What Do Micro Data Reveal About the User Cost Elasticity?: New Evidence on the Responsiveness of Business Capital Formation

by

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Abstract

The price sensitivity of business investment spending is a central element in economic analysis. A substantial response of capital spending to its user cost, which combines interest, tax, and depreciation rates with relative prices, is critical to evaluating the effectiveness of monetary policy, deficit reduction, and tax reform. In spite of this central role, however, the supporting evidence for a substantial user cost elasticity (UCE) is modest. Several important concerns suggest a downward bias in elasticities estimated from the aggregate data typically employed in UCE research. These biases may arise from firm heterogeneity, measurement error, capital market frictions, and simultaneity. While such biases are theoretically plausible, their empirical importance remains to be substantiated.

With a particularly rich data set, containing over 26,000 observations, this paper explores what can be learned about the UCE from micro data. Investment and firm-level control variables are taken from an extensive panel of Compustat firms. To construct the user cost, we tap a new data source that provides variation across firms as well as across time. A number of the econometric biases mentioned above have a substantial impact on the estimated UCE. After correcting for the biases, we obtain a precisely estimated but small value for the UCE of about -0.25. The effects of capital gains tax cuts and the "flat-tax" proposal on investment are evaluated with this estimated UCE.

The price sensitivity of business investment spending is a central element in economic analysis. A substantial response of capital spending to its user cost, which combines interest, tax, and depreciation rates with relative prices, is critical in controversies surrounding the transmission of monetary policy, the conduct of aggregate stabilization policy, and the impact of fiscal policy. With a particularly rich data set, this paper takes a fresh look at the user cost elasticity, exploring what can be learned about this key parameter from microeconomic data.

The user cost elasticity (UCE) plays a significant role in the long-standing controversy about how monetary policy impacts real variables. The standard description of the monetary transmission mechanism holds that monetary policy affects real activity by altering the level of reserves in the banking system that, in turn, affects short-term interest rates and, through the term structure, long-term interest rates. With a substantial UCE, monetary policy can have an important effect on business investment spending. The absence of a significant UCE casts doubt on the validity of this version of the monetary transmission mechanism.[1]

Implicit assumptions about the UCE also loom large in real business cycle models. For example, Christiano and Eichenbaum (1992, p. 433) use a Cobb-Douglas production function, and hence they maintain that the UCE is unity. Thus, the ability of RBC models to reproduce certain features of macroeconomic data is based in part on capital formation (defined in terms of foregone consumption) being quite responsive to variations in interest rates. This responsiveness remains unconfirmed econometrically.

The price sensitivity of investment is also a key element in analyzing fiscal policies. The simulation models of Auerbach and Kotlikoff (1987) and Razin and Yuen (1996), for

[1] This empirical shortcoming of the money view, along with new insights from the economics of information, has led many to favor a credit view of the transmission mechanism, which holds that variations in the availability of credit is the

example, is based on a Cobb-Douglas technology. This technology and its UCE of unity may play a large role in assessing the quantitative effects of fiscal policy changes. Indeed, the UCE is likely to be important in estimating the effects of a wide variety of fiscal measures designed to spur capital formation, such as cuts in the capital gains tax rate and the institution of a "flat tax." We consider the implications of our results for the effectiveness of both of these policies.

Despite the key role played by the UCE across a wide spectrum of economic analyses, the supporting evidence for a substantial UCE is modest. A recent survey of a variety of econometric investment models found little compelling evidence that, as historically implemented, tax and interest rate policies are effective in stimulating business fixed investment (Chirinko, 1993). Blanchard (1986, p. 153) writes "[i]t is well known that to get the user cost to appear at all in the investment equation, one has to display more than the usual amount of econometric ingenuity." Bernanke and Gertler (1995, p. 27) add that "empirical studies of supposedly 'interest-sensitive' components of aggregate spending have in fact had great difficulty in identifying a quantitatively important effect of the neoclassical cost-of-capital variable." What should one make of the apparent inconsistency between widely held beliefs about a large UCE and the paucity of empirical support for such beliefs? Is the true UCE much lower than most economists assume (possibly due to low substitution possibilities in production) or is there some fundamental misspecification in econometric models that prevents empirical research from uncovering the true UCE? It is important to note that most empirical studies of the UCE are based on aggregate data.[2] Several important concerns, however, have

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channel through which monetary policy affects the real economy. The key implication of this view is that monetary policy remains effective even with a low UCE. See Bernanke and Gertler (1995) for further discussion.

[2] See Chirinko (1993). Studies that have used firm-level data include Eisner (1967, 1978), Jorgenson and Siebert (1968), Cummins and Hassett (1992), and Cummins, Hassett, and Hubbard (1994, 1996). The latter three studies conclude that some historical tax policy changes have had a substantial impact on investment.

been raised about elasticities estimated from aggregate data that suggest such estimates may be biased downward due to problems with firm heterogeneity, simultaneity, measurement error, and capital market frictions. While these biases are theoretically plausible, their empirical importance remains to be explored and substantiated.

Such an exploration is undertaken in this paper, which uses an extensive body of microeconomic data to estimate the sensitivity of business capital formation to the user cost of capital. Micro data clearly are essential to control for firm heterogeneity. The substantial variation in the data at our disposal also may improve the quality of instruments needed to control for simultaneity. The sample is constructed from Compustat "full coverage" files and contains 4,112 manufacturing and non-manufacturing firms. After computing the necessary variables and lags, the regression data include over 26,000 observations from 1981 to 1991. These firms account for roughly half of aggregate U.S. capital spending in the middle of the sample period. To the best of our knowledge, the coverage of our sample is greater than available in any previous study of U.S. investment with firm-level data. This extensive coverage allows us to use econometric panel methods to isolate biases, and it increases confidence when extrapolating the empirical results to the economy at large.

In addition to the Compustat data, we tap a new source to construct the user cost of capital. Previous studies, including some that employ micro-data, typically test the sensitivity of investment to user cost components, such as interest rates and tax parameters, that only vary over time and are assumed constant across firms. We have merged user cost variables defined at the industry level with Compustat firm data. Thus, the user cost data vary in both time-series and cross-sectional dimensions. This variation attenuates concerns about bias due to measurement error. Furthermore, cross-sectional variation permits us to account for firm heterogeneity that may have affected prior UCE estimates from aggregate data.

Initial results suggest that the UCE estimated from micro data may be much larger (in absolute value) and more precisely estimated than is usually the case with aggregate data. Consider the following OLS equation regressing the investment/capital ratio for firm i at time t ($I_{i,t} / K_{i,t-1}$) on distributed lags of the percentage changes in the user cost ($U_{i,t}$, contemporaneous and six lags) and sales ($S_{i,t}$, contemporaneous and 4 lags) and an intercept (ϕ). (A detailed discussion of this equation will be presented in Section 3):

$$I_{i,t} / K_{i,t-1} = \alpha_6(L)(\Delta U_{i,t} / U_{i,t-1}) + \beta_4(L)(\Delta S_{i,t} / S_{i,t-1}) + \phi + \varepsilon_{i,t} \tag{1}$$

$$\text{SUM}(\alpha) = \underset{(0.041)}{-0.660} \qquad \text{SUM}(\beta) = \underset{(0.009)}{0.488} \qquad R^2 = 0.120$$

The sum of the estimated α's is the UCE, and it is a substantial -0.660 with a standard error of only 0.041. This estimate is much larger than the near-zero values frequently reported in studies that employ aggregate data.

While this initial result is promising, several biases may affect the estimated UCE, and their impact can be assessed with our data. We find that firm heterogeneity, measurement error, and simultaneity biases all affect the estimated UCE. In addition, the omission of variables that measure firms' access to internal funds causes an omitted variable bias. While controlling for these biases raises the absolute value of the UCE in some cases, the net effect is to substantially reduce the UCE relative to the OLS estimate presented above. We conclude that the UCE is in the neighborhood of -0.25 with a standard error of 0.03 to 0.06 (depending on the particular estimator employed). This point estimate is much lower than the UCE often assumed in academic and policy research. But the precision of the estimate is striking, allowing us to clearly reject the hypotheses that the UCE is zero or unity.

The paper is organized as follows. The data set combining Compustat and user cost information is central to this study, and it is described in section 1. Substantial firm heterogeneity is documented. Section 2 derives the equation used in our econometric exploration and discusses the interpretation of the coefficient estimates. Throughout the paper, we focus on the UCE as the measure of the price sensitivity of capital. Section 3 begins with a UCE estimated from aggregate data and shows potential benefits of micro data. We then explore various biases and identify our preferred instrumental variables estimates, including results from the new "orthogonal deviations" estimator presented in Arellano and Bover (1995). The estimates fall in a narrow range from -0.18 to -0.25. They are precisely estimated, statistically far from both zero and unity, and hence much different from values often assumed in calibration and policy studies. Section 4 presents some simple policy evaluations and section 5 concludes.

1. Data and Firm-Specific Variation

To estimate the UCE, we link two unique data sources that each provide information particularly well-suited to our objectives. The investment, sales and cash flow data come from the extensive Compustat "full coverage" files. The user cost variable is constructed from industry-level information maintained by Data Resources, Inc. The marriage of these data sources allows us to conduct empirical analyses that are not possible with the aggregate time-series information used in most previous research on investment and the user cost.

We employ the version of Compustat that covers the 20-year period 1972-1991. After selecting usable data for regressions and computing the necessary lags, we have a sample of 4,095 firms from all sectors of the economy that provide 26,071 annual observations for the regressions from the period 1981 to 1991.[3] In the middle of the sample (1987) our data account for 48 percent of aggregate U.S. non-residential fixed investment. The sample contains 43 percent of sales of final and intermediate goods for the same year.

Compustat firm data provide us with substantial benefits *vis-à-vis* the aggregate time-series used in most of the empirical literature on the UCE. One clear benefit arises from statistical efficiency. Obviously, we have a huge number of degrees of freedom. Even though many of the questions of interest deal with the effect of economy-wide changes (such as movements in tax or interest rates that affect all firms), micro data give us a large number of replicated "experiments" that greatly improve the precision of our results. Improved precision may be important for identifying the UCE, especially to the extent that aggregate results are imprecisely estimated and are therefore not able to reject the hypotheses of a UCE equal to zero or unity. Furthermore, micro data allow us to estimate a given parameter over a relatively short time frame, thus lessening the role played by parameter instability across time. Finally, firm data help us to address and quantify a variety of econometric biases in ways that would be difficult, if not impossible, with aggregate time series data.

The user cost data complement the extensive firm heterogeneity available from Compustat by providing additional micro-level variation. We obtained information on the user costs for 26 different capital assets (24 types of equipment and two types of structures). These

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[3] To protect against results driven by a small number of extreme observations, we exclude observations in the one percent tail from the distribution for each independent variable in the regression. We estimate some regressions with fewer than

underlying user costs, based on Hall and Jorgenson (1967) and modified by DRI, can be represented as:

$$(2) \qquad U_{i,j,t} = [p^{I}_{j,t} / p^{Y}_{i,t}]\,[(1 - m_{j,t} - z_{j,t}) / (1 - \tau_t)]\,[r_t + \delta_j]$$

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, r_t is the financial cost of capital (the same for all industries and assets),[4] and δ_j is the asset-specific economic depreciation rate. The investment tax credit ($m_{j,t}$) and discounted value of tax depreciation allowances ($z_{j,t}$) also vary across assets. We created industry-specific user costs as a weighted average of the asset user costs. The weights are the proportion of capital accounted for by each asset for 26 different industries.[5] This industry information was then merged with the firm-level Compustat data using each firm's S.I.C. code.[6]

Table 1 provides summary statistics for the main variables that enter our regression. The variable I_t / K_{t-1} is the investment-capital ratio (firm and industry subscripts are suppressed for simplicity). Investment is Compustat's capital expenditure variable from firms' uses of funds statement. Capital is the estimated constant dollar replacement value of plant and equipment.[7] The t-1 subscript on the capital stock indicates that it is measured at the

26,071 observation because differencing the data lowers the observation count.

[4] The financial cost of capital is defined as 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 cost of debt is lowered by its tax deductibility and the expected inflation rate, defined as a weighted average of past GDP deflator growth rates.

[5] 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.

[6] Because the DRI user cost data are quarterly, we average them to obtain an annual user cost. The averages are computed at the firm level to account for the fact that firms have different fiscal years. The user cost information is therefore tailored to each firm's specific accounting period, which introduces further cross-sectional heterogeneity in the data.

[7] The capital stock replacement value estimates are based upon the iterative perpetual inventory method presented in Salinger and Summers (1983) modified to account for acquisitions and divestitures as described in appendix B.

beginning of each accounting year. Output is measured by sales.[8] Nominal sales data are taken from the Compustat net sales figure, and they are deflated by the industry-specific output price deflator used to define the user cost in equation 2 (p^Y_{it}). The growth rate of real sales is represented by $\Delta S_t / S_{t-1}$. Cash flow (CF_t), which is scaled by the beginning-of-period capital stock, is net after-tax income plus non-cash expenses. The latter consists primarily of depreciation. The $\Delta U_t / U_{t-1}$ variable is the percentage change in the user cost defined in equation (2). Further details about data definitions appear in appendix B.

Summary statistics for our data appear in table 1. The Compustat variables in the first three rows have skewed distributions as one would expect in firm data. The gross investment-to-capital ratios (mean of 0.173 and median of 0.125) are consistent with moderate capital stock growth, assuming that typical depreciation rates are in the range of 10 to 12 percent. Mean real sales grew by 3.0 percent per year in our 1981 to 1991 sample, although median sales growth was more modest at 1.8 percent. The summary statistics for $\Delta U_t / U_{t-1}$ reveal that the user cost fell on average from 1981 to 1991 (mean of -1.3 percent, median of -2.3 percent). The within-firm standard deviations reported in table 1 show substantial variability of the firm data across time.[9] The within-firm standard deviations exceed the means for all three Compustat variables.

Of particular note, given the emphasis here on microeconomic variation, is the information on the percentage of firm-specific time variation in the data. This percentage is 1 minus the R-squared statistic from the regression:

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[8] The primary variation in output is due to sales. Blinder and Maccini (1991, Table 3) report that the ratio of the variance of output to the variance of sales is 1.03.

[9] These standard deviations measure variability in the data across time, not across firms. To accomplish this, we subtract the firm-by-firm means from each variable prior to computing the standard deviation.

(3) $$(X_{i,t} - a_i) = b_t + e_{i,t}$$

where $X_{i,t} - a_i$ represents mean-differenced variables for firm i at time t, b_t is the coefficient on a time dummy that is one for period t and zero otherwise, and $e_{i,t}$ is an error term. Because the data are mean differenced, they represent time series variation alone. The statistic reported in table 1, therefore, indicates the proportion of time variation in the data that cannot be explained by aggregate time effects, i.e., the variance of $e_{i,t}$ relative to the variance of $(X_{i,t} - a_i)$. If this statistic equals zero, firm-specific variation is completely absent. For the Compustat variables (I_t / K_{t-1}, $\Delta S_t / S_{t-1}$, and CF_t / K_{t-1}), over 97 percent of variation is firm specific. This statistic is lower for the user cost because variation in the interest rate and the tax parameters is determined to a greater degree by aggregate factors. Nonetheless, over 67 percent of the variation in the composite user cost is not explained by aggregate time dummies, indicating that the data we construct from the DRI source also has substantial micro-level variation.

2. Econometric Investment Equations: Specification Issues

In choosing an econometric specification to estimate the UCE, the major problem facing the applied econometrician is to relate unobservable expectations of future conditions to observable variables. The primary choice is whether to employ a structural model, with estimating equations derived explicitly from an optimization problem, or a distributed lag model that relies less on theory. The strengths and weaknesses of each approach are evaluated in the first subsection below. A brief derivation of the investment equation used in this study is presented in the second subsection.[10]

Distributed Lag versus Structural Models

Econometric investment models can be divided into one of two classes: distributed lag and structural models. Based on formal static theory and plausible intuitions, the distributed lag approach specifies several factors that could affect investment spending. Among other variables that have been included are sales, output, capacity utilization, profits, the flow or stock of "liquidity," balance sheet ratios, debt service, depreciation charges, the gross or net capital stock, the age of the capital stock, equity yields, interest and inflation rates, prices of output, labor, and capital, and taxes either as statutory rates or payments. Contemporaneous and lagged values of these variables usually enter the regression and, combined with the estimated coefficients, proxy for unobservable future expectations.

While early studies with distributed lag models employed various combinations of these variables, the focus has been narrowed considerably by the work of Dale Jorgenson (1963, 1971) and his numerous collaborators. In the "Jorgensonian Neoclassical" model, investment depends on the percentage changes in sales and the user cost of capital. Additionally, a measure of liquidity has frequently been included, reflecting that finance may not be readily available or internal funds may increase the speed with which firms acquire the desired amount of capital. Thus, the primary determinants of investment spending are sales (or output), the user cost of capital, and liquidity.

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[10] See Chirinko (1993) for a more detailed survey of econometric investment models and empirical results and an extensive list of references to several of the issues discussed in this section.

Distributed lag models perform well empirically. They explain much of the variation in aggregate data and, apart from the user cost, usually generate precisely estimated, economically significant coefficients that have the theoretically predicted sign. Furthermore, despite the availability of alternative specifications, distributed lag models continue to be the model of choice among forecasters.[11]

Questions arise, however, about interpreting the estimated coefficients. As noted above, distributed lag coefficients are used to forecast future variables. The coefficients also represent the parameters of the underlying technology, such as the production function, delivery lags, and expenditure lags. Estimated coefficients are thus an amalgam of the underlying technology and expectations parameters and, without further information, it is difficult to identify separately these underlying parameters.

This lack of identification makes inferences potentially problematic. As argued by Lucas (1976), the underlying expectation parameters may not remain stable in the face of policy interventions. Instability in expectation parameters will lead to instability in the estimated coefficients over the sample period and during counterfactual policy analyses.

This concern has led to an alternative approach for specifying investment models that imposes more structure on the econometric model.[12] In these structural models, dynamic elements are incorporated explicitly into an optimization problem of a firm looking far into the future, and the conditions characterizing optimizing behavior are used to derive an econometric equation. These investment equations contain a shadow price for capital that extends into the future and is usually unobservable to the econometrician. Moreover, the estimated coefficients

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[11] For example, see the forecasting models described in Prakken, Varvares, and Meyer (1991) and Sinai (1992).

are linked explicitly to the underlying technology and expectation parameters that can be identified separately. Thus, this class of models is immune to the Lucas Critique.

This immunization, however, proves somewhat costly. There are three general solutions to the problem created by the unobservable shadow price of capital. First, the shadow price can be equated to financial market data (i.e., the Brainard-Tobin Q). Second, the investment equation can be transformed so that most of the future unobservable variables are eliminated; the resulting Euler equation is relatively straightforward to estimate. Third, the terms constituting the shadow price from period t onward can be forecasted using data available in period t (e.g., Abel and Blanchard, 1986). Unfortunately, the resulting investment models do not usually perform well empirically.[13] Structural models provide attractive frameworks for ultimately understanding investment behavior, but their overall empirical performance raises questions about the ability of the current generation of models to deliver empirical estimates useful in the analysis of public policies.[14]

The applied econometrician is thus faced with the dilemma of choosing between distributed lag models that are empirically dependable but conceptually fragile, or structural models that have a solid theoretical foundation but an unsteady empirical superstructure. Both approaches have strengths and weaknesses, and thus both provide useful and complementary information. The Lucas Critique with its emphasis on structural models has resulted in dramatic changes in the formulation of models and direction of research, but its empirical

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[12] It is not, however, the only response. Believing that the assumptions needed to achieve identification are "incredible," Gordon and Veitch (1986) and a few other authors impose less structure than in distributed lag models, and estimate hybrid VARs.

[13] See Chirinko (1993, Section 3) for further discussion and Oliner, Rudebusch, and Sichel (1995) for a comparison of the forecasting performance of structural and distributed lag models.

[14] This is not to say that progress is not being made; for example, see the innovative analyses of Goulder and Summers (1989) and Jorgenson and Yun (1991).

relevance has been questioned.[15] (In section 4 we present a new test of the empirical importance of the Lucas Critique that exploits panel data.) Furthermore, distributed lag models provide a direct estimate of the user cost elasticity of primary concern to this study. Thus, we proceed with estimating a distributed lag model, though our policy assessments must be tempered by the above caveats.

A Distributed Lag Investment Model

The distributed lag investment model developed in this subsection is based on a firm's demand for capital and, with the addition of dynamics, demand for investment. The demand for capital follows directly from the first-order conditions for profit-maximizing behavior when expectations are static. Maintaining that the production function has a constant elasticity of substitution (σ) between capital and variable inputs, we obtain the following well-known relation between the desired (or optimal) stock of capital (K^*_t), the level of sales (or output), and the user cost (or rental price) of capital (U_t),

$$(4) \qquad K^*_t = \zeta\, S_t\, U_t^{-\sigma},$$

where U_t is defined in (2) and ζ is the CES distribution parameter.

Absent any dynamic considerations, the firm would achieve K^*_t instantaneously. Dynamics enter when specifying the demand for investment, which is divided between replacement and net components. In the present model, the translation from a stock demand to a flow demand depends on depreciation and delivery lags. Capital is assumed to depreciate

[15] For example, the impact of the Lucas Critique on investment models is examined in Chirinko (1988) who assumes that the volatile fiscal environment of the 1980s reflected unanticipated changes in the policy regime. The instability

geometrically at a constant mechanistic rate (δ); hence, replacement investment (I^r_t) is proportional to the capital stock available at the beginning of the period,

(5) $$I^r_t / K_{t-1} = \delta.$$

Net investment (I^n_t) is the change in the capital stock between periods t-1 and t, and is scaled by the existing stock. This ratio (plus 1.0) equals K_t / K_{t-1}, and it adjusts according to the weighted geometric mean of relative changes in the desired capital stock,

(6) $$\begin{aligned} I^n_t / K_{t-1} + 1.0 = K_t / K_{t-1} &= \prod_{h=0}^{H} [K^*_{t-h} / K^*_{t-h-1}]^{\mu_h} \\ &= \prod_{h=0}^{H} [\Delta K^*_{t-h} / K^*_{t-h-1} + 1.0]^{\mu_h} \end{aligned}$$

where the μ's represent the delivery lag distribution extending for H+1 periods.[16] Taking logs of (6), using the approximation $\ln(1+x) \approx x$, differencing the logarithm of (4) and substituting it into (6) for ($\Delta K^* / K^*$), using (5) for replacement investment, and appending a stochastic error (ε_t), we obtain the distributed lag investment equation:

(7) $$\begin{aligned} I_t / K_{t-1} &= I^r_t / K_{t-1} + I^n_t / K_{t-1} \\ &= \delta + \sigma \sum_{h=0}^{H} \mu_h (\Delta U_{t-h} / U_{t-h-1}) + \sum_{h=0}^{H} \mu_h (\Delta S_{t-h} / S_{t-h-1}) + \varepsilon_t \cdot \end{aligned}$$

There are two extensions of (7) that are important for understanding the empirical results from distributed lag investment equations. First, it has been frequently argued that a measure of liquidity should enter the model to account for access to investment funds that affect the timing of investment along the transition path between steady states. In this model,

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associated with the Lucas Critique is identified, but it is not quantitatively important. Using a much different framework, Taylor (1989) arrives at a similar conclusion.

[16] The geometric adjustment process is employed in (6) because, with the pronounced trends in I_t and ΔS_t, it is preferable to specify the investment equation with all variables as ratios or rates.

liquidity is measured as cash flow (CF_t) and, to avoid units problems, cash flow enters relative to the existing capital stock (see Fazzari, Hubbard, and Petersen, 1988b). The specification of this variable — CF_t/K_{t-1} — implies that the effects of liquidity on investment expenditures are short-run, perhaps distributed over several periods. If financing constraints affect K^*_t in the long-run, then, like sales and the user cost, CF_t would enter as a percentage change (see Chirinko and Schaller, 1995). There is no evidence in our data that the percentage change in CF_t has any positive effect on investment.

Second, in the presence of non-static expectations and delivery lags, the terms in (4) would be distributed over current and future periods and interpreted as expected values. Approximating K^*_t linearly and assuming that expectations of the output and user cost terms are based on extrapolations of their past values, we obtain an investment equation with distributed lag coefficients that are a mixture of expectation and technology parameters. Because the number of lags used in the extrapolations need not be equal, the assumption of extrapolative expectations suggests that the lengths of the sales and user cost lags may differ. In addition, the possibility that capital is "putty-clay" implies that output changes lead to a more rapid investment response than user cost changes (Eisner and Nadiri, 1968; Bischoff, 1971), and hence the coefficients on $\Delta U_{i,t-h} / U_{i,t-h-1}$ and $\Delta S_{i,t-h} / S_{i,t-h-1}$ may differ. An examination of alternative lag lengths indicated that annual lags of 0 to 6 for $\Delta U_{i,t} / U_{i,t-1}$ and lags of 0 to 4 for $\Delta S_{i,t} / S_{i,t-1}$ and $CF_{i,t} / K_{i,t-1}$ are adequate. These considerations lead to the following specification:

$$(8) \quad \begin{aligned} I_{i,t}/K_{i,t-1} &= \sum_{h=0}^{6}\alpha_h(\Delta U_{i,t-h}/U_{i,t-h-1}) + \sum_{h=0}^{4}\beta_h(\Delta S_{i,t-h}/S_{i,t-h-1}) \\ &+ \sum_{h=0}^{4}\gamma_h(CF_{i,t-h}/K_{i,t-h-1}) + \delta_i + \varepsilon_{i,t} \end{aligned}$$

In (8), all of the variables are firm-specific, and hence are subscripted by "i". The coefficients are assumed to be the same across firms except for the depreciation rate, which varies depending on a firm's mix of capital assets. The response of the long-run capital stock to percentage changes in the user cost (uniform across firms) is captured by the sum of the α's, which we refer to as the UCE.[17]

3. Econometric Results

In this section, we present a sequence of regression estimates of the UCE. For clarity, we report the sum of the distributed lag coefficients on the $\Delta U_t / U_{t-1}$ and $\Delta S_t / S_{t-1}$ variables from equation (8) (the SUM(α) and SUM(β) coefficients). Full regression results appear in appendix A. As we proceed through the results, we observe how various econometric biases affect the UCE. Detailed consideration of each bias provides information about possible pitfalls that arise in estimating the UCE. We conclude this section with our preferred estimate of the UCE of approximately -0.25.

[17] To see that the sum of the α's represents the elasticity of the long-run capital stock with respect to the user cost, consider the following abbreviated version of (8):

$$I / K = \delta + I^n / K = \delta + \Delta K / K = \delta + \mathrm{SUM}(\alpha)*(\Delta U / U) + \ldots$$

Canceling δ's and rearranging yields an expression for the elasticity: $(\Delta K / K)/(\Delta U / U) = \mathrm{SUM}(\alpha)$. Note that this derivation assumes that $\Delta U / U$ is uniform across all firms. This assumption is relaxed when analyzing policy in section 4.

Results with Aggregate Data Versus Micro Data

Our empirical exploration begins with an aggregate data regression similar to those in the literature. Table 2 presents summary estimates for two such equations. In column 1, we report a baseline with a specification and lag lengths identical to those we use in the micro data regressions. The user cost data are taken from DRI to ensure a definition of user cost comparable to what we use with the micro data.[18] The estimated UCE (SUM(α)) is positive and insignificant. The regression in column 2 includes two lagged dependent variables to correct serial correlation in the residuals indicated by the Lagrange multiplier statistic. We obtain a negative SUM(α) in this model, but its standard error is very large.[19]

What happens when we estimate this same specification with micro data? The answer is given by the first column of table 3. This is the regression presented as equation (1) in the introduction, and it shows that the results from microeconomic data regressions can be dramatically different from those in the corresponding aggregate regressions. The SUM(α) of -0.662 is precisely estimated.[20] The hypothesis that the UCE is unity, as often assumed in policy analyses and calibrated models, can be rejected. An estimate of -0.662 , in contrast to what we and others find from aggregate data, would support the central importance of the

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[18] The sales growth variable in our micro data regression is replaced by GDP growth in the aggregate regressions. Our derivation of the investment model is independent of whether the firm's optimization problem is specified with value-added or gross output, as long as the production technology is strongly separable in its arguments.

[19] In addition to the specifications reported in table 2, we searched for negative SUM(α)'s in equations that disaggregated equipment and structures investment as well as equations that excluded volatile computer and auto investment spending. We also searched over all possible combinations of shorter lag lengths for the ΔU_t / U_{t-1} and ΔGDP_t / GDP_{t-1} to see if we could obtain negative and significant SUM(α)'s. In most cases, the SUM(α) was positive. When it was negative, is was never significantly different from zero. See table A2 in appendix A for more detailed discussion of these results.

[20] Detailed regression results with coefficients for each lag appear in appendix A. Extending the lag lengths by two years had negligible effects on the sum of the coefficients for both sales grown and percentage change in user costs. The estimated distributed lag for the percentage change in the user cost typically follow an approximate hump-shaped pattern. They rise in absolute value between the contemporaneous and first lag estimates, fall at the second lag, and drop off substantially after the second lag.

UCE in a broad range of economic analyses. This result, however, is only suggestive. There are a variety of econometric biases that may raise or lower this estimate. We now address these issues to determine the robustness of these micro-data results.

Firm Heterogeneity: Fixed Versus Random Effects

The regression in the first column of table 3 assumes that the intercepts are the same for all firms. Even if user cost elasticities are similar across firms, the assumption of a common intercept is dubious. Among other factors, different depreciation rates cause intercepts to vary across firms (as in equation 8), and slope coefficients to be biased.

The final three columns of table 3 present summary results from three estimators that model firm-specific effects as fixed or random. The mean-difference regression is presented in the second column. The R^2 statistic rises substantially when fixed effects are included and an F test resoundingly rejects the equality of the firm intercepts.[21] Note that introducing fixed firm effects with the mean-difference estimator makes the estimated SUM(α) modestly more negative relative to the pooled model (-0.721 rather than -0.660). It appears therefore that heterogeneity bias could be in part responsible for difficulty in finding negative user cost elasticities from aggregate data, although the change in SUM(α) between the pooled and mean-difference regressions is small, both economically and statistically.[22]

First-difference and random effects estimators are alternative ways to eliminate firm-specific effects. In the first-difference regression presented in the third column of table 3 the

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[21] See appendix A for the R^2 definition for models that include fixed effects.

[22] In addition, note that mean differencing reduces the estimated SUM(β) relative to the pooled regression. This result would be expected if firms' investment response to permanent sales shocks exceeds their response to temporary shocks.

estimates of SUM(α) (-0.538) and SUM(β) (0.192) are lower than their mean-difference counterparts. This result may signal measurement error, a possibility explored later in this section. The random effects estimate of SUM(α) is -0.634 and, as expected with this more efficient estimator, the standard error falls sharply. However, a Hausman (1978) test statistic of 116.3 (distributed as $\chi^2(12)$ under the null hypothesis) implies that the random effects estimates are inconsistent, owing to a correlation between the firm effects and regressors. Having rejected the pooled and random effects models, we subsequently restrict attention to fixed effect models.

Omitted Variable Bias and Financing Constraints

Until the mid-1980s, many empirical studies of investment assumed that firms operate in perfect capital markets, and investment can therefore be modeled without reference to firm financial conditions.[23] An extensive body of recent research tests this assumption and, in most cases, finds an important role for variables that measure access to finance in investment equations. The financial variable used most often in this context is internal cash flow. If a firm has access to internal sources of funds for investment, it need not resort to debt or new equity that may be rationed or involve higher costs due to capital market imperfections. If cash flow is an important determinant of investment, omitting it from the regression will bias the estimated UCE insofar as cash flow and the change in user cost are correlated.

We examine this possibility by including cash flow in the regressions reported in table 4. For the mean-difference and first-difference models in the first and second columns the.

Permanent shocks to sales are more likely reflected in the cross-sectional dimension of the data, which is eliminated by the mean-difference transformation. Eisner (1978) considers similar issues.

estimated SUM(γ)'s and their standard errors lead us to strongly reject the null hypothesis that investment is independent of cash flow. Including cash flow lowers the SUM(β) effect of sales growth, which is not surprising given the likely positive correlation between sales growth and cash flow.[24] More important for our purposes, however, including cash flow lowers the absolute value of SUM(α) from -0.721 to -0.502 in the mean-difference regression and from -0.538 to -0.421 in the first-difference regression.

One explanation for this finding is "income effects" induced by financing constraints. For a firm operating in perfect capital markets, a user cost change induces substitution effects only. But as discussed in Fazzari, Hubbard, and Petersen (1988a), changes in user costs will change firms' total costs and their available internal finance. Changing internal finance can affect the behavior of financially constrained firms over and above the effects arising from substitution alone. A lower investment tax credit, for example, may have standard incentive effects on the demand for capital and investment but, for financially constrained firms, the resulting decline in cash flow could reduce investment further than if the firm operated in perfect capital markets. The existence of these "income effects" is consistent with our findings in table 4. In the regressions without cash flow, the estimated SUM(α) captures both the conventional substitution effect as well as the income effect induced by financing constraints, which go in the same direction. When we add cash flow, however, the estimated SUM(α) can be interpreted as the user cost elasticity holding cash flow constant, that is, as a measure of the

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[23] Jorgenson gives a clear statement of this view in his 1971 survey.

[24] The effect of cash flow on the sales growth coefficients leads to the question of whether the importance of cash flow arises from financing constraints or cash flow's role as a proxy for expected demand. This issue has been considered extensively in the financing constraint literature (see the survey in Hubbard, 1995). Results vary across different studies, but evidence has been compiled to support the view that much of the cash flow effect is due to financing constraints. This issue is not of major concern in our context, however, because of our focus on the UCE.

conventional substitution effect alone. As noted in section 2, it is this substitution effect that represents the long-run impact of user cost changes on the desired capital stock. "Income effects" through cash flow operate only in the short run.

Measurement Error Bias

As mentioned above, one explanation for the low SUM(α) in the first-difference regression compared with the mean-difference regression is the presence of measurement error in the regressors (Hsiao, 1986, p.64). For example, user cost measures do not reflect all the intricacies of the tax code (see Ballentine, 1986 and Devereux, Keen, and Schiantarelli, 1994). To examine the importance of measurement error, we compare coefficients estimated by first-difference and "long-difference" models. For the long-difference model, each variable is transformed by subtracting its value lagged two years. Griliches and Hausman (1986) observe that, in the presence of measurement error, coefficients from the first-difference estimator will be less (in absolute value) than coefficients from the long-difference estimator, which appear in the third column of table 4. The SUM(α) coefficient is virtually the same in the first-difference and long-difference regressions. Measurement error in the user cost variable does not appear to be a quantitatively important problem. A prime suspect in prior low estimates of the user cost elasticity is found "not guilty."

Simultaneity Bias and Time Dummies

Several concerns with the least squares estimates presented to this point suggest the need to account for simultaneity in the estimation. Indeed, simultaneity bias provides one possible explanation for low estimates of the UCE. Investment comprises an important and volatile component of aggregate demand. Short-run fluctuations of investment therefore correlate with the business cycle, and business cycle movements correlate with interest rates. Positive aggregate investment shocks, for example, can cause positive movements in output, the demand for money, and the demand for credit that affect the required rates of return on debt and equity. The conventional wisdom suggests (Mankiw and Summers, 1988, p. 716) that simultaneity biases the UCE toward zero.

Panel data with microeconomic variation in all regressors provide an opportunity to address aggregate sources of simultaneity in a particularly simple way. To the extent that the correlation between the error term and the change in the user cost is due to aggregate factors common to all firms, this correlation can be swept out of the data with aggregate time dummies (ψ_t). The results from including time dummies in the mean-difference, first-difference, and long-difference regressions appear in table 5. Rather than making investment more sensitive to the percentage change in the user cost, however, elimination of aggregate simultaneity reduces the absolute value of the SUM(α) substantially with all estimators. Aggregate simultaneity appears important, but it has the opposite effect on the UCE than has been often assumed.[25]

Simultaneity Bias and Instrumental Variables

While time dummies control for simultaneity arising from aggregate shocks, one must also consider the possibility of additional correlations between the investment error term and micro-level regressors. Firm investment shocks may be contemporaneously correlated with sales and cash flow, or industry investment shocks may affect the relative price of the capital goods it purchases. Problems such as these suggest the need for instrumental variables estimation. Indeed, the extensive variation in our micro data will likely provide better instruments than can be obtained at the aggregate level.

Following common practice, we employ undifferenced lags of the regressors as instruments. There is a problem with this approach, however, for the mean-difference estimator when, as in the present case, instruments are pre-determined but not strictly exogenous. The problem arises because the transformed error term in period t will be correlated with the pre-determined instruments dated period t, t-1, t-2, etc. In a mean-difference model, the transformed error term contains the mean of the firm's error over the entire sample; that is, $(\varepsilon_1 + \varepsilon_2 + \ldots + \varepsilon_T) / T$. The presence of this mean error invalidates the use of lags of pre-determined regressors as instruments.[26] To solve this problem, Arellano (1988) and Arellano and Bover (1995) propose an "orthogonal deviation" transformation for panel data that allows one to remove fixed effects by subtracting the mean of future observations from each regressor. With this transformation, lagged, pre-determined regressors are valid instruments. The orthogonal deviations estimator is asymptotically equivalent to the first-

[25] A possible explanation for this result is a negative correlation between aggregate demand shocks and the relative price of capital goods (P_I / P_Y). Such correlation would result if the expansionary cyclical effect of aggregate demand shocks caused output prices in general to rise more than the price of investment goods.

[26] The bias in the mean-difference estimator with pre-determined variables as instruments is of order 1/T, where T is the number of time observations in the panel. Hence, this estimator is consistent as T goes to infinity. In practice, however, panel data sets usually provide a relatively small number of time-series observations for each firm. Our regressions are based on twelve time periods, which is larger than many panels, but not sufficiently large that we can confidently rely on asymptotic results that depend on large T. See Arellano and Bover (1995) and Urga (1992). The problem with pre-determined but not strictly exogenous instruments does not arise for the first-difference estimator because the first-difference transformation subtracts a single lagged value of each regressor rather than the mean value of the regressor over the panel. With first differences, lagged values of the regressors are legitimate instruments as long as they are lagged enough periods to avoid correlation with the first difference of the error term.

difference instrumental variables estimator, and it may be more efficient when, as usually happens in practice, a subset of the available orthogonality conditions is used.

We present instrumental variables results in table 6 for the mean-difference (possibly biased), first-difference, long-difference, and orthogonal deviations estimators. (The instrument list for each regression appears in the footnote to table 6.) Hausman tests reject the least squares specifications with p values of two percent or less, implying that consistent estimation requires instrumental variables. The point estimates of SUM(α) range from the first-difference value of -0.060 to the orthogonal deviations estimate of -0.557.

The results in table 6 lead to some interesting conclusions. The SUM(α) estimates imply that the UCE is likely negative. It is clear that the UCE is significantly below unity (the Cobb-Douglas benchmark used in much applied research). Yet, the standard errors of the SUM(α) estimates are relatively large, both economically and statistically. One cannot formally reject the hypothesis that the UCE is zero for the first-difference and the long-difference estimates. Moreover, the policy implications of a UCE near zero versus a UCE near one half are likely much different.

The relatively large standard errors of SUM(α) in table 6 and the corresponding variation in their economic interpretation could be due to inefficient estimation arising from including too many lags. To explore this possibility and determine the source of this imprecision, we examine the individual lag coefficient estimates (presented in appendix table A6), rather than focusing exclusively on SUM(α). Across the four instrumental variables regressions, the contemporaneous and sixth lag $\Delta U_t / U_{t-1}$ coefficients are insignificantly different from zero. Most of the coefficients at lags three or longer are also insignificant.[27]

The results in table 7 support the conjecture that more precise estimates can be obtained from a more parsimonious lag structure. Here, we present summary results from a model that includes only the first and second lag of $\Delta U_t / U_{t-1}$. The standard errors decline by a factor of at least three and the range of point estimates for SUM(α) narrows substantially across the estimators. All the SUM(α) estimates are negative and precisely estimated. They are much smaller in absolute value than typically assumed, however, ranging from -0.176 to -0.249.[28]

Summary: What Is the User Cost Elasticity?

The information about the user cost elasticity obtained from our micro data (table 7) is vastly superior to that obtained from the aggregate data regression (table 2). The UCE,

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[27] We examined many different lag lengths for $\Delta U_t / U_{t-1}$ between two and six years. There was little evidence of significant $\Delta U_t / U_{t-1}$ effects beyond the second lag in regressions that included three, four, and five lags of $\Delta U_t / U_{t-1}$ (both with and without the insignificant contemporaneous value in the regression). The one exception is the orthogonal deviations model in which the fifth lag is large statistically and economically and the distributed lag pattern is bimodal. We find this bimodal pattern implausible. Furthermore, when an orthogonal deviations regression is estimated with lags one through four for $\Delta U_t / U_{t-1}$, SUM(α) is quite close to the estimates in table 7.

[28] Cummins, Hassett, and Hubbard (1994, 1996) employ micro data at times of major tax reforms to estimate adjustment cost parameters in a q model and a cost-of-capital model based on Auerbach (1989). The authors are successful in obtaining more precisely estimated and economically reasonable adjustment cost parameters than have typically been found in empirical q models employing aggregate data. The emphasis in Cummins, Hassett, and Hubbard is on adjustment cost parameters rather than the UCE and their results are not directly comparable to ours. With some additional assumptions, however, we can roughly compare some of their results with those presented here. The U.S. data regression Cummins, Hassett, and Hubbard (1994) use to obtain the estimates in their table 9 has the form: $I/K = a + b\,U$, where I/K is the gross investment-capital ratio and U is a distributed lead of the level of the user cost with preset weights that decline geometrically and sum to unity. Assuming that the intercept of this equation contains the geometric depreciation rate, and subtracting the depreciation rate from both sides of this equation, yields the percentage change in the capital stock (the net investment-capital ratio) as a linear function of leads in the user cost level. Cummins, Hassett, and Hubbard report an average value for their user cost of about 25 percent and an average estimated value for b of -0.66 in years of major tax reform. At these average values, a one percent permanent change in future user costs yields a 0.165 percent change in the capital stock ($.01 \times .25 \times -0.66 = 0.00165$). Thus, the implied UCE is -0.165, very close to the range of our findings even though the Cummins, Hassett, and Hubbard study employs a very different empirical approach.

investment from 1987 to 1985 or 1986.[30] These results help to mitigate concerns about the quantitative importance of the Lucas Critique in our context.

The Effects of Current Tax Initiatives

We follow a two-step process to estimate the effect of specific tax initiatives on the capital stock. First, we determine the effect of the tax change on the user cost of capital. Because user costs differ across firms, this calculation is performed at the firm level, and therefore requires micro data. Second, the percentage change in the aggregate capital stock for our sample (K) is estimated from:

$$\text{(9)} \qquad \Delta K / K = \frac{1}{K}\sum_i \Delta K_i = \sum_i \frac{\Delta K_i}{K_i}\frac{K_i}{K} = \sum_i SUM(\alpha)\frac{\Delta U_i}{U_i} w_i$$

where w_i is firm i's share of the total capital stock. While the Compustat sample may not perfectly represent the U.S. economy, its substantial coverage suggests that these estimates will be a good approximation to the aggregate effect of policies that change the user cost.

To estimate the firm-specific percentage decline in the user cost as the result of the recent proposal to cut the top marginal capital gains tax rate from 28 percent to 19.8 percent, we follow the approach of Fazzari and Herzon (1996), who use assumptions about corporate financial structure that are representative for the U.S. economy.[31] Weighting these percentage

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[30] The range of UCE estimates from the instrumental variable regressions with time dummies was marginally higher in absolute value than those reported in table 7: -0.231 for mean differences, -0.279 for first difference, and -0.326 for orthogonal deviations.

[31] These assumptions include the following: firms pay 50 percent of their income as dividends and 50 percent as capital gains; 30 percent of new investment is financed with debt and 70 percent with equity; the real required rate of return on equity is 6 percent; and expected inflation is 3 percent. For the results reported here, each firm's percentage decline in the user cost is determined as follows. The user cost can be expressed as the product of components representing relative prices (P_i), corporate taxes (T_i), and a required rate of return (R_i) that includes depreciation and the tax-adjusted opportunity cost of funds r that the firm must attain to compensate its investors: $U_i = P_i{*}T_i{*}R_i$ and $R_i = r+\delta_i$. The capital gains tax rate affects r, and the percentage change in the user cost from a capital gains tax rate cut can be

The Lucas Critique and the Tax Reform Act of 1986

The Tax Reform Act of 1986 was a significant policy change that raised the user cost during our sample period and provides an opportunity to test the empirical importance of the Lucas Critique. If it were the case that the empirical UCE (which is not derived from an explicit, policy-invariant structural model) changed with the Tax Reform Act of 1986, one would expect to observe large residuals around the time of the policy change in our specification that maintains a uniform UCE over the sample. Because the user cost increases were, at least in part, anticipated prior to implementation we might expect systematic increases of investment in 1985, possibly 1986, relative to 1987 when the when the user cost rose.[29]

Including time dummies in the panel data regressions (which cannot be done with aggregate data) provides a test for the systematic changes in the investment-capital ratio implied by the Lucas Critique. We include time dummies in the instrumental variables regressions reported in table 7 and perform pair-wise equality tests on the 1985, 1986, and 1987 time dummy coefficients. We also test the joint equality of the time dummy coefficients for 1985, 1986, and 1987. The lowest p-values we obtain from these tests are 0.241 for mean differences, 0.343 for first differences, and 0.165 for orthogonal deviations. The null hypothesis of stability over the tax reform period cannot be rejected. Moreover, the time dummy coefficient for 1987 is slightly higher than those for 1985 and 1986, further evidence against the view that the anticipation of tax reform led firms to intertemporally substitute

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[29] The effective implementation dates varied for different parts of the Tax Reform Act of 1986.

investment from 1987 to 1985 or 1986.[30] These results help to mitigate concerns about the quantitative importance of the Lucas Critique in our context.

The Effects of Current Tax Initiatives

We follow a two-step process to estimate the effect of specific tax initiatives on the capital stock. First, we determine the effect of the tax change on the user cost of capital. Because user costs differ across firms, this calculation is performed at the firm level, and therefore requires micro data. Second, the percentage change in the aggregate capital stock for our sample (K) is estimated from:

$$\text{(9)} \qquad \Delta K / K = \frac{1}{K}\sum_i \Delta K_i = \sum_i \frac{\Delta K_i}{K_i}\frac{K_i}{K} = \sum_i SUM(\alpha)\frac{\Delta U_i}{U_i}w_i$$

where w_i is firm i's share of the total capital stock. While the Compustat sample may not perfectly represent the U.S. economy, its substantial coverage suggests that these estimates will be a good approximation to the aggregate effect of policies that change the user cost.

To estimate the firm-specific percentage decline in the user cost as the result of the recent proposal to cut the top marginal capital gains tax rate from 28 percent to 19.8 percent, we follow the approach of Fazzari and Herzon (1996), who use assumptions about corporate financial structure that are representative for the U.S. economy.[31] Weighting these percentage

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[30] The range of UCE estimates from the instrumental variable regressions with time dummies was marginally higher in absolute value than those reported in table 7: -0.231 for mean differences, -0.279 for first difference, and -0.326 for orthogonal deviations.

[31] These assumptions include the following: firms pay 50 percent of their income as dividends and 50 percent as capital gains; 30 percent of new investment is financed with debt and 70 percent with equity; the real required rate of return on equity is 6 percent; and expected inflation is 3 percent. For the results reported here, each firm's percentage decline in the user cost is determined as follows. The user cost can be expressed as the product of components representing relative prices (P_i), corporate taxes (T_i), and a required rate of return (R_i) that includes depreciation and the tax-adjusted opportunity cost of funds r that the firm must attain to compensate its investors: $U_i = P_i{*}T_i{*}R_i$ and $R_i = r+\delta_i$. The capital gains tax rate affects r, and the percentage change in the user cost from a capital gains tax rate cut can be

changes by the firm capital shares from 1991, the final year in our sample, yields a weighted average reduction in the user cost of 1.89 percent. The estimated impact of this change on the long-run capital stock is given in the first column of table 8 for a UCE of -0.25, consistent with our regression results. This policy yields only about half a percentage point increase in the long-run capital stock. Assuming a typical output elasticity with respect to capital of 0.3, the capital gains tax cut is predicted to have an impact on the level of output of only 0.14 percent.

The flat-tax proposal has a more substantial impact. The flat tax would allow firms to "expense" investment, and it would drive the tax component of the user cost measure to unity.[32] We calculated the tax component for the final year in the sample (1991) for each firm and computed the percentage change in the firm's user cost that would result if this tax component went to unity. The weighted average of these percentage changes (with 1991 capital shares as weights) is -14.15 percent, which is the figure we use to estimate the impact of the Hall-Rabushka flat tax proposal on the long-run capital stock and output. As the calculations in table 8 show, our UCE estimate of -0.25 leads to a predicted increase in the capital stock of 3.5 percent and a predicted increase in the long-run level of output of 1.1 percent. In his simulation of the Hall-Rabushka (1995) flat tax, Auerbach (1996, table 3,

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expressed as $\Delta U_i / U_i = \Delta r / (r+\delta_i)$. The term $(r+\delta_i)$ is taken from our micro data. Fazzari and Herzon's estimates imply that r will fall by 7.42 percent from a base of 4.53 percent after the capital gains tax rate cut, which implies that Δr equals .0742 * .0453. Note that δ, which is ignored in many studies, plays a large role in determining $\Delta U / U$. If δ is set to zero, the percentage change in the user cost triples. In our calculations, and in contrast with Fazzari and Herzon, we have not adjusted the capital gains tax rate for the expected holding period of assets. Thus our figures are an upper bound on the impact of cutting the capital gains tax rate.

[32] The flat tax would have another effect on the user cost that we do not measure in this exercise. Interest payments would no longer be deductible for corporate tax purposes. This change would raise the user cost, holding pre-tax interest rates constant. Debt has only a one-third weight in our user cost, however, and proponents of the flat tax argue that other aspects of the tax reform that encourage saving would lower pre-tax interest rates. For these reasons, we believe the effect of eliminating the corporate interest expense deduction is not substantial. The calculations presented in table 8 should be viewed as an upper bound on the magnitude of the effect.

column 2) finds that output per capita increases by 8.4 percent in the long run.[33] This result is based on a unitary UCE implicit in the Cobb-Douglas production function. Our results are also less than a third of the increase predicted by Hall and Rabushka due to the increase in the capital stock alone.[34]

5. Conclusion

What do micro data reveal about the user cost elasticity? The initial pooled regression suggested that, in contrast to estimates based on aggregate data that are close to zero, the UCE takes on the rather sizable value of negative two-thirds. The UCE, however, is affected by a variety of econometric biases. Estimates can be raised or lowered by biases stemming from heterogeneity across firms, omission of cash flow variables, errors in measuring the user cost, and simultaneity among regressors and errors. The extensive panel data at our disposal allow us to investigate these biases. Several prove important. Evidence from a variety of panel-data estimators indicates that the true UCE is negative, and, in contrast with most studies based on aggregate data, precisely estimated. The point estimate is approximately one quarter, a much lower elasticity than the value of unity typically assumed in applied research.

This low elasticity has important implications for several areas of macroeconomic research. It suggests that models that rely heavily on prices to allocate capital — especially those in the real business cycle tradition — may be misspecified. Our modest UCE estimate

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33 Auerbach's estimate reflects general equilibrium effects not accounted for in our analysis.

34 This calculation is based on the mid-point of the 2 to 4 percent output increase range that Hall and Rabushka (1995, p. 87) predict over seven years. Because Hall and Rabushka assume a 0.25 elasticity of output with respect to capital, a 3 percent output increase translates into a 12 percent increase in capital, which can be compared to our figures in table 7. Hall and Rabushka also argue that the flat tax would increase the efficiency of the capital stock resulting in further increases in output. We cannot assess this prediction in our framework that focuses on the overall quantity of capital.

implies a correspondingly modest effect of interest rates on investment, weakening the traditional monetary transmission mechanism. Finally, the effects of policy initiatives to stimulate capital formation by cutting taxes are likely to be attenuated. Reducing the capital gains tax rate from 28 to 19.8 percent would raise the long-run capital stock by only a trivial amount with a UCE in the range of our estimates. Replacing the current tax system by a flat tax would increase the long-run capital stock by about 3.5 percent, much less than is claimed by proponents of the flat tax. There may be good reasons for supporting these tax policies, and thus for shifting the burden of taxation away from upper-income taxpayers. A substantial increase in the capital stock is not one of them.

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Table 1: Summary Statistics for Micro Data

Variable	Mean	Median	Within-Firm Standard Deviation	Firm-Specific Time Variation
I_t / K_{t-1}	0.173	0.125	0.163	0.979
$\Delta S_t / S_{t-1}$	0.030	0.018	0.223	0.976
CF_t / K_{t-1}	0.226	0.185	0.272	0.987
$\Delta U_t / U_{t-1}$	-0.013	-0.023	0.071	0.674

Note: Panel data for Compustat firms from 1981 to 1991, as described in the text. I_t / K_{t-1} is the ratio of firm capital spending to the beginning of period capital stock, $\Delta S_t / S_{t-1}$ is firm sales growth, CF_t / K_{t-1} is the ratio of firm cash flow to the beginning-of-period capital stock and $\Delta U_t / U_{t-1}$ is the percentage change in the user cost of capital. The within-firm standard deviation is computed after subtracting firm-by-firm means of each variable from each observation. This statistic therefore measures variation in the time dimension of the panel only. The firm-specific time variation is one minus the R^2 statistic from a regression of each mean-differenced variable on a set of time dummies, as described further in the text.

Table 2: Aggregate Data Regressions

$$I_t / K_{t-1} = \alpha_6(L)\, \Delta U_t / U_{t-1} + \beta_4(L)\, \Delta GDP_t / GDP_{t-1} + \lambda_2(L)\, I_t / K_{t-1} + \phi + \varepsilon_t$$

	Baseline Specification	Addition of Two Lagged Dependent Variables
SUM(α)	0.246	-0.025
	(0.232)	(0.067)
SUM(β)	0.557	0.164
	(0.428)	(0.114)
SUM(λ)	—	0.860
		(0.086)
LM_1	0.885	-0.439
	(0.246)	(0.475)
Adjusted R^2	0.013	0.936

Note: Ordinary least squares estimates with annual data for 1972-1994. Standard errors are in parentheses. The symbols $\alpha_6(L)$, $\beta_4(L)$, and $\lambda_2(L)$ represent polynomials in the lag operator of order 6, 4, and 2, respectively. The $\alpha_6(L)$ and $\beta_4(L)$ functions begin with order 0 and the $\lambda_2(L)$ function begins with order 1. SUM(α), SUM(β), and SUM(λ) are the sums of the estimated coefficients; ϕ is an estimated constant. The dependent variable (I_t / K_{t-1}) is the flow of real investment spending divided by the current dollar replacement value of the capital stock (beginning of the period) deflated by the price index for investment. (The results are robust when K_t is measured by the constant dollar replacement value of the capital stock.) U_t is the user cost of capital as computed by DRI (discussed in detail in the text), and is a weighted average of five components: public utility structures, building and other structures (excluding mining, exploration and farms), automobile equipment, office-computing-accounting equipment, and other equipment. GDP_t is real GDP in 1987 prices. LM_1 is a modified Lagrange Multiplier statistic that evaluates the null hypothesis of no first-order serial correlation; it is distributed t under the null.

Table 3: Micro Data Regressions and Heterogeneity Bias

$$I_{i,t} / K_{i,t-1} = \alpha_6(L)\,\Delta U_{i,t} / U_{i,t-1} + \beta_4(L)\,\Delta S_{i,t} / S_{i,t-1} + \phi_i + \varepsilon_{i,t}$$

	Pooled Regression ($\phi_i = \phi$ for all i)	Fixed Effects Mean Difference	Fixed Effects First Difference	Random Effects
SUM(α)	-0.660	-0.721	-0.538	-0.634
	(0.041)	(0.054)	(0.117)	(0.031)
SUM(β)	0.488	0.322	0.192	0.405
	(0.009)	(0.012)	(0.025)	(0.012)
R^2	0.120	0.411	0.422	0.119

Note: Estimates with micro data (1981-1991) and ordinary least squares as described in the text. Standard errors are in parentheses. Individual coefficient estimates appear in appendix table A3. The polynomials in the lag operator $\alpha_6(L)$ and $\beta_4(L)$ are of order 6 and 4 and contain contemporaneous values. SUM(α) and SUM(β) are the sums of the estimated coefficients; ϕ_i is an estimated, firm-specific constant. The sample for the random effects regression is a randomly selected subset of 19,108 observations from the full data set of 26,071 observations. The reduction in sample size is due to limitations on data size in the LIMDEP software used to perform this regression. To maintain comparability across fixed effect estimators, the R^2 statistic is defined to account for firm-specific intercepts as described in appendix A.

Table 4: Omitted Variable Bias and Measurement Error

$$I_{i,t} / K_{i,t-1} = \alpha_6(L)\, \Delta U_{i,t} / U_{i,t-1} + \beta_4(L)\, \Delta S_{i,t} / S_{i,t-1} + \gamma_4(L)\, CF_{i,t} / K_{i,t-1} + \phi_i + \varepsilon_{i,t}$$

	Mean Difference	First Difference	Long Differences
SUM(α)	-0.502	-0.421	-0.402
	(0.053)	(0.114)	(0.087)
SUM(β)	0.153	0.049	0.115
	(0.012)	(0.025)	(0.019)
SUM(γ)	0.265	0.296	0.285
	(0.007)	(0.016)	(0.012)
R^2	0.457	0.466	0.484

Note: See notes to table 3. Estimation with ordinary least squares. Individual coefficient estimates appear in appendix table A4. The lag operator polynomial $\gamma_4(L)$ incorporates contemporaneous and four annual lags of cash flow.

Table 5: Simultaneity Bias and Aggregate Time Dummies

$$I_{i,t} / K_{i,t-1} = \alpha_6(L)\, \Delta U_{i,t} / U_{i,t-1} + \beta_4(L)\, \Delta S_{i,t} / S_{i,t-1} + \gamma_4(L)\, CF_{i,t} / K_{i,t-1} + \phi_i + \psi_t + \varepsilon_{i,t}$$

	Mean Difference	First Difference	Long Difference
SUM(α)	-0.289	-0.087	-0.107
	(0.106)	(0.143)	(0.103)
SUM(β)	0.150	0.041	0.114
	(0.021)	(0.025)	(0.019)
SUM(γ)	0.258	0.290	0.281
	(0.012)	(0.016)	(0.012)
R^2	0.460	0.463	0.480

Note: See notes to table 3. Estimation is with ordinary least squares. Individual coefficient estimates appear in appendix table A5. The symbol ψ_t represents a time dummy coefficient for each year in the data.

Table 6: Simultaneity Bias and Instrumental Variables Regressions

$$I_{i,t} / K_{i,t-1} = \alpha_6(L)\,\Delta U_{i,t} / U_{i,t-1} + \beta_4(L)\,\Delta S_{i,t} / S_{i,t-1} + \gamma_4(L)\,CF_{i,t} / K_{i,t-1} + \phi_i + \varepsilon_{i,t}$$

	Mean Difference	First Difference	Long Difference	Orthogonal Deviations
SUM(α)	-0.254	-0.060	-0.320	-0.557
	(0.140)	(0.228)	(0.192)	(0.157)
SUM(β)	0.080	0.155	-0.004	0.084
	(0.068)	(0.091)	(0.065)	(0.107)
SUM(γ)	0.421	0.511	0.478	0.472
	(0.092)	(0.077)	(0.052)	(0.050)

Note: See notes to table 3. Individual coefficient estimates appear in appendix table A6. The instruments for the mean-difference and orthogonal deviations regressions are the levels (undifferenced) of $\Delta U_{i,t} / U_{i,t-1}$, lagged one through nine years and $\Delta S_{i,t} / S_{i,t-1}$, and $CF_{i,t} / K_{i,t-1}$ lagged one through seven years. The instruments for the first-difference regression are the levels of $\Delta U_{i,t} / U_{i,t-1}$, lagged two through ten years and $\Delta S_{i,t} / S_{i,t-1}$, and $CF_{i,t} / K_{i,t-1}$ lagged two through eight years. The instruments for the long-difference regression are the levels of $\Delta U_{i,t} / U_{i,t-1}$, lagged three through eleven years and $\Delta S_{i,t} / S_{i,t-1}$, and $CF_{i,t} / K_{i,t-1}$ lagged three through nine years.

Table 7: Instrumental Variables Regressions with Short Lags for $\Delta U_{i,t} / U_{i,t-1}$

$$I_{i,t} / K_{i,t-1} = \alpha_2(L)\, \Delta U_{i,t} / U_{i,t-1} + \beta_4(L)\, \Delta S_{i,t} / S_{i,t-1} + \gamma_4(L)\, CF_{i,t} / K_{i,t-1} + \phi_i + \varepsilon_{i,t}$$

	Mean Difference	First Difference	Long Difference	Orthogonal Deviations
SUM(α)	-0.207	-0.239	-0.176	-0.249
	(0.026)	(0.060)	(0.033)	(0.032)
SUM(β)	0.118	0.170	0.025	0.202
	(0.062)	(0.077)	(0.053)	(0.070)
SUM(γ)	0.497	0.487	0.487	0.468
	(0.063)	(0.068)	(0.043)	(0.045)

Note: See notes to table 3. Individual coefficient estimates appear in appendix table A7. The SUM(α) coefficient is the sum of the coefficients on the first and second lags of $\Delta U_{i,t} / U_{i,t-1}$. Note that this distributed lag excludes the contemporaneous value for reasons described in the text. Instruments are the same as those described in the note to table 6.

Table 8: Policy Effects

	Capital Gains Tax Rate Cuts	Flat Tax
User Cost Elasticity:	**-0.25**	**-0.25**
$\Delta U / U$	-1.89%	-14.15%
$\Delta K / K$	+0.47%	+3.54%
$\Delta Y / Y$	+0.14%	+1.06%

Note: The $\Delta U / U$ row shows the estimated percentage decline in the user cost of capital which is a weighted average of estimated firm-specific percentage changes in the user cost. The weights reflect each firm's share of capital in the data sample. The $\Delta U / U$ for the capital gains tax is based on Fazzari and Herzon (1996), as described in the text. The decline for the flat tax policy is based on the authors' calculations as described in the text. The $\Delta K / K$ row shows the percentage change in the long-run capital stock as a result of the user cost decline given a user cost elasticity of -0.25. The $\Delta Y / Y$ is the long run percentage change in output as a result of the increase in the capital stock assuming a 0.3 elasticity of output with respect to the capital stock.

Appendix A: Detailed Regression Results

The following tables give detailed information about the summary regression results presented in tables 2 through 6 in the text. The appendix tables are numbered to correspond to the text tables. (Table A2 corresponds to table 2 in the text, for example.)

In tables A3 through A6, the variable mnemonics correspond to the symbols in the text as follows:

PCUCI	$\Delta U_{i,t} / U_{i,t-1}$
SG	$\Delta S_t / S_{t-1}$
CF_K1	$CF_{i,t} / K_{i,t-1}$

A single digit following any of the symbols above indicates a lag of the number of years given by the digit. Time dummies are denoted by DUMnn, where nn is the appropriate year. Rsq. stands for the R-squared statistic.

To maintain comparability in the R^2 statistic across models with firm-specific intercepts we compute R^2 as follows. For the models that include lags of the percentage change in the user cost and the percentage change in sales, R^2 is defined with regression residuals ($e_{i,t}$) from:

$$\text{(A1)} \quad e_{i,t} = (I/K)_{i,t} - \hat{\phi}_i - \sum_{h=0}^{6} \hat{\alpha}_h \frac{\Delta U_{i,t-h}}{U_{i,t-h-1}} - \sum_{h=0}^{4} \hat{\beta}_h \frac{\Delta S_{i,t-h}}{S_{i,t-h-1}}$$

where $\hat{\alpha}_h$ and $\hat{\beta}_h$ are regression coefficients. The estimated firm-specific intercept is given by:

$$\text{(A2)} \quad \hat{\phi}_i = (1/T) \sum_{t=1}^{T} \left((I/K)_{i,t} - \sum_{h=0}^{6} \hat{\alpha}_h \frac{\Delta U_{i,t-h}}{U_{i,t-h-1}} - \sum_{h=0}^{4} \hat{\beta}_h \frac{\Delta S_{i,t-h}}{S_{i,t-h-1}} \right)$$

where T is the number of years in the panel. This definition of the residuals gives the conventional R^2 for the mean-difference estimator. For the first-difference and long-difference estimators, this definition may result in R^2 statistics that do not necessarily rise when additional variables are added to the regression model. We use this definition of R^2, appropriately modified to account for alterations in the regression equation, for all the OLS fixed effects regressions reported in the paper.

Table A2: Aggregate Data Regressions

$$I_t / K_{t-1} = \alpha_6(L)\, \Delta U_t / U_{t-1} + \beta_4(L)\, \Delta GDP_t / GDP_{t-1} + \lambda_2(L)\, I_t / K_{t-1} + \phi + \varepsilon_t$$

	Structures and Equipment	Structures	Equipment	Equipment without Computers and Autos
	(1)	(2)	(3)	(4)
A. Without Lagged Dependent Variable				
SUM(α)	0.246	0.548	-0.065	0.472
	(0.232)	(0.142)	(0.508)	(0.602)
SUM(β)	0.557	0.455	0.764	10.107
	(0.428)	(0.366)	(0.840)	(0.910)
$\bar{R}^2$	0.013	0.381	-0.235	0.348
LM_1	0.885	0.627	10.356	10.070
	(0.246)	(0.271)	(0.207)	(0.244)
B. With Lagged Dependent Variables				
SUM(α)	-0.025	0.201	0.076	-0.036
	(0.067)	(0.091)	(0.178)	(0.153)
SUM(β)	0.164	0.145	0.512	0.353
	(0.114)	(0.187)	(0.211)	(0.234)
SUM(λ)	0.860	0.685	0.946	0.935
	(0.086)	(0.126)	(0.152)	(0.093)
$\bar{R}^2$	0.936	0.856	0.923	0.919
LM_1	-0.439	-0.921	0.015	0.154
	(0.475)	(0.556)	(0.531)	(0.463)

Table footnote appears on the following page.

Ordinary least squares estimates with annual data for 1972-1994. Standard errors are in parentheses. $\alpha_6(L)$, $\beta_4(L)$, and $\lambda_2(L)$ are polynomials in the lag operator of order 6, 4, and 2, respectively; the polynomials for $\alpha_6(L)$ and $\beta_4(L)$ begin with 0; for $\lambda_2(L)$ with 1. SUM(α), SUM(β), and SUM(λ) are the sums of the estimated coefficients; ϕ is an estimated constant. The dependent variable (I_t/K_{t-1}) is the flow of real investment spending divided by the current dollar replacement value of the capital stock (beginning of the period) deflated by the price index for investment. (The results are robust when K_t is measured by the constant dollar replacement value of the capital stock.) The capital goods included in these investment and capital series vary across the four columns. U_t is the rental price of capital as computed by DRI (discussed in detail in the text), and is a weighted average of five components: public utility structures, building and other structures (excluding mining, exploration and farms), automobile equipment, office-computing-accounting equipment, and other equipment. The weighted average changes so that RP_t corresponds to the capital goods included in the investment and capital series for a model in a given column; the weights depend on current dollar capital stocks and vary over time. GDP_t is real GDP in 1987 prices. LM_1 is a modified Lagrange Multiplier statistic that evaluates the null hypothesis of no first-order residual serial correlation; it is distributed t under the null. The lag lengths in panel A are identical to those used with the micro data. A search over various lag lengths (all possible combinations of less than or equal to 6 for $\alpha(L)$ and less than or equal to 4 for $\beta(L)$) to find the most negative value of SUM(α) in the aggregate model yielded -.003, 0, -.188, and -.105 (all with large standard errors) for the models in columns (1)-(4), respectively.

Table A3: Micro Data Regressions and Heterogeneity Bias

	Pooled OLS		Mean-diff. OLS		First-diff. OLS		Random Effects	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
PCUCI	-0.126	0.016	-0.144	0.016	-0.082	0.018	-0.134	0.019
PCUCI1	-0.201	0.016	-0.205	0.015	-0.142	0.023	-0.191	0.018
PCUCI2	-0.159	0.017	-0.155	0.015	-0.100	0.024	-0.159	0.018
PCUCI3	-0.043	0.016	-0.060	0.015	-0.015	0.025	-0.037	0.017
PCUCI4	-0.051	0.015	-0.054	0.015	-0.046	0.026	-0.044	0.017
PCUCI5	-0.088	0.016	-0.099	0.015	-0.116	0.027	-0.086	0.017
PCUCI6	0.009	0.025	-0.004	0.023	-0.037	0.026	0.017	0.028
Sum	-0.660	0.041	-0.721	0.054	-0.538	0.117	-0.634	0.031
SG	0.151	0.005	0.120	0.004	0.085	0.006	0.136	0.005
SG1	0.114	0.005	0.082	0.004	0.051	0.007	0.097	0.005
SG2	0.102	0.005	0.067	0.005	0.039	0.007	0.089	0.005
SG3	0.060	0.005	0.033	0.004	0.008	0.007	0.047	0.005
SG4	0.061	0.005	0.021	0.005	0.009	0.006	0.038	0.005
Sum	0.488	0.009	0.322	0.012	0.192	0.025	0.405	0.012
INTERCEPT	0.144	0.001					0.151	0.003
Rsq.	0.120		0.411		0.422		0.119	
Obs.	26071		26071		21939		19108	

Table A4: Omitted Variable Bias and Measurement Error

	Mean-diff. OLS		First-diff. OLS		Long-diff. OLS	
	Coef.	Std.	Coef.	Std.	Coef.	Std.
PCUCI	-0.088	0.016	-0.055	0.018	-0.098	0.024
PCUCI1	-0.155	0.014	-0.117	0.022	-0.095	0.020
PCUCI2	-0.123	0.014	-0.086	0.023	-0.080	0.024
PCUCI3	-0.024	0.014	-0.001	0.025	-0.028	0.023
PCUCI4	-0.037	0.014	-0.038	0.025	-0.012	0.027
PCUCI5	-0.087	0.014	-0.101	0.026	-0.068	0.023
PCUCI6	0.012	0.022	-0.023	0.025	-0.020	0.030
Sum	-0.502	0.053	-0.421	0.114	-0.402	0.087
SG	0.079	0.004	0.047	0.006	0.080	0.006
SG1	0.033	0.004	0.004	0.007	0.002	0.006
SG2	0.029	0.005	0.006	0.007	0.035	0.008
SG3	0.006	0.005	-0.011	0.007	-0.003	0.006
SG4	0.006	0.005	0.002	0.006	0.001	0.007
Sum	0.153	0.012	0.049	0.025	0.115	0.019
CF_K1	0.102	0.004	0.130	0.005	0.110	0.005
CF_K11	0.101	0.004	0.105	0.005	0.137	0.006
CF_K12	0.036	0.004	0.041	0.005	0.018	0.006
CF_K13	0.018	0.004	0.015	0.005	0.017	0.006
CF_K14	0.009	0.004	0.003	0.005	0.004	0.005
Sum	0.265	0.007	0.296	0.016	0.285	0.012
Rsq.	0.457		0.466		0.484	
Obs.	26071		21939		18368	

Table A5: Simultaneity Bias and Aggregate Time Dummies

	Mean-diff. OLS		First-diff. OLS		Long-diff. OLS	
	Coef.	Std.	Coef.	Std.	Coef.	Std.
PCUCI	-0.088	0.020	-0.080	0.022	-0.111	0.032
PCUCI1	-0.136	0.017	-0.117	0.027	-0.075	0.023
PCUCI2	-0.110	0.017	-0.071	0.030	-0.070	0.029
PCUCI3	0.008	0.016	0.050	0.032	0.047	0.028
PCUCI4	-0.002	0.017	0.029	0.033	0.021	0.032
PCUCI5	-0.013	0.018	0.026	0.036	0.056	0.031
PCUCI6	0.051	0.029	0.076	0.034	0.025	0.043
Sum	-0.289	0.061	-0.087	0.143	-0.107	0.103
SG	0.077	0.004	0.044	0.006	0.079	0.006
SG1	0.031	0.004	-0.001	0.007	-0.003	0.006
SG2	0.030	0.005	0.006	0.007	0.037	0.008
SG3	0.005	0.005	-0.012	0.007	-0.005	0.006
SG4	0.008	0.005	0.005	0.006	0.006	0.007
Sum	0.150	0.012	0.041	0.025	0.114	0.019
CF_K1	0.099	0.004	0.129	0.005	0.108	0.005
CF_K11	0.099	0.004	0.104	0.005	0.135	0.006
CF_K12	0.036	0.004	0.040	0.005	0.017	0.006
CF_K13	0.017	0.004	0.014	0.005	0.017	0.006
CF_K14	0.007	0.004	0.003	0.005	0.004	0.006
Sum	0.258	0.007	0.290	0.016	0.281	0.012
DUM82	-0.015	0.005	-0.020	0.005		
DUM83	-0.031	0.005	-0.036	0.007	-0.032	0.006
DUM84	-0.000	0.005	-0.001	0.009	0.021	0.007
DUM85	-0.013	0.005	-0.010	0.010	-0.013	0.008
DUM86	-0.010	0.006	-0.006	0.011	0.015	0.010
DUM87	-0.014	0.006	-0.012	0.012	-0.020	0.010
DUM88	-0.020	0.006	-0.020	0.013	-0.004	0.010
DUM89	-0.026	0.005	-0.029	0.014	-0.035	0.011
DUM90	-0.038	0.005	-0.041	0.015	-0.024	0.012
DUM91	-0.047	0.006	-0.052	0.016	-0.056	0.013
Rsq.	0.460		0.463		0.480	
Obs.	26071		21939		18368	

Table A6: Simultaneity Bias and Instrumental Variables Regressions

	Mean-diff. IV		First-diff. IV		Long-diff. IV		Orthog-dev. IV	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
PCUCI	0.021	0.062	0.128	0.100	-0.015	0.098	-0.020	0.080
PCUCI1	-0.129	0.021	-0.121	0.047	-0.163	0.045	-0.212	0.037
PCUCI2	-0.120	0.022	-0.110	0.047	-0.033	0.027	-0.128	0.033
PCUCI3	0.013	0.024	0.066	0.042	-0.027	0.034	-0.023	0.029
PCUCI4	-0.009	0.022	0.015	0.040	0.000	0.039	-0.051	0.030
PCUCI5	-0.063	0.023	-0.033	0.047	-0.049	0.041	-0.095	0.042
PCUCI6	0.034	0.041	-0.006	0.041	-0.032	0.080	-0.028	0.049
Sum	-0.254	0.140	-0.060	0.228	-0.320	0.192	-0.557	0.157
SG	0.028	0.048	0.055	0.097	-0.046	0.077	-0.106	0.130
SG1	0.021	0.009	0.035	0.021	0.055	0.016	0.074	0.018
SG2	0.022	0.009	0.039	0.013	-0.019	0.007	0.051	0.008
SG3	0.002	0.007	0.011	0.012	0.027	0.010	0.033	0.010
SG4	0.007	0.006	0.015	0.009	-0.021	0.008	0.031	0.008
Sum	0.080	0.068	0.155	0.091	-0.004	0.065	0.084	0.107
CF_K1	0.316	0.115	0.528	0.102	0.443	0.074	0.514	0.097
CF_K11	0.049	0.026	-0.045	0.039	0.004	0.030	-0.053	0.039
CF_K12	0.033	0.005	0.024	0.010	0.016	0.006	0.010	0.008
CF_K13	0.015	0.005	0.002	0.008	0.008	0.008	-0.002	0.008
CF_K14	0.008	0.005	0.003	0.007	0.007	0.006	0.002	0.006
Sum	0.421	0.092	0.511	0.077	0.478	0.052	0.472	0.052
Obs.	26071		21939		18368		21939	

Table A7: Instrumental Variables Regressions with Short Lags for PCUCI

	Mean-diff. IV		First-diff. IV		Long-diff. IV		Orthog-dev. IV	
	Coef.	Std.	Coef.	Std.	Coef.	Std.	Coef.	Std.
PCUCI1	-0.112	0.016	-0.138	0.035	-0.138	0.031	-0.145	0.021
PCUCI2	-0.094	0.018	-0.101	0.031	-0.038	0.022	-0.104	0.023
Sum	-0.207	0.026	-0.239	0.060	-0.176	0.033	-0.249	0.032
SG	0.060	0.044	0.047	0.077	-0.019	0.059	0.036	0.081
SG1	0.017	0.008	0.044	0.018	0.055	0.014	0.057	0.013
SG2	0.026	0.009	0.044	0.013	-0.019	0.007	0.052	0.008
SG3	0.006	0.007	0.019	0.011	0.028	0.009	0.028	0.009
SG4	0.009	0.007	0.016	0.008	-0.021	0.008	0.029	0.007
Sum	0.118	0.062	0.170	0.077	0.025	0.053	0.202	0.070
CF_K1	0.419	0.079	0.493	0.086	0.454	0.061	0.502	0.087
CF_K11	0.024	0.018	-0.033	0.034	0.002	0.026	-0.047	0.036
CF_K12	0.031	0.005	0.024	0.010	0.016	0.006	0.011	0.008
CF_K13	0.014	0.005	0.001	0.008	0.008	0.008	0.001	0.007
CF_K14	0.009	0.005	0.002	0.007	0.007	0.006	0.002	0.006
Sum	0.497	0.063	0.487	0.068	0.487	0.043	0.468	0.045
Obs.	26071		21939		18368		21939	

Appendix B: Data Definitions

This appendix describes the firm-specific variables in the study. All of the accounting data are from the Compustat Industrial Database maintained by Standard and Poor.

Sales

This variable is gross sales during the year reduced by cash discounts, trade discounts, and returned sales or allowances to customers.

Cash Flow

Cash flow is the sum of several variables from Compustat. It includes:

1. Income before extraordinary items;
2. Depreciation and amortization;
3. Deferred Taxes;
4. Equity in net loss (earnings); and
5. Extraordinary items and discontinued operations.

The first two components of cash flow (income and depreciation) are seldom missing from firms' balance sheets. If the a firm reports a missing value for either one of these variables, we produce a missing value for cash flow. The last three items, however, are missing a greater percentage of the time. We assume that when they are missing, their values are economically insignificant, and we set them to zero.

The Replacement Value of Capital

The capital stock appears in the denominator of our dependent variable. The problem with using the book values of gross or net property, plant, and equipment is that if the capital is many years old, its book value may severely understate the current value of the capital, especially in periods of high inflation. Salinger and Summers (1983) present an algorithm for approximating the current replacement value of capital using accounting data such as that supplied by Compustat. Since its initial introduction, many researchers have used variations of the Salinger-Summers algorithm to construct capital stock series. We modified the original algorithm to make it more useful in approximating capital stocks for a wider variety of firms.

The basic idea behind the algorithm is to build iteratively a replacement value series using three steps. First, take the previous year's value and inflate it in proportion to aggregate inflation to obtain the capital stock's replacement value today in the absence of other changes. Second, add the value of the current year's investment, and third, account for capital lost to depreciation. In constructing the series, Salinger and Summers make several assumptions:

1. All of a firm's capital has the same life (LIFE).
2. Firms use the straight-line method for book depreciation.
3. All investments are made at the beginning of the year, and all depreciation is taken at the end of the year.

Given these assumptions, they estimate the useful capital stock life in any year as

(B1) $$LIFE_t = \frac{GPLANT_{t-1} + I_t}{DEPR_t}$$

where

$GPLANT_t$ = the book value of gross plant in year t;
I_t = capital expenditures in year t; and
$DEPR_t$ = book depreciation in year t.

Because $LIFE_t$ fluctuates from year to year, Salinger and Summers substitute the average life for each firm over the sample ($LIFE$). They further assume that the actual depreciation rate is exponential with depreciation rate $\delta = 2 / LIFE$, equivalent to double declining balance depreciation.

The main formula for the iterative algorithm is:

$$RK_t = \left(RK_{t-1} \frac{P_t}{P_{t-1}} + I_t \right)(1-\delta). \tag{B2}$$

where RK_t is the replacement value of the capital stock at time t and P_t is the implicit price deflator for non-residential capital goods. There are three major extensions to the algorithm which we use in this study. First, we make the treatment of changes in capital more general. A drawback to the original Salinger-Summers specification is that it implicitly assumes that capital spending (I_t) is the only way to change the capital stock from year to year. In fact, acquisitions and divestitures can augment and deplete the capital stock independent of reported investment. To obtain a more flexible specification for RK_t, we replace I_t in equation (B2) with a more general capital change variable, $KCHG_t$:

$$RK_t = \left(RK_{t-1} \frac{P_t}{P_{t-1}} + KCHG_t \right)(1-\delta). \tag{B3}$$

To derive a formula for the variable $KCHG_t$, we appeal to the accounting identities:

(B4) $$\Delta GPLANT_t = I_t + ACQUIS_t - RETIRE_t$$

(B5) $$\Delta NPLANT_t = I_t + ACQUIS_t - DEPR_t$$

where

$\Delta GPLANT_t$	=	the change in gross plant from year $t-1$ to year t;
$\Delta NPLANT_t$	=	the change in net plant from year $t-1$ to year t;
$ACQUIS_t$	=	acquisitions in year t;[1] and
$RETIRE_t$	=	retirements in year t.[2]

In the event of an acquisition, the change in capital, $KCHG_t$, equals $I_t + ACQUIS_t$.

Because Compustat does not have reliable figures for $ACQUIS_t$, we rearrange equation A4 to obtain:

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

(B7) $$\text{or } KCHG_t = \Delta GPLANT_t + RETIRE_t$$

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

(B8) $$KCHG_t = \Delta NPLANT_t$$

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

(B9) $$KCHG_t = I_t$$

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[1] According to the Compustat manual, acquisitions are defined as "cash outflow or funds used for, and/or costs relating to, acquisition of a company in the current year or effects of an acquisition in a prior year carried over to the current year."

[2] 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."

The task, now, is to derive 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, $\Delta GPLANT_t$ is normally less than I_t because of retirements. Therefore, if $\Delta GPLANT_t > I_t$ by a "substantial" amount, it signals an acquisition with a high probability. Second, $\Delta GPLANT_t$ is normally greater than $RETIRE_t$ because retirements are the only way to reduce $GPLANT_t$. Therefore, if $\Delta GPLANT_t < RETIRE_t$ 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 Salinger-Summers formula when there is clear evidence that this formula is misleading. In this case, if

$$\text{(B10)} \qquad \frac{\Delta GPLANT_t - I_t}{GPLANT_{t-1}} > 0.1,$$

then we assume an acquisition and set $KCHG_t = \Delta GPLANT_t + RETIRE_t$ from equation (B7). In contrast, if

$$\text{(B11)} \qquad \frac{\Delta GPLANT_t + RETIRE_t}{GPLANT_{t-1}} < -0.1,$$

then we assume a divestiture and $KCHG_t = \Delta NPLANT_t$ from equation (B8). If neither rule holds, we simply set $KCHG_t$ equal to I_t.

The second major extension to the algorithm deals with the measurement of depreciation. There are two potential problems associated with the depreciation rate calculated by Salinger and Summers. First, they assume that it follows a double declining balance yielding a depreciation rate $\delta = 2 / LIFE$. If this estimate of depreciation is too large, it could lead us to devalue the capital stock too quickly. An alternate (and commonly made) assumption is a single declining balance, or $\delta = 1 / LIFE$. This method, however, may be too extreme in the other direction. We use a depreciation rate of $\delta = 1.5 / LIFE$. This value makes the average depreciation rate we estimate for the Compustat sample similar to depreciation rates obtained from aggregate data.

The second problem that arises in this area is in the reported depreciation of firms which may be inconsistent with their *GPLANT* and *NPLANT* figures. This over-estimate of depreciation could again lead us to devalue the capital stock too quickly. To obtain an alternate measure of depreciation, subtract equation (B5) from equation (B4) to obtain:

(B12) $$\Delta GPLANT_t - \Delta NPLANT_t = DEPR_t - RETIRE_t$$

(B13) $$\text{or } DEPR_t = \Delta GPLANT_t - \Delta NPLANT_t + RETIRE_t$$

If RK_T (computed using the firm-supplied depreciation number) is *less* than $NPLANT_T$ where T is the maximum year for each firm, then the imputed depreciation rate is probably too large because the book value of *NPLANT* should be lower than the replacement value of capital in an inflationary environment. In this case, we compute an alternate RK_t series using the depreciation figures derived in equation A13 as long as the new RK_T is larger than the old one. If RK_T using the original method is *larger* than $NPLANT_T$, then we use it.

The third extension provides an efficient means to get the algorithm started. To implement the original algorithm, Salinger and Summers rely on pre-sample aggregate data to provide seed values for the firms' capital stock. We simply use the reported book value of net property, plant, and equipment (*NPLANT*) for the first observation of each firm. That is, if a firm's data starts in 1975, RK_{75} equals NPLANT in that year with each year thereafter computed using equation (B3) above.

Because the book value of NPLANT will usually be less than the replacement cost, the use of this seed value creates a distortion in the algorithm. This distortion will be offset, however, by several factors. First, any firm that is in the sample at the beginning of the dataset in the early seventies did not experience historically large inflation rates in the preceding years, so its book value's understatement of its replacement cost should be relatively small. Second, the capital stock of any new firm that enters the dataset thereafter is presumably new capital, so that, again, its book value should be fairly close to its replacement cost. In addition, even if there is a large difference between the actual and estimated initial replacement cost, any distortionary effect will decline over time as the initial capital depreciates away.