Panel Cointegration Estimates of the Effect of Interest Rates, Capital Goods Prices, and Taxes on the Capital Stock

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Abstract: The effect of interest rates, capital goods prices, and taxes on the capital stock is an issue of central importance in economics, with implications for monetary policy, business cycle models, tax policy, economic development, growth, and other areas. For more than 30 years it has been difficult to obtain precise estimates of these effects, and there is little consensus in the profession on their magnitude, despite their importance for both theory and policy. In this paper, we therefore turn to panel data, specifically a newly constructed data set with more than 50 years of firm-level data on the capital stock and with detailed industry-specific data on the interest rate, the price of investment goods, and tax parameters. Using this rich panel data set, we implement recently developed tests for cointegration in panel data. These tests allow us to determine whether the long-run implications of Jorgensonian neoclassical, q, irreversibility, and (s,S) theories are supported by the data. Using the same data, we then use recently developed panel cointegration estimators to assess the quantitative effect of the interest rate, capital goods prices, and taxes on the capital stock.

Keywords: investment, capital stock, user cost elasticity, interest rate, taxes, capital goods prices, panel cointegration

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1 Introduction

According to neoclassical growth theory, the capital stock is one of the main determinants of the long-run standard of living. In some versions of endogenous growth theory, the capital stock plays an even more important role by influencing the rate of economic growth.

According to standard economic theory, the long-run capital stock is determined by the interest rate, taxes, and capital goods prices. The quantitative magnitude of these effects is of crucial importance for many areas of economics, including monetary policy, business cycle models, tax policy, trade, economic development, and growth. Unfortunately, there is little consensus on the magnitude of these effects. For example, Chirinko (1993) concludes that "the response of investment to price variables tends to be small and unimportant relative to quantity variables," while Hassett and Hubbard (2002) conclude that the user cost elasticity is probably between -0.5 and -1.

Caballero (1994, 1999) and Schaller (2006) argue that there are serious problems in obtaining unbiased estimates of user cost elasticity from short-run movements in investment, as the great majority of the previous literature has tried to do. Empirical researchers are trying to estimate the elasticity of the demand for capital, but the equilibrium quantity and price depend on both supply and demand. At business cycle frequencies, there are substantial movements in demand. If the supply curve for capital is upward sloping in the short run, as we believe most supply curves are, econometric methods that emphasize high-frequency fluctuations in the data will tend to pick up movements along this supply curve, biasing the elasticity toward more positive values.

On the basis of these economic issues – and their implications for the appropriate econometric techniques – Caballero (1994, 1999) and Schaller (2006) argue that it will be possible to obtain better estimates of user cost elasticity by using low-frequency movements in the variables. To see this, note that shifts in the supply curve for capital are probably due primarily to technological change and productivity shocks, which tend to have persistent effects on the price of investment goods and the real interest rate, and tax reforms, which also tend to be relatively persistent. This implies that techniques that emphasize low-frequency movements will tend to trace out points on the demand curve for capital while techniques that emphasize high-frequency movements are more likely to trace out points on the supply curve.

There is a second problem with trying to estimate the elasticity from short-run movements in investment: economic theories make quite different predictions about investment dynamics.[1] However, a wide variety of theories predict the same long-run relationship between the capital stock and the components of user cost. Again, this suggests that better estimates can be obtained by using techniques that focus on low-frequency movements in the data.

One reason that we turn to panel data is the traditional one: more variation in the data is usually helpful in obtaining better estimates. In panel data, there is considerably more variation – both in the capital/output ratio and in interest rates, tax parameters, and capital goods prices – than in aggregate data. For example, the weighted average cost of

[1] In the neoclassical model without adjustment costs, the capital stock will respond immediately to shocks. In a Q model with convex adjustment costs, the transition path to the new steady state will depend on whether shocks are anticipated (or realized) and transitory (or persistent). In a model with irreversibility at the micro level, the estimated short-run elasticity at a higher level of aggregation will depend on the sequence of previous shocks and the cross-sectional distribution at a lower level of aggregation (e.g., at the plant level) of the gap between the desired and actual capital stock.

capital differs across firms because of differences in the relative importance of debt and equity and because of cross-sectional differences in risk. We do not want to emphasize the advantages of additional cross-sectional variation too heavily, however, because existing Monte Carlo evidence on panel cointegration estimators suggests that increases in N have only modest effects in reducing bias, relative to increases in T.[2]

A more important reason for our recourse to panel data is economic, rather than purely econometric. There are theoretical reasons for suspecting that user cost elasticity is more complex than a single production function parameter (as would be the case if all firms had Cobb-Douglas technology, capital markets were frictionless, and fixed adjustment costs never led to nonconvexities). For example, in a model with investment irreversibility, Bertola and Caballero (1994) show that there will be an "irreversibility premium" that will be added to the usual discount rate. We know very little about how large this irreversibility premium is and how it covaries with the observable market interest rate. By making cross-sectional comparisons, we may be able to get some understanding of how nonconvexities affect the long-run user cost elasticity. Similar issues arise from financial market imperfections. As Fazzari, Hubbard, and Petersen (1988) point out, asymmetric information can lead to a "lemons premium" that drives a wedge between the interest rate and the shadow cost of finance. Again, we know relatively little about the time series behaviour – or even the quantitative importance – of the lemons premium. Influential papers have argued that financial market imperfections are an issue of first-order importance for both macroeconomic fluctuations and economic

[2] See, e.g., Kao and Chiang (2000).

growth.[3] On the other hand, prominent papers have argued that there are serious flaws in the main existing evidence for important financial market imperfections (such as finance constraints).[4] Again, by using cross-sectional comparisons, we may be able to get a better understanding of how financial market imperfections affect the user cost elasticity and, more broadly, the accumulation of capital and economic growth.

In the empirical work, we make use of an unusually rich panel data set. In the econometrics of non-stationary variables, the time dimension of the data is of crucial importance. Our panel data covers the period 1954-2004 and includes firm-level data on the capital stock and output. To get a sense of how long this time dimension is for *panel* data, note that Caballero (1994) uses 31 years of data, while Schaller (2006) uses 38 years of data. Both of these studies use *aggregate* time series data. The firm-level data has been linked to industry-specific data on variables like prices, risk, taxes, and depreciation. The data includes the carefully constructed, firm-specific weighted average cost of capital, rather than an aggregate measure of the cost of capital. The firm-level cost of capital takes into account variation in risk using standard techniques from financial economics. In addition, careful attention has been paid to tax parameters (including industry-specific measures of the present value of depreciation allowances per dollar of capital spending), which are based on state-of-art work by Dale Jorgenson.

The paper uses recently developed econometric techniques for non-stationary panel data, including recently developed panel unit root tests, tests for cointegration in panel data, and panel cointegrating regression estimators. These techniques are discussed in more detail in the section on empirical results.

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[3] See, e.g., Bernanke and Gertler (1989) and Jermann and Quadrini (2003). {To be supplemented by additional references.}

[4] See, e.g., Kaplan and Zingales (1997), Gomes (2001), and Erickson and Whited (2000).

The estimated user cost elasticity is considerably higher than many of the previous estimates, which are largely based on high-frequency movements in the data. This is consistent with the econometric analysis and Monte Carlo evidence in Caballero (1994).

2 Review of Previous Estimates

2a Studies that emphasize high-frequency movements in the data

The great majority of previous estimates of user cost elasticity come from studies that emphasize high-frequency movements in the data. Within these studies, there is a tendency to find relatively low values of user cost elasticity. (Throughout this paper, we will use "low" to refer to user cost elasticities that are close to zero.) But there is also considerable variation in elasticity estimates based on these types of studies. For example, Cummins and Hassett (1992) obtain an estimate of slightly more than -1 using US firm-level data. In contrast, Chirinko, Fazzari, and Meyer (1999) obtain a preferred elasticity of about -0.25, again using US firm-level data.[5] Clark (1993) finds an estimated elasticity of -0.01 using aggregate US data, while Tevlin and Whelan (2003) estimate the user cost elasticity at -0.18, also using aggregate US data. In a slightly different type of study, Goolsbee (2000) finds that a 10% investment tax credit raises investment by about 4 to 5%, using US data that is differentiated by the type of asset. Using aggregate data for Japan, Kiyotaki and West (1996) obtain an estimate of -0.05 to -0.07.

[5] When the same authors try to avoid the problems with econometric methods that emphasize high-frequency variation in the data (but without estimating the cointegrating relationship), they obtain a slightly larger elasticity estimate of -0.4. See Chirinko, Fazzari, and Meyer (2001).

2b Studies that emphasize low-frequency movements in the data

Studies that are based on the cointegrating relationship between the capital stock and user cost tend to emphasize low-frequency movements in the data. The pioneering study of this type is Caballero (1994), which obtained an estimate of about -0.9 using aggregate US data for equipment capital. Using data from a small, open economy (Canada) and Dynamic OLS (DOLS), Schaller (2006) obtains a preferred estimate of -1.42 for equipment and 0 for structures. Like Caballero (1994), Schaller (2006) uses aggregate data.

The only previous study that estimates the cointegrating relationship between the capital stock and user cost using disaggregated data is Caballero, Engel, and Haltiwanger (1995), which uses data for 20 two-digit SIC industries. Unlike our paper, however, they do not treat the time-series-cross-sectional data as a panel. (In all probability, this is because the first papers describing panel cointegration estimators were published after their work.) Instead, they treat each industry as an individual time series. Using this approach, they obtain estimates that range from -0.01 for transportation to -2.0 for textiles.[6] The wide dispersion of estimated elasticities across industries is striking. In this paper, we test several explanations that might account for differences in user cost elasticity across different types of firms.

3 Data

The capital stock is constructed using a standard perpetual inventory method and is based primarily on firm-level financial statement data from CompuStat. Output is

[6] Interestingly, when they estimate the corresponding short-run elasticities, they obtain estimates that are much smaller, typically only one-tenth of the corresponding long-run elasticity estimated using the cointegrating relationship.

calculated using firm-specific sales data from CompuStat. This firm-specific data is linked with Bureau of Economic Analysis data that we use to construct sector-specific, time-varying depreciation rates and capital goods price indexes.

User cost is calculated as follows

$$\tilde{R}_{f,t} = (r_{f,t} + \delta_{s,t})\left(\frac{1 - z_{s,t} - u_{s,t}}{1 - \tau_t}\right)\frac{p_{s,t}^K}{p_{s,t}^Y} \quad (1)$$

where r is the real, risk-adjusted interest rate, z is the sector-specific present value of depreciation allowances, u is the sector-specific investment tax credit rate, τ is the corporate tax rate, p^K is the price of capital goods, and p^Y is the price of output. The data on z were provided by Dale Jorgenson.

The real interest rate is calculated using a weighted average of the costs of debt and equity (with sector-specific leverage ratios). We adjust for differences in risk using a standard CAPM technique (with sector-specific CAPM βs).

In general, the data is of very high quality because it comes directly from firms' financial statements, but our work and the previous literature have identified certain instances in which data problems can arise. We deal with this in two ways. First, our own careful analysis of the data showed that there are more frequent data problems with extremely small firms, so firms with initial book value of capital of less than $1,000,000 are omitted. Second, consistent with other papers that use firm-specific panel data, we trim extreme observations as a way of removing data that is contaminated by accounting problems (e.g., those that arise from acquisitions) and reporting errors.

Further details are provided in the Data Appendix.

Table 1a reports summary statistics for the full sample. The time span of the data is important for low-frequency econometrics. We therefore report some results for subsamples of firms for which we have long spans of continuous data. Table 1b reports summary statistics for firms that have at least 40 years of continuous data.

4 Cointegrating Relationship

Suppose that

$$k_t = \alpha_0 + \alpha_R R_t + z_t \quad (2)$$
$$\Delta R_t = u_{2t}$$

where k is the log capital/output ratio, R (=ln $\tilde{R}$) is the log of user cost, and z and u_2 are stationary.[7] [8] The variables k and R will then be cointegrated.

Cointegration between k and R is a good description of the data. First, Levin-Lin-Chu (2002) panel unit root tests suggest unit roots in both k and R, as shown in Table 2. The Levin-Lin-Chu test is a one-sided test, so a sufficiently large negative value of t* would lead to rejection of the null hypothesis of a unit root. In fact, in our data, the p-value is 1.00 for both k and R, so there is no evidence against the existence of a unit root. We focus on the Levin-Lin-Chu test because it is very popular, but it does not allow for cross-sectional dependency. We therefore also report the results of a second panel unit root test [Chang (2004)], which allows for cross-sectional dependency. As shown in Table 3, the results are very similar, yielding p-values of 1.00 for the null hypothesis of a unit root for both k and R.

[7] As discussed by Caballero (1999, p. 816-821), this relationship can be obtained by solving the firm's problem (under the consumption of Cobb-Douglas technology) for the frictionless capital stock and then relaxing the unit user cost elasticity constraint.
[8] To keep the notation simple and straightforward, we only include the time subscript (suppressing the firm subscript) in this section and the next section (where we provide intuition for small sample bias and how dynamic OLS reduces the bias).

Second, panel cointegration tests show that k and R are cointegrated. We consider three different panel cointegration tests that have been proposed by Kao (1999) – the Kao Dickey-Fuller test, the Kao Phillips-Perron test, and the Kao Augmented Dickey-Fuller test. As shown in Table 4, all three tests strongly reject the null hypothesis of no cointegration.

5 Econometric Issues

5a Small sample bias

Asymptotically, Static OLS (SOLS) yields consistent estimates of the coefficients in the cointegrating regression. (SOLS is OLS estimation of a cointegrating relationship.) In the presence of adjustment frictions, however, SOLS will tend to produce biased estimates. Analytical results in Caballero (1994) show that SOLS could be downward biased (i.e., biased towards 0) in time series data by 50 to 60% for a sample of 120 observations and 70 to 80% for a sample of 50 observations, if adjustment frictions are important. There are no analytical results, Monte Carlo simulations, or empirical evidence on the bias of SOLS in panel data in situations where adjustment frictions are important.

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

$$k_t^* = \alpha_R R_t \quad (3)$$

(For convenience, we ignore the constant term and explain the intuition for a single time series.) Adjustment frictions (broadly defined) will cause a gap z_t between the actual capital stock k_t and the frictionless capital stock. Thus the actual capital stock will be equal to the frictionless capital stock plus z_t:

$$k_t = \alpha_R R_t + z_t \quad (4)$$

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

$$\text{var}(k) = \text{var}(k^*) + \text{var}(z) + 2\,\text{cov}(k^*, z) \quad (5)$$

so the variance of k can be smaller than the variance of k^* only if cov(k^*,z) is negative. However, the OLS estimates of k^* and z (i.e., $\hat{k}^* = \hat{\alpha}_R R$ and $\hat{z} = k - \hat{\alpha}_R R$) are orthogonal by construction, which implies $\text{var}(\hat{k}^*)$ is less than var(k). In order to achieve this, OLS will tend to bias the estimate of α_R toward 0.[9]

5b Dynamic OLS

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

$$\begin{aligned}\text{cov}(R_t, z_t) &= \text{cov}(R_0 + \Delta R_1 + \Delta R_2 + \ldots + \Delta R_t, z_t) \quad (6)\\ &= \text{cov}(u_{21} + u_{22} + \ldots + u_{2t}, z_t)\end{aligned}$$

One solution to the problem of small sample bias in SOLS is the DOLS estimator proposed by Stock and Watson (1993).[10] Dynamic OLS (DOLS) addresses the problem of finite sample bias by replacing the original error term z by a new error term v, which is constructed to be orthogonal to R. The intuition is straightforward. OLS projects the

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

[10] Kao and Chiang (2000) provide the panel cointegration DOLS counterpart to the original Stock and Watson (1993) DOLS estimator.

dependent variable onto the space spanned by the right hand side variables. The remaining variation in the dependent variable is orthogonal to the right hand side variables. Suppose z were projected onto the space spanned by all leads and lags of ΔR (which is equivalent to the space spanned by u_2). The error term v_t from this regression will be orthogonal to R_s since:

$$\operatorname{cov}(R_s, v_t) = \operatorname{cov}(R_0 + \Delta R_1 + ... + \Delta R_s, v_t) = 0 \quad (7)$$

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

In practice, it is not possible to include all leads and lags of ΔR_t in the regression. Instead, a finite number p are included, resulting in the following empirical specification:

$$k_t = \alpha_0 + \alpha_R R_t + \sum_{s=-p}^{p} \beta_s \Delta R_{t-s} + \varepsilon_t \quad (8)$$

6 Estimates of the User Cost Elasticity

As noted above, the time dimension is of important in estimating the cointegrating regression. In this section, we therefore focus on a sample of 209 firms for which we have at least 40 years of continuous data. The first column of Table 5 presents SOLS estimates of user cost elasticity for this panel. The estimated elasticity is close to 0 (and insignificantly different from 0). The second column of Table 5 presents the DOLS estimate of user cost elasticity (for p=1). The DOLS estimate is -0.827. Clearly, this is a dramatically different estimate from the SOLS estimate, consistent with our analysis of the SOLS bias toward 0.

The DOLS estimate provides support for the relatively high estimates of user cost elasticity obtained by Caballero (1994) and Schaller (2006). As noted above, their estimates were based on aggregate data. Our study is the first to estimate the cointegrating relationship between capital stock and user cost using panel data.

In explaining the intuition for why DOLS tends to yield less biased estimates, we discuss the case where all leads and lags of ΔR_t are included in the empirical specification to illustrate how this guarantees the orthogonality of R_t and ε_t, the error term in the regression. In Table 5, however, we set p=1, so only one lead and lag of ΔR_t are included. Table 6 shows that the elasticity estimate is reasonably robust to other choices of p. If anything, setting p=1 leads to a relatively conservative estimate of user cost elasticity.

7 Financial Market Imperfections and User Cost Elasticity

Figure 1 presents a simplified diagram of the supply and demand of finance for a firm that faces a binding finance constraint.[11] Under asymmetric information, there may be a difference between the cost of internal finance (the opportunity cost; i.e., the interest rate at which the firm lends) and the cost of external finance, leading to a step function in the supply of finance with the step at the point where the firm exhausts its internal finance. If the firm's demand for finance intersects the supply of finance along this step, there will be a wedge between the observable market interest rate r and the shadow cost of finance $r+\omega$.

[11] The diagram is adapted from Fazzari, Hubbard, and Petersen's (1988) classic paper on finance constraints. It is strictly applicable only to a one-period model where investment is the same as the capital stock but provides helpful intuition for the more general case.

Relatively little is known about ω. In fact, there has been an extensive debate over the evidence on the existence of finance constraints. Fazzari, Hubbard, and Petersen (1988) and a series of subsequent papers used differences across classes of firms in the coefficient on cash flow in a Q investment equation as evidence of finance constraints. This line of research has been criticized by Kaplan and Zingales (1997), Erickson and Whited (2000), and Gomes (2001), among others.

If ω is small, it should make little difference to the estimated user cost elasticity.[12] Moreover, finance constraints might only be relevant for young firms – for example, in the first few years of their existence. More generally, if shocks to ω are transitory, they will have little effect on the long-run elasticity estimated from the cointegrating regression, even for firms that were constrained in some years. Finally, the effect of finance constraints on the estimated user cost elasticity depends on the covariance between ω and R.

One possibility is that shocks to ω and R are orthogonal. In this case, there will be an errors-in-variables problem with R, since the true discount rate will be the shadow cost of external finance $r+\omega$, but the econometrician will use the observed market interest rate r in calculating user cost. In general, the errors-in-variables problem will tend to bias the estimated elasticity toward 0.

A second possibility is suggested by the work of Bernanke, Gertler, and Gilchrist (1996). They argue that changes in the interest rate (e.g., induced by monetary policy) will have larger effects when there are financial market imperfections. This could mean that the covariance between ω and r is positive. In this case, k would move more for

[12] Direct estimates of ω by Whited (1992), Ng and Schaller (1996), and Chirinko and Schaller (2004), however, suggest that it may be substantial for some firms – on the order of several hundred basis points.

finance constrained firms than if only the conventional user cost effects were present. This could lead to a larger estimated elasticity for constrained firms than unconstrained firms.

Our approach is to compare user cost elasticity across classes of firms, focusing on classes of firms that are more likely to be finance constrained. Most of the classes are based on persistent firm characteristics. For example, young firms are defined as firms that have not been in the sample for more than two years before the beginning of the 20 years of continuous data. (Thus, they are not very young firms, only relatively young firms.) Firms are finance constrained if they have good investment opportunities but not enough internal finance (or access to external finance) to be able to carry out their investment projects. We use the firm's Tobin's Q to measure investment opportunities, averaging Tobin's Q over the 20 years for which data are continuously available. One exception to the use of persistent characteristics is size, where we use the firm's size at the end of the 20 years of continuous data.

In all cases, we construct balanced panels with 20 years of data for each class of firms. One reason for doing this is because of the potential for small sample bias when we use only 20 years of data.[13] By maintaining a consistent time dimension across subsamples, we ensure that we will induce no difference in the estimated elasticity between classes of firms through differential small sample bias.

Table 7 presents estimates of user cost elasticity for all firms for which we have 20 years of continuous data. As in Table 6, the estimated elasticity is reasonably similar

[13] In fact, a comparison of Tables 6 and 7 suggests that there may be some small sample bias in estimating user cost elasticity using subsamples with a time dimension of 20 years. The estimates in Table 6 are based on a subsample of firms with 40 years of continuous data and the elasticity is larger with this longer time dimension.

regardless of the choice of p. In subsequent tables, we therefore report estimates for p = 3.

Table 8 presents user cost elasticity estimates for several classes for firms that are more likely to be finance constrained – including young firms, small firms, and firms with good investment opportunities. The elasticity for young firms is roughly the same as for all firms. The same is true for small firms. Firms with good investment opportunities have a higher estimated user cost elasticity. We are reluctant to draw strong conclusions based on the small differences in estimated elasticity in Table 8. However, we can say that there is certainly not strong evidence for the possibility that the existence of finance constraints introduces a persistent errors-in-variables problem into measured user cost which causes the elasticity estimate to be biased toward 0 for finance constrained firms. The results for firms with good investment opportunities provide mild support for the financial accelerator view.

8 Corporate Governance and User Cost Elasticity

Corporate governance problems can also introduce a wedge between the observed market interest rate and the discount rate used by a firm. To see the intuition for this, consider an empire building manager whose utility function puts some weight on the size of his firm and some weight on the firm's profit. Chirinko and Schaller (2004) have shown that such a manager will use a lower discount rate in evaluating investment projects. Specifically, such a manager will set the marginal product of capital (in the absence of taxes, which we ignore for simplicity) as follows.

$$F_K = r - \frac{\gamma}{\beta}\frac{\pi}{K} + \delta = r - \phi + \delta$$

where F_K is the marginal product of capital, γ is the weight on size in manager's utility function, β is the weight on profit (π) in manager's utility function, and the other variables have already been defined in equation (1). Since γ, β, and K are positive, corporate governance problems will introduce a "corporate governance discount" ϕ (for $\pi > 0$). The corporate governance discount will be larger, the larger the weight on size in the manager's utility function and the smaller the weight on profit.

Little is known about the magnitude of the corporate governance discount.[14] Nothing is known about the persistence of ϕ and its covariance with user cost. To the best of our knowledge, there is no counterpart to the financial accelerator for the corporate governance discount. If ϕ is sufficiently large, less than perfectly correlated with r, and persistent, the errors in variables problem could be substantial, and estimates of user cost elasticity may be biased toward 0.

Based on Jensen (1986), the firms that are most likely to suffer from corporate governance problems are those with high free cash flow and poor investment opportunities. Table 9 presents user cost elasticity estimates for firms with high free cash flow and poor investment opportunities, where investment opportunities are measured by Tobin's Q.[15] The firms that are likely to have corporate governance problems (-0.204) have a substantially lower estimated user cost elasticity than all firms (-0.618).

The model in Chirinko and Schaller (2004) shows that firms require some degree of market power in order to give reign to corporate governance problems (i.e., to have

[14] To the best of our knowledge, the only direct estimates of ϕ are provided by Chirinko and Schaller (2004), whose estimate is in the range of 300 to 400 basis points.
[15] Specifically, we classify firms as having poor investment opportunities if Tobin's Q is below the median for their industry.

non-zero ϕ). At this point, we do not have data on the market power of the firms in our sample, but we can compare firms that are likely to have corporate governance problems (i.e., firms with high free cash flow and low Q) that are also large firms with all firms that are likely to have corporate governance problems. In fact, the elasticity estimate is lower for the large firms (-0.164), despite the fact that size is a highly imperfect measure of market power.

Overall, these preliminary results suggest that the corporate governance discount may be significant (and that ϕ may be both imperfectly correlated with r and persistent).

9 Non-convex Adjustment Costs and User Cost Elasticity

Bertola and Caballero (1994) show that there will be a wedge between the market interest rate and the discount rate used by firms when investments in capital stock are irreversible. They derive the following condition for the optimal capital stock in the presence of non-convex adjustment costs (specifically, irreversibility).

$$F_K = r + \frac{1}{2}\Sigma^2 A + \delta = r + \theta + \delta$$

where Σ^2 is a variance (specifically, of the ratio of the state of demand/technology Z to the price of capital goods P, in their notation) and A is a non-negative scalar. Thus, in the presence of non-convex adjustment costs, there is an "irreversibility premium" θ that increases the discount rate used by firms in choosing their desired capital stock.

Little is known about the magnitude of θ, its covariance with r, or its persistence. However, if θ is sufficiently large, not too strongly correlated with r, and persistent, the estimated user cost elasticity may be biased towards 0.

The literature on irreversible investment suggests several characteristics that make it more likely that firms will encounter a binding irreversibility constraint. Two of the most important are the drift rate of the stochastic process for Z and the depreciation rate. A low drift rate means that a firm that inadvertently acquires too much capital will find it difficult to grow out of the problem. In contrast, a firm with rapid growth in demand for its product is less likely to encounter a binding irreversibility constraint and far less likely to encounter a persistently binding constraint. The depreciation rate works in a similar way. If a firm's capital stock depreciates rapidly, a shock that leaves it with too much capital will quickly be overcome by depreciation of the capital stock.

We use two characteristics to identify firms that are more likely to encounter persistent binding irreversibility constraints. First, we use the mean growth rate of real sales over the 20 years of continuous data as our measure of the drift rate. We classify firms with real sales growth below the median for the sample as low drift rate firms. Similarly, we divide firms into classes based on the mean depreciation rate over our sample period; firms with a mean depreciation rate below the median for the sample are classified as low depreciation firms.

As shown in Table 10, the results are dramatic. The estimated user cost elasticity for firms with a low drift parameter is close to 0 (-0.036). The same is true for firms with a low depreciation rate. Their estimated user cost elasticity is 0.051.

The results suggest that non-convex adjustment costs are important, that the covariance of θ and r is small, and that shocks to θ are persistent.

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Data Appendix

Capital Stock and Investment

For the first observation for firm f, the capital stock is based on the net plant (NPLANT), the nominal book value of net property, plant, and equipment (CompuStat item 8). To convert this to real terms, we divide by the sector-specific price index for capital goods (p^K). Since book value is not adjusted for changes in the value of capital goods purchased in the past, we adjust the initial capital stock using the sector-specific ratio of nominal replacement cost to historical cost:

$$K_{f,t_0^f} = \frac{NPLANT_{f,t_0^f}}{p^K_{s,t_0^f}} \frac{K\$_{s,t_0^f}}{KHIST_{s,t_0^f}} \qquad \text{(A1)}$$

where K$ is the current cost net stock of private fixed assets by sector, KHIST is historical-cost net stock of private fixed assets by sector, s is a NAICS sector index (for firm f's sector), and t_0^f is the year of the first observation for firm f.

For subsequent observations, a standard perpetual inventory method is used to construct the capital stock,

$$K_{f,t+1} = (1-\delta_{s,t})K_{f,t} + \frac{I_{f,t+1}}{p^K_{s,t+1}} \qquad \text{(A2)}$$

where δ is the depreciation rate and I is capital expenditures in the firm's financial statements (CompuStat item 128). The firm reports the additions in nominal terms, so we divide by p^K to convert to real terms.

In some cases, there is a data gap for a particular firm. In this case, we treat the first new observation for that firm in the same way as we would if it were the initial observation. This avoids any potential sample selection bias that would result from dropping firms with gaps in their data.

We construct sector-specific, time-varying depreciation rates using data from the BEA. Specifically,

$$\delta_{s,t} = \frac{D\$_{s,2000} DQUANT_{s,t}}{K\$_{s,2000} KQUANT_{s,t}} \qquad \text{(A3)}$$

where D$ is current-cost depreciation of private fixed assets by sector (BEA, Table 3.4ES), DQUANT is the chain-type quantity index of depreciation of private fixed assets by sector (BEA, Table 3.5ES), K$ is the current cost net stock of private fixed assets by sector (as defined above), and KQUANT is the chain-type quantity index of the net stock of private fixed assets by sector (BEA, Table 3.2ES).

We construct the sector-specific price index for capital goods using BEA data:

$$p^K_{s,t} = \frac{100(I\$_{s,t} / I\$_{s,2000})}{IQUANT_{s,t}} \qquad \text{(A4)}$$

where I$ is historical-cost investment in nonresidential private fixed assets by sector (BEA, Nonresidential Detailed Estimates: Investment, historical cost) and IQUANT is the chain-type quantity index of investment in private fixed assets by sector (BEA, Table 3.8ES).

After constructing the capital stock, firms with a value of GPLANT less than $1 million are dropped, where GPLANT is gross property, plant, and equipment (CompuStat item 7), and the first observation for each firm is excluded. We then trim the sample, eliminating the 1% most extreme observations in each tail for the following four variables: I/K, Sales/K, Cost/K, and real sales growth.

Cost of Capital

The cost of capital is calculated as follows

$$R_{f,t} = (r_{f,t} + \delta_{s,t})\left(\frac{1 - z_{s,t} - u_{s,t}}{1 - \tau_t}\right)\frac{p^K_{s,t}}{p^Y_{s,t}} \qquad \text{(A5)}$$

where *r* is the real, risk-adjusted interest rate, *z* is the sector-specific present value of depreciation allowances, *u* is the sector-specific investment tax credit rate, τ is the corporate tax rate, p^K is the price of capital goods, and p^Y is the price of output. *R* is expressed as an annual rate, so *r* and δ are both expressed as annual rates. Where variables are available at a monthly or quarterly frequency, we take the average for the calendar year. The corporate tax rate is the U.S. federal tax rate on corporate income. The present value of depreciation allowances – for non-residential equipment and structures, respectively – were provided by Dale Jorgenson. (The data provided by Dale Jorgenson end in 2001: for 2002-04, we use 2001 values.) To calculate z, we took the weighted sum of Jorgenson's z's for equipment and structures, where the weights are the share of equipment investment and the share of structures investment (for a given year) in nominal gross private non-residential investment in fixed assets from the Bureau of Economic Analysis (from table 1IHI, where equipment investment is referred to as equipment and software). Because the investment tax credit applies only to equipment, *u*=0 for structures, we multiply the statutory ITC rate for each year by the ratio of equipment investment to the sum of structures and equipment investment for that year. The corporate tax rates were provided directly by the Treasury Department, and investment tax credit rates are drawn from Pechman (1987, p.160-161). The sector-specific price index for output is the "Chain-Type Price Index for Value Added by Industry" from the BEA GDP-by-Industry Accounts, normalized to 1 in 2000.

The Real Risk-Adjusted Market Discount Rate

The real, risk-adjusted market discount rate is defined as follows,

$$r_{f,t} = ((1+r^{NOM}_{f,t}) / (1+\pi^e_t)) - 1.0. \qquad \text{(A6)}$$

The equity risk premium is calculated using CAPM. The components of $r_{f,t}$ are defined and constructed as follows,

$r_{f,t}^{NOM}$ = Nominal, short-term, risk-adjusted cost of capital

= $\lambda_s (1-\tau_t)\ r_t^{NOM,DEBT} + (1-\lambda_s)\ r_{s,t}^{NOM,EQUITY}$.

$r_t^{NOM,DEBT}$ = Nominal corporate bond rate (Moody's Seasoned Baa Corporate Bond Yield)

$r_{s,t}^{NOM,EQUITY}$ = Nominal, short-term, risk-adjusted cost of equity capital for firms in sector s.

= $r_t^{NOM,F} + \sigma_s$.

$r_t^{NOM,F}$ = Nominal, one-year, risk-free rate (One-Year Treasury Constant Maturity Rate)

$\pi_{s,t}^{e}$ = Sector-specific capital goods price inflation rate from t to t+1. Sector-specific data was not yet available for 2005 at the time of data construction, so $\pi_{s,t}^{e}$ for 2003 was also used for 2004.

σ_s = Equity risk premium.

τ_t = Marginal rate of corporate income taxation.

λ_s = Sector-specific leverage ratio calculated as the mean of book debt for the sector divided by the mean of (book debt + book equity) for the sector. In two sectors (Fabricated Metal Product Manufacturing, NAICS industry 332, and Broadcasting and Telecommuniations, NAICS industries 515-517), book equity is negative, so we set λ_s to 1.

Under the CAPM,

$$\sigma_s = \beta_s (\mu^{EQUITY} - \mu^{F}), \qquad \text{(A7)}$$

where

β_s = CAPM β for sector s

μ^{EQUITY} = Total return on equities from 1950-2004. The source is the value-weighted CRSP index (including dividends).

μ^F = Total return on risk-free Treasury bills from 1950-2004. The source is the FRED database, specifically the series for 1-Year Treasury Constant Maturity Rate.

Table 1a
Summary Statistics – Full Sample

	Mean	Median	Standard Deviation	Skewness	Kurtosis
kr	1138.041	57.872	5290.592	14.509	321.373
yr	1398.936	159.867	6344.198	15.197	340.104
kryr	1.208	0.401	6.537	333.133	128443.312
$\tilde{R}$	0.074	0.067	0.049	2.450	18.604
ct	0.421	0.421	0.109	0.733	2.197
cp	1.159	1.068	0.609	3.348	38.389
cr	0.163	0.159	0.071	0.531	0.806
yrg	0.114	0.063	0.314	3.006	17.815
krg	0.100	0.044	0.196	3.336	16.106

The variable kr is the replacement value of the capital stock, measured in millions of 1996 dollars, yr is output measured in millions of 1996 dollars, kryr is the ratio kr/yr, $\tilde{R}$ is user cost, ct is the tax component of user cost (the second term in parentheses in equation (1)), cp is the price of capital goods component (the third term in parentheses in equation (1)), cr is the interest rate component (the first term in parentheses in equation (1)), yrg is the growth rate of yr, and krg is the growth rate of kr.

Table 1b
Summary Statistics – Firms with At Least 40 Years of Continuous Data

	Mean	Median	Standard Deviation	Skewness	Kurtosis
kr	3793.850	718.395	11383.967	7.894	82.350
yr	5417.892	1650.594	13129.286	7.511	79.461
kryr	0.845	0.434	1.238	4.083	21.707
$\tilde{R}$	0.067	0.065	0.038	1.210	5.347
ct	0.423	0.421	0.097	0.693	2.406
cp	1.197	1.131	0.537	1.634	8.956
cr	0.138	0.135	0.053	0.127	0.551
yrg	0.067	0.053	0.179	2.437	20.365
krg	0.063	0.046	0.095	3.345	26.214

The variable kr is the replacement value of the capital stock, measured in millions of 1996 dollars, yr is output measured in millions of 1996 dollars, kryr is the ratio kr/yr, $\tilde{R}$ is user cost, ct is the tax component of user cost (the second term in parentheses in equation (1)), cp is the price of capital goods component (the third term in parentheses in equation (1)), cr is the interest rate component (the first term in parentheses in equation (1)), yrg is the growth rate of yr, and krg is the growth rate of kr.

Table 2
Levin-Lin-Chu Test Results for Unit Root

Variable	Parameter	t*	P>t
k	-0.0834	95.607	1.000
R	-0.6213	47.587	1.000

Table 3
Chang Test Results for Unit Root

Variable	Test	P>t
k	-1.201	1.000
R	0.736	1.000

Table 4
Tests for Cointegration

DF Test	P>t	PP Test	P>t	ADF Test	P>t
-35.263	0.000	-3.345	0.000	21.088	0.000

DF Test is the Kao Dickey-Fuller test, PP Test is the Kao Phillips-Perron test, and ADF Test is the Kao Augmented Dickey-Fuller test.

Table 5
SOLS Estimate of User Cost Elasticity

SOLS Estimate	DOLS Estimate
-0.0031 (-0.287)	-0.827 (-75.895)

The main entry in the cell is the SOLS estimate of user cost elasticity. The t-statistic is in parentheses under the elasticity estimate. The DOLS estimate is for p=1.

Table 6
DOLS Estimates of User Cost Elasticity for Different Values of p
Subsample with 40 years of continuous data

p	DOLS Estimate
1	-0.827 (-75.895)
2	-0.8885 (-76.746)
3	-0.941 (-76.965)
4	-0.957 (-73.567)

The first column reports p, the number of leads and lags of first differences of the right-hand-side variable (user cost) used in DOLS estimation. The main entries in the cells of the second column are the DOLS estimate of user cost elasticity. The t-statistic is in parentheses under the elasticity estimate.

Table 7
DOLS Estimates of User Cost Elasticity for Different Values of p
Subsample with 20 years of continuous data

p	DOLS Estimate
1	-0.827 (-75.895)
2	-0.888 (-76.746)
3	-0.941 (-76.965)
4	-0.957 (-73.567)

The first column reports p, the number of leads and lags of first differences of the right-hand-side variable (user cost) used in DOLS estimation. The main entries in the cells of the second column are the DOLS estimate of user cost elasticity. The t-statistic is in parentheses under the elasticity estimate.

Table 8
Finance Constraints and User Cost Elasticity

Class	N	DOLS (t-statistic)
Young	455	-0.596 (-18.43)
Small	1660	-0.631 (-34.01)
Good investment opportunities	1046	-0.748 (-33.62)

Table 9
Corporate Governance and User Cost Elasticity

Class	N	DOLS (t-statistic)
High free cash flow and poor investment opportunities	218	-0.204 (-4.91)
High free cash flow and poor investment opportunities and large	56	-0.164 (-2.44)

Table 10
Non-convex Adjustment Costs and User Cost Elasticity

Class	N	DOLS (t-statistic)
Low drift parameter	1041	-0. 036 (-1.85)
Low depreciation rate	882	0.051 (2.91)

Figure 1
Finance Constraints and the Lemons Premium