studies. The parameter estimates prove somewhat unstable, a result that may be due to estimating both long-run and short-run parameters in the ECM with transitory time-series variation. Kiyotaki and West (1996) specify a model that includes deviations of the desired from the actual capital stock, and estimate desired capital in terms of a future projection from a two-step VAR procedure. With quarterly aggregate data for Japan, they find that the short-run and long-run user cost elasticities are 0.05 and 0.07, respectively. The authors attribute these very small responses to transitory variation in the user cost series as represented by a pronounced tendency for mean reversion. Caballero, Engel, and Haltiwanger (1995) estimate a model similar to Caballero (1994) with plant-level equipment spending. They obtain a range of elasticities across two-digit industries from 0.01 to 2.00, with an unweighted average of approximately unity. If we assume that the structures elasticity is one-third as large as that for equipment (per the results of Cummins and Hassett, 1992), then the overall user cost elasticity is approximately 0.70.

The elasticity estimates of Caballero, Engel, and Haltiwanger and those

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[21] See Chirinko, Fazzari, and Meyer (1999, section 5) for further details.

presented in this paper are both based on a panel, but are not directly comparable for a variety of reasons, including the use of plant-level vs. firm-level data, the specification of the long-run determinants of the capital stock, and the manner in which the problem of capital stock dynamics is addressed. The Caballero, Engel, and Haltiwanger estimates are based on a cointegrating relation that emphasizes the time dimension of the panel, and deviations from long-run values are accounted for with the Stock-Watson correction. By contrast, our approach uses the time dimension of panel data to measure long-run variables in each interval, and then estimates the user cost elasticity from the cross-section dimension of the panel. Given these differences, it is not surprising that we obtain different results.

IV. Summary And Conclusions

The elasticity of business capital to its user cost has been the focus of much research attention over the past 40 years. Among other issues, this parameter is central in translating the effects of tax policy into real outcomes, and has been the subject of numerous econometric investigations. Prior work has relied in almost all cases on time-series variation in investment data at the aggregate, industry, or firm level to estimate this elasticity. This paper offers a different approach. The estimation strategy developed here classifies the time periods into three intervals, and then averages the firm-level panel data within each interval. The data are differenced across intervals, and production function parameters are estimated in a cross-section of time-averaged, differenced firm data. Our approach accounts for a variety of productivity shocks, omitted variables, and firm effects. This econometric model does not *solve* the estimation problems inherent with investment models -- difficult-to-specify dynamics, transitory time-series variation, and positively sloped supply schedules -- that may bias estimates of the user cost elasticity. Instead, our approach *avoids* these problems by exploiting panel data in an original way and estimating directly the first-order condition for capital.

We find that the user cost elasticity can be consistently and precisely estimated by OLS, and is approximately 0.40. Relative to a comparable investment study (Chirinko, Fazzari, and Meyer, 1999), the results here suggest that investment models impart a discernible bias toward zero in estimates of the user cost elasticity. To the central question of whether the Cobb-Douglas assumption is valid, our results offer a strikingly negative answer. This robust finding raises questions about the frequent use of the Cobb-Douglas production function in theoretical and empirical models and about the cost-effectiveness of various tax proposals for stimulating capital formation.

Apart from our immediate objective, the method developed here may prove useful in estimating other structural parameters from long-panel datasets. Our method of using interval averages to estimate long-run desired values of regression variables could be applied to other problems where short-run dynamics may obscure long-run structural relations. There are likely to be a number of applications in, for example, labor and industrial organization, where the availability of long-panels and interest in structural parameters may make the method developed here feasible and informative.

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Appendix A: Trending Variables

This appendix considers the effects of trending variables on the specification of the model. To evaluate the effects of trending variables, we begin with the following decomposition for variable $X_{f,\tau,t}$ into non-growth (ng) and growth (g) components, where X corresponds to any of the model variables, K, Y, or C. Note that, unlike in the text, we explicitly include an index for the τ interval even when it is redundant:

$$\text{(A-1)} \quad X_{f,\tau,t} \;/\; X^{ng}_{f,\tau,t} + X^{g}_{f,\tau,t},$$

$$\text{(A-2)} \qquad X^{ng}_{f,\tau,t} \;/\; \mu^{ng}_{f,\tau} + \nu^{ng}_{f,\tau,t},$$

$$\mu^{ng}_{f,\tau} = \sum_{\tau 0 T_\tau} X^{ng}_{f,\tau,t} / T_\tau,$$

$$\sum_{\tau 0 T_\tau} \nu^{ng}_{f,\tau,t} / T_\tau = 0,$$

$$\text{(A-3)} \qquad X^{g}_{f,\tau,t} \;/\; \mu^{ng}_{f,\tau} \left[(1+g_f)^t - 1\right].$$

In (A-2), the non-growth component equals the mean over the τ interval ($\mu^{ng}_{f,\tau}$) and a deviation from the mean value ($\nu^{ng}_{f,\tau,t}$) that averages to zero. These summations are over all T_τ time periods that are in the τ interval. In (A-3), the growth component is proportional to the mean, and increases at a firm–specific rate of g_f.

As in Section I, we measure the long-run value of X as a time-average over a τ interval,

$$\text{(A-4)}\quad X_{f,\tau} \;/\; \sum_{t0T_\tau} X_{f,\tau,t} / T_\tau$$

$$= \sum_{t0T_\tau} X^{ng}_{f,\tau,t} / T_\tau \;+\; \sum_{t0T_\tau} X^{g}_{f,\tau,t} / T_\tau \,,$$

$$= \mu^{ng}_{f,\tau} \;+\; \sum_{t0T_\tau} \nu^{ng}_{f,\tau,t} / T_\tau \;+\; \sum_{t0T_\tau} \mu^{ng}_{f,\tau} \,[(1+g_f)^t - 1] / T_\tau \,,$$

$$= \mu^{ng}_{f,\tau} \;+\; 0 \;+\; \mu^{ng}_{f,\tau} \sum_{t0T_\tau} [(1+g_f)^t - 1] / T_\tau \,,$$

$$= \mu^{ng}_{f,\tau} \;*\; H[g_f],$$

$$H[g_f] \;/\; 1 \;+\; \sum_{t0T_\tau} [(1+g_f)^t - 1] / T_\tau \,.$$

The estimator uses the difference between the τ=2 and τ=1 intervals in the logarithms of $X_{f,\tau}$,

$$\text{(A-5)}\quad \Delta x_{f\tau} \;/\; \mathrm{Ln}\{ X_{f,\tau=2}\} - \mathrm{Ln}\{ X_{f,\tau=1}\},$$

$$= \mathrm{Ln}\{\mu^{ng}_{f,\tau=2}\} \;+\; \mathrm{Ln}\{H[g_f]\} \;-\; \mathrm{Ln}\{\mu^{ng}_{f,\tau=1}\} \;-\; \mathrm{Ln}\{H[g_f]\},$$

$$= \mathrm{Ln}\{\mu^{ng}_{f,\tau=2} / \mu^{ng}_{f,\tau=1}\},$$

which is the percentage change in the non-growth component of X. Thus, the model variables are not distorted by firm-specific growth.

Appendix B: The Replacement Value of Capital

The capital stock is a key variable in this study, and this appendix provides details about how we overcome several significant problems in measuring the capital stock from accounting data. The obvious proxies for the capital stock in the Compustat data, book values of gross or net property, plant, and equipment, are not acceptable measures of the economic value of the capital stock for two reasons. First, they value assets at the historical cost prevailing when the assets were acquired and therefore contain a mix of historical price levels that cannot be easily adjusted for inflation. Second, accounting depreciation rules likely do not capture economic depreciation correctly. The iterative "perpetual inventory" algorithm described here addresses these problems.

The first step in our procedure is to choose a seed value for the iteration. We use the nominal book value of net property, plant, and equipment for firm f from its first observation in the data set ($NPLANT_{f,0}$). To convert this value to real terms we employ data on the share of different kinds of capital assets (indexed by j) in the firm's two-digit SIC industry i. Denote this share as $\alpha_{i,j}$. The amount of capital ($\alpha_{i,j}$ $NPLANT_{f,0}$) should be deflated by the asset-specific price index $p_{j,0}$. Then the real seed value of the capital stock ($K_{f,0}$) is defined as:

$$(B1) \qquad K_{f,0} = \sum_{j} \frac{\alpha_{i,j} NPLANT_{f,0}}{p_{j,0}}.$$

Starting from this seed value, the remainder of the capital stock for firm k is constructed iteratively from:

$$\text{(B2)} \qquad K_{f,t+1} = K_{f,t}\sum_j \alpha_{i,j}(1-\delta_j) + KCHG_{f,t}\sum_j \frac{\alpha_{i,j}(1-\delta_j)}{p_{j,t}}.$$

The first term in equation (B2) is the depreciated value of the period t capital stock that remains in period t+1. The depreciation rate δ_j for each asset j is determined by DRI from the "double declining balance" formula:

$$\text{(B3)} \qquad \delta_j = 1 - e^{-2/LIFE_j},$$

where $LIFE_j$ represents the estimated average service life for capital asset j. The second term in equation (B2) represents the addition (or deletion) to the period t+1 capital stock accounted for by new investment, acquisitions, or divestitures in period t. The variable $KCHG_{f,t}$ (discussed in detail below) represents the nominal addition (or subtraction) of new capital goods for firm f in period t prices. The deflation method for $KCHG_{f,t}$ is the same as for the seed value in equation (B1). We assume that new capital is acquired at the beginning of period t and depreciates one full year before entering the period t+1 capital stock. (We also constructed capital stock series using a half year's depreciation for KCHG and found that it had only a trivial impact on the results.) If a firm adds to its capital stock in period t only through conventional capital spending, the $KCHG_{f,t}$ variable in equation (B2) would equal the firm's investment ($I_{f,t}$), that we obtain from Compustat's capital expenditure data in the sources and uses of funds statement. In practice, acquisitions and divestitures can augment and deplete the capital stock independent of reported investment. Many panel studies delete firms with substantial acquisitions or divestitures. However, there are a large number of observations with acquisitions and divestitures in the Compustat data. Deleting these observations reduces the sample size and could induce a selection bias. We therefore develop a method to account for acquisitions and divestitures when constructing the capital stock data. (To the extent that acquisitions or divestitures create outliers in the data, these should be captured by our outlier detection algorithm described in section II.)

The capital change variable ($KCHG_{f,t}$) in equation (B2) is defined in a way that accounts for large acquisitions and divestitures. We appeal to the following accounting identities to derive a formula for $KCHG_{f,t}$,:

(B4) $$\Delta GPLANT_{f,t} = I_{f,t} + ACQUIS_{f,t} - RETIRE_{f,t}$$

(B5) $$\Delta NPLANT_{f,t} = I_{f,t} + ACQUIS_{f,t} - DEPR_{f,t}$$

$\Delta GPLANT_{f,t}$ = the change in gross plant and equipment from the end of year t-1 to the end of year t;

$\Delta NPLANT_{f,t}$ = the change in net plant and equipment from the end of year t-1 to the end of year t;

$ACQUIS_{f,t}$ = acquisitions in year t;

$RETIRE_{f,t}$ = retirements in year t,[22] and

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[22] Compustat defines retirements as “a deduction from a company’s property, plant, and equipment account resulting from the retirement of obsolete or damaged goods and/or physical structures.”

$DEPR_{f,t}$ = accounting depreciation in year t.

In the event of an acquisition, $KCHG_{f,t}$ equals $I_{f,t}$ + $ACQUIS_{f,t}$. Because Compustat does not have reliable figures for $ACQUIS_{f,t}$, we rearrange equation (B4) to obtain:

(B6) $I_t + ACQUIS_t = \Delta GPLANT_t + RETIRE_t$ or

$KCHG_t = \Delta GPLANT_t + RETIRE_t$

In the event of a divestiture, we want to decrease the capital stock by the *depreciated* value of the capital sold. In this case:

(B7) $KCHG_t = \Delta NPLANT_t$

If there is no major acquisition or divestiture, then we retain the basic formula:

(B8) $KCHG_t = I_t$

We now need an empirical test to determine whether a firm has undergone an acquisition or divestiture in a given year. There are two rules of thumb that aid us in this search. First, $\Delta GPLANT_{f,t}$ is normally less than $I_{f,t}$ because of retirements. Therefore, if $\Delta GPLANT_{f,t} > I_{f,t}$ by a substantial amount, it signals an acquisition with a high probability. Second, $\Delta GPLANT_{f,t}$ is normally greater than $RETIRE_{f,t}$ because retirements are the only way to reduce gross plant and equipment in the absence of a divestiture. Therefore, if $\Delta GPLANT_{f,t} < RETIRE_{f,t}$ by a substantial amount it signals a divestiture.

We define a "substantial" amount as a discrepancy of ten percent or more.

The point of imposing the ten percent limit is to make acquisition and divestiture adjustments conservative. That is, we only deviate from the standard formula when there is clear evidence that this formula is misleading. In this case, if

$$\text{(B9)} \qquad \frac{\Delta GPLANT_{f,t} - I_{f,t}}{GPLANT_{f,t-1}} > 0.1,$$

then we assume an acquisition and define $KCHG_{f,t}$ from equation (B6). In contrast, if

$$\text{(B10)} \qquad \frac{\Delta GPLANT_{f,t} + RETIRE_{f,t}}{GPLANT_{f,t-1}} < -0.1,$$

then we assume a divestiture and define $KCHG_{f,t}$ from equation (B7). If neither rule holds, we simply define $KCHG_{f,t}$ as investment spending, as in equation (B8).

Table 1 – Summary Statistics

Variable	**$\tau = 0$ (1974-1980)**			**$\tau = 1$ (1981-1986)**			**$\tau = 2$ (1987-1992)**			**Percentage Change $\tau = 1$ to $\tau = 2$**		
	Mean	Med.	S.D.	Mean	Med.	S.D.	Mean	Med.	S.D.	Mean	Med.	S.D.
Capital (K)	320.8	33.1	848.7	434.2	50.7	1141.3	529.2	62.3	1410.1	36.4	16.9	81.9
Output (Y)	948.1	161.7	2562.0	1169.5	211.9	3180.5	1404.2	253.7	4237.4	27.5	14.6	66.2
User Cost (C)	0.282	0.291	0.056	0.242	0.246	0.046	0.219	0.218	0.028	-6.9	-11.8	18.7

Note: The mean, median (Med.), and standard deviations (S.D.) are derived from a sample of 1,860 firms constructed from Compustat and DRI sources as described in section II of the text. The standard deviations represent cross-sectional differences arising from firm heterogeneity in levels within an interval (in the first three panels) and from firm heterogeneity in percentage changes across the τ=1 and τ=2 intervals (in the fourth panel).

Table 2 – Ordinary Least Squares Estimates

	Unconstrained Regressions		**Constrained Regressions**	
	Benchmark Model	**Model with Two-Digit SIC Dummies**	$\eta = 1$	$\sigma = 1$ **and** $\eta = 1$
σ	0.367 (0.067)	0.440 (0.293)	0.372 (0.067)	1.0
η	1.135 (0.042)	1.152 (0.102)	1.0	1.0
β	0.925 (0.019)	0.926 (0.019)	1.0	1.0
γ	0.084 (0.014)	-0.055 (0.114)	0.063 (0.013)	0.020 (0.013)
R^2	0.564	0.593	0.560	0.540

Note: Estimates of equation (7) with firm-level panel data as described in section II.. Standard errors appear in parentheses. The parameters are σ (the user cost elasticity), η (the returns to scale elasticity), β (the regression coefficient on output growth) and γ (the intercept). See section III.A for the formula used to compute η and its standard error.

Table 3 – Instrumental Variables Estimates

	Unconstrained Regressions		**Constrained Regressions**	
	Benchmark Model	**Model with Two-Digit SIC Dummies**	$\eta = 1$	$\sigma = 1$ **and** $\eta = 1$
σ	0.390 (0.108)	0.373 (0.286)	0.434 (0.093)	1.0
η	0.603 (0.074)	0.633 (0.120)	1.0	1.0
β	1.402 (0.110)	1.364 (0.118)	1.0	1.0
γ	-0.049 (0.034)	-0.324 (0.134)	0.059 (0.014)	0.020 (0.013)

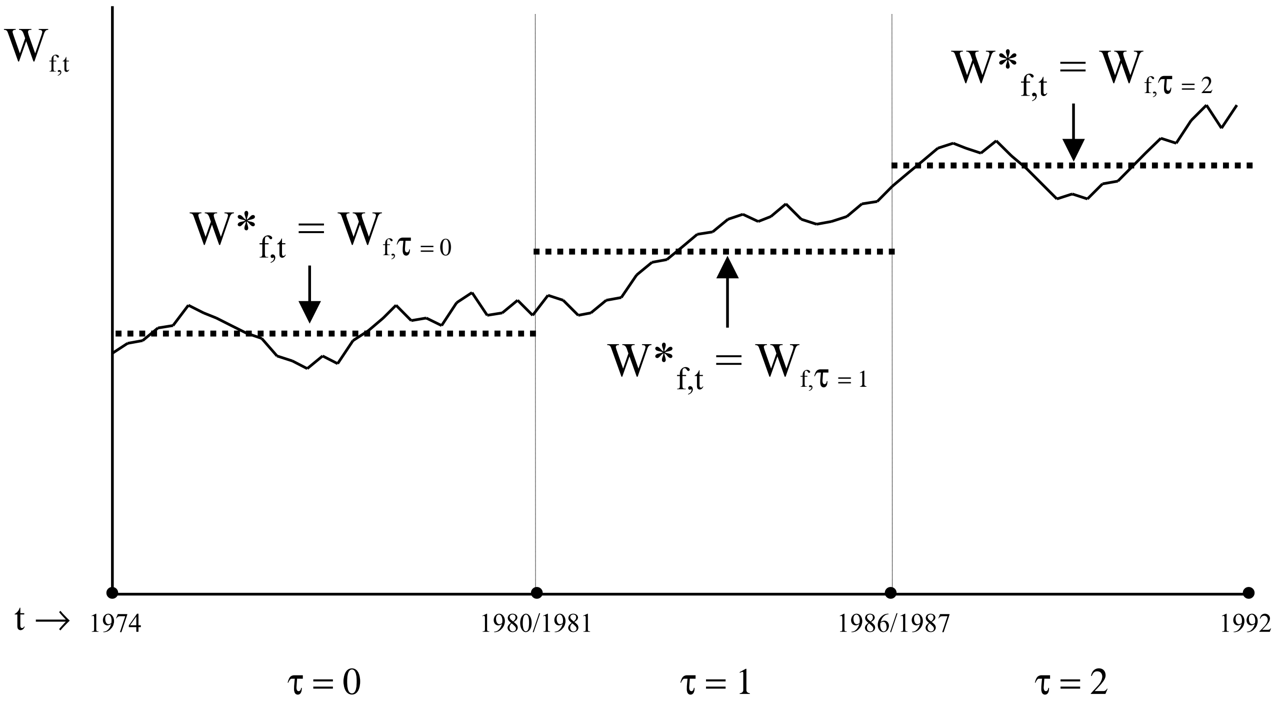
Note: Estimates of equation (7) with firm-level panel data as described in section II. Standard errors appear in parentheses. The parameters are σ (the user cost elasticity), η (the returns to scale elasticity), β (the regression coefficient on output growth), and γ (the intercept). The instrument list is defined in section III.C. In the second column, the industry dummies are instrumented by themselves. See section III.A for the formula used to compute η and its standard error.

Table 4 – Ordinary Least Squares And Instrumental Variable Estimates:
Various Sample Splits

	Split by Cash Flow-Capital Ratio				**Split by Capital Stock Size**				**Split by Tobin-Brainard Q**			
	OLS		**IV**		**OLS**		**IV**		**OLS**		**IV**	
	Low CF/K	High CF/K	Low CF/Kl	High CF/K	Low Capital	High Capital	Low Capital	High Capital	Low Q	High Q	Low Q	High Q
σ	0.278 (0.075)	0.407 (0.127)	0.364 (0.102)	0.317 (0.198)	0.435 (0.139)	0.294 (0.066)	0.226 (0.226)	0.363 (0.094)	0.320 (0.076)	0.349 (0.114)	0.448 (0.110)	0.290 (0.163)
η	1.308 (0.071)	1.019 (0.049)	0.989 (0.197)	0.673 (0.128)	1.042 (0.056)	1.284 (0.064)	0.646 (0.104)	0.782 (0.120)	1.214 (0.061)	1.046 (0.054)	0.736 (0.169)	0.688 (0.162)
β	0.830 (0.025)	0.989 (0.028)	1.007 (0.128)	1.331 (0.178)	0.977 (0.029)	0.844 (0.024)	1.424 (0.172)	1.177 (0.120)	0.880 (0.025)	0.972 (0.032)	1.198 (0.168)	1.322 (0.234)
γ	0.040 (0.017)	0.125 (0.024)	0.000 (0.031)	0.014 (0.066)	0.105 (0.026)	0.064 (0.016)	-0.016 (0.058)	-0.019 (0.033)	0.057 (0.016)	0.107 (0.027)	-0.006 (0.034)	-0.018 (0.090)
θ	-0.129 (0.144)		0.047 (0.214)		0.141 (0.144)		-0.137 (0.226)		-0.029 (0.137)		0.158 (0.197)	
R^2	0.541	0.575			0.556	0.582			0.631	0.562		

Note: Estimates of equation (7) with firm-level panel data as described in section II. Standard errors appear in parentheses. The parameters are σ (the user cost elasticity), η (the returns to scale elasticity), β (the regression coefficient on output growth), and γ (the intercept). The instrument list is defined in section III.C. See section III.A for the formula used to compute $\eta$and its standard error. Sample splits are based on the median value of the classifying variable in the τ=0 (1974-1980) interval. θ is the coefficient measuring the difference between the σ's for the contrasting classes, and is distributed asymptotic t under the null hypothesis of equality. See section III.D for further details about this statistic.

Figure 1: Defining the τ-Intervals



$$W_{f,\tau=0} = \sum_{t=1974}^{1980} W_{f,t}/7$$

$$W_{f,\tau=1} = \sum_{t=1981}^{1986} W_{f,t}/6$$

$$W_{f,\tau=2} = \sum_{t=1987}^{1992} W_{f,t}/6$$