Using Consumer Theory to Test Competing Business Cycle Models

Mark Bils

University of Rochester and National Bureau of Economic Research

Peter J. Klenow

University of Chicago and National Bureau of Economic Research

Consumer theory suggests that expenditures on luxuries and durables should be more cyclical than expenditures on necessities and nondurables. Estimating luxuriousness and durability for 57 consumer goods, we confirm this prediction in U.S. data. We exploit this finding to test predictions of cyclical utilization and increasing returns models of business cycles. Both models predict more cyclical productivity for durable luxuries, a prediction borne out in the data. The utilization model predicts procyclical relative prices for durables and luxuries; the increasing returns model does not. Prices are more procyclical for durables and luxuries, discriminating in favor of cyclical utilization.

I. Introduction

Since Kydland and Prescott (1982), many researchers have given a central role to technology shocks in business cycles. The size and persistence of such shocks have often been estimated from observed changes in productivity. But Jorgenson and Griliches (1967) and

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many others argue that cyclical productivity reflects unmeasured cyclical utilization of capital and labor rather than changes in technology. Still another interpretation of cyclical productivity holds that it reflects increasing returns. Recently, a number of authors have incorporated increasing returns into business cycle models (e.g., Baxter and King 1991; Farmer and Guo 1994).[1]

We test for both cyclical utilization and increasing returns in the production of consumer goods. Consumer theory predicts a shift in expenditures toward consumer durables and luxuries in a boom. We use the U.S. Consumer Expenditure Surveys to estimate "Engel curves"—elasticities of expenditure with respect to a household's total nondurable consumption—for each of 57 consumer goods. This measure tells us how consumers wish to shift consumption across goods when their total consumption increases. We estimate durability across the same 57 goods from the depreciation rates employed by a major U.S. insurance company to honor claims for destroyed or stolen property. We construct an instrument for shifts in relative industry output by interacting our industry measures of durability and Engel curves with aggregate growth in nondurable consumption. For these 57 goods, we then examine the cyclical behavior of productivity, prices, and output for the period 1958–91 using industry data derived from the U.S. Annual Survey of Manufactures.

Our identifying assumption is that the aggregate business cycle is uncorrelated with any relative technology shock with respect to producing durables versus nondurables or luxuries versus necessities. We do allow for aggregate and industry-specific technology shocks. We also allow the aggregate shocks to have differential impact across industries, provided that the pattern of these differences is not related to durability or luxuriousness.

In Section II we begin by describing a baseline model with constant returns to scale and a fixed rate of capital utilization. We then extend the model to allow first for procyclical utilization of capital and then for increasing returns in production. We formally show each model's predictions for the cyclicality of output, total factor productivity (TFP), and prices across consumer goods industries.

The constant-returns, constant-utilization model implies no cyclical increase in relative TFP for durables and luxuries. By contrast,

[1] Shapiro (1993), using data on the workweek of capital, finds evidence of important procyclical movements in capital utilization. The empirical evidence on increasing returns is limited. Hall (1988) finds supporting evidence, but modifications of his work by Basu and Fernald (1997) and others result in smaller estimates of returns to scale.

the models with cyclical capital utilization and increasing returns do. Consider the model with cyclical capital utilization. As an industry hires more labor, it becomes optimal to expand the hours of capital use. The TFP measures that do not adjust for capital utilization will be procyclical, and particularly so for the highly cyclical industries producing durables and luxuries. This model further predicts that durable and luxury industries will display a relative price increase in booms. The model with increasing returns also features procyclical TFP, again most strongly for the durable and luxury industries. If increasing returns are sufficiently strong, the relative prices of the more cyclical durable luxuries will not rise (and could even fall) in an expansion—a prediction opposite that of the utilization model.

In Section III we describe our data on consumer expenditures and present our values for each good's durability and each good's Engel curve with respect to nondurable consumption. In Section IV we describe the industry data and present the model estimates.

Our primary findings are as follows. Prices and TFP are more procyclical for goods that are more durable and that are luxuries. For instance, a 1 percent cyclical increase in an industry's labor/capital ratio relative to other industries, induced by greater luxuriousness or durability, is associated with a statistically very significant 0.23 percent increase in TFP. This finding favors the cyclical utilization and increasing returns models over the standard model with constant returns and fixed capital utilization. Second, a 1 percent cyclical increase in an industry's relative labor/capital ratio induced by greater luxuriousness or durability is associated with a statistically significant increase in that good's relative price of 0.22 percent. The joint behavior of TFP and prices is very consistent with the model of procyclical utilization. The joint behavior of TFP and prices, strictly speaking, does not formally reject models with increasing returns to scale. But the procyclicality of relative prices for durables and luxuries argues against any substantial increasing returns.

II. Competing Models of Cyclical Output, Productivity, and Prices

We begin with a general model that nests three models of business cycles based on, respectively, constant returns and fixed capital utilization, procyclical capital utilization, and increasing returns. We then describe the restrictions that reduce the general model to each of the three models. For each model we analytically characterize the cyclical behavior of output, productivity, and prices across industries.

Households consume and work, maximizing expected discounted utility

$$E_0\left\{\sum_{t=0}^{\infty} \beta^t \sum_{i=1}^{M} \left\{\frac{c_t(i)^{1-[1/\sigma(i)]}}{1-[1/\sigma(i)]} - \lambda n_t(i) s_t(i)^{\phi}\right\}\right\}, \tag{1}$$

where M is the number of consumer good varieties, $c(i)$ is consumption of good i, $n(i)$ is hours worked in industry i, $s(i)$ is the shift schedule in industry i, and a period is 1 year.

The luxuriousness of good i is determined by $\sigma(i)$. Consider food (a low-σ good by our estimates) and furniture (a high-σ good). Food's lower σ implies that its share of consumption falls relative to that of furniture with an increase in total consumption. This conforms to the textbook notion that food is a necessity relative to furniture.

Consumption of each variety is equal to the stock of that variety:

$$c_t(i) = [1 - \delta(i)]c_{t-1}(i) + x_t(i), \tag{2}$$

where δ's are depreciation rates and x's are the flows of real purchases of the good. For nondurables such as food and gasoline, $\delta = 1$ and consumption equals current purchases. For durable goods such as cars and consumer electronics, $\delta < 1$ and consumption equals current purchases plus the undepreciated stock from last period.

The capital stock is owned by households and follows

$$K_t = \sum_{i=1}^{M} k_t(i) + k_t(I),$$

$$K_{t+1} = (1 - \delta_k)K_t + I_t,$$

where $k(i)$ is capital rented by consumer good industry i, $k(I)$ is capital rented by the capital good industry, δ_k is the depreciation rate of capital, and I is capital production.

Each firm rents capital and labor in competitive spot markets. Firms maximize static profits: firm j's production in consumer good industry i maximizes

$$p_t(i)y_t(i,j) - w_t[s_t(i,j)]n_t(i,j) - r_t(i)k_t(i,j), \tag{3}$$

where $p(i)$ is the price of good i, y is the firm's output, $w[s]$ is the hourly wage for shift schedule s, and $r(i)$ is the rental rate on capital goods for a firm producing good i. Both firms and workers take as given the shift premium schedule $w[s]$. Note that the rental price of capital may vary by industry i. This can result despite a competitive capital market if capital is predetermined in each industry, not just in the aggregate, for a period.

The firm's production technology is

$$y_t(i, j) = A_t(i)n_t(i, j)^{\gamma\alpha}[s_t(i, j)k_t(i, j)]^{\gamma(1-\alpha)} - \mu s_t(i, j)k_t(i, j). \quad (4)$$

The shift schedule s determines the extent of capital utilization because, as we shall show below, s equals the number of hours during the year in which the capital is used by a positive amount of labor. The last term represents output lost from using the capital stock more intensively. All parameters are positive, $\alpha < 1$, and $\gamma \geq 1$. The term $A_t(i)$ is an exogenous technology index that is identical across firms within each industry. An industry's technology shock decomposes into aggregate shock a and idiosyncratic shock ϵ:

$$\Delta \ln A_t(i) = \eta(i)a_t + \epsilon_t(i). \quad (5)$$

Specifically, $E[a_t \cdot \epsilon_t(i)] = 0$ for all i and $E[\epsilon_t(i) \cdot \epsilon_t(l)] \neq 0$ for all $i \neq l$. We place no restrictions on the signs of the η's or on the relative size and persistence of the two types of shocks.

Now consider the consumer side of the economy. Combining first-order conditions from household utility maximization for *nondurable* goods i and l yields

$$\frac{c_t(i)^{-1/\sigma(i)}}{c_t(l)^{-1/\sigma(l)}} = \frac{p_t(i)}{p_t(l)}. \quad (6)$$

That is, relative prices equal the ratio of marginal utilities. Because these are nondurables, industry output equals household consumption.[2] Equation (6) implies that relative output growth in industry i depends systematically on the luxuriousness of good i. More exactly, consider an aggregate expansion that is associated with no relative price movements between industries i and l and no shift in preferences between goods i and l. Then $c_t(i)$ will display an elasticity of $\sigma(i)/\sigma(l)$ with respect to $c_t(l)$. For example, when output of a necessity such as food rises 1 percent, output of a luxury such as pet supplies tends to rise over 1 percent (luxuries have higher σ's than necessities).

The assumption here that relative prices are unchanged is made simply for the sake of exposition. In general, the models we consider do imply systematic changes in relative prices with responses in

[2] In the data these are not equal because of inventories and net imports. When we incorporate domestic expenditures into estimation in Sec. IV, we add net imports and subtract manufacturers' inventory investment from domestic production to arrive at domestic expenditures.

quantities as dictated by equation (6). In fact, these price and quantity predictions are crucial to our tests of the models.

Combining first-order conditions from utility maximization for durable good i and nondurable good l yields

$$\frac{c_t(i)^{-1/\sigma(i)}}{c_t(l)^{-1/\sigma(l)}} = E_t\left\{\frac{p_t(i)}{p_t(l)} - \beta[1 - \delta(i)]\frac{p_{t+1}(i)}{p_{t+1}(l)}\left[\frac{c_{t+1}(l)}{c_t(l)}\right]^{-1/\sigma(l)}\right\}, \quad (7)$$

where E_t denotes expectations conditional on time t information. The durability of good i introduces dynamic considerations into the choice of relative consumption. But the striking point is that expenditures will tend to be much more cyclical for durables: a given change in the *stock* requires a greater percentage change in the *flow* of expenditures the more durable the good is. The ratio of actual to replacement expenditures for good i is

$$\frac{x_t(i)}{\delta(i)c_{t-1}(i)} = \frac{c_t(i) - [1 - \delta(i)]c_{t-1}(i)}{\delta(i)c_{t-1}(i)},$$

where x denotes expenditures. Consider refrigerators. Below we report an estimated annual depreciation rate, δ, for refrigerators equal to .067. Increasing consumption of refrigerators by 1 percent, from a steady stock of refrigerators, requires a 15 percent increase in expenditures on refrigerators. For nondurables the percentage increase in expenditure would equal only the 1 percent increase in consumption.

Identification

We wish to test competing business cycle models by examining how the cyclicality of TFP and prices varies with the durability and luxuriousness of the good. Consumer theory tells us that these characteristics should be relevant for explaining cyclicality across goods (we define the cycle by aggregate nondurable consumption). We take the number of consumer goods to be large, so that relative shocks to TFP across industries net out in their impact on aggregate consumption. For durability and luxuriousness to be appropriate instruments, it is further necessary that these characteristics not be correlated with relative technology shocks over the cycle. That is, it is not allowable that durable luxuries happen to exhibit systematically positive or negative relative technology shocks during aggregate expansions.

Our instruments consist of the luxury and durability parameters interacted with aggregate growth in nondurable consumption. More precisely, for instruments we interact the industry-specific terms $\sigma(i)/\sigma$ and $\ln \delta(i)$ and their product $[\sigma(i)/\sigma] \ln \delta(i)$ with aggregate nondurable consumption growth for periods $t-2$, $t-1$, t, and $t+1$. This yields an instrument set, $z_t(i)$, of 12 variables:

$$z_t(i) = \left[\frac{\sigma(i)}{\sigma}, \ln \delta(i), \frac{\sigma(i)}{\sigma} \ln \delta(i)\right] \otimes (\Delta \ln c_{t-2}, \Delta \ln c_{t-1}, \Delta \ln c_t, \Delta \ln c_{t+1}).$$

We outline below, in light of the explicit models, that these instruments should be relevant for relative industry shifts in inputs.

Our identifying assumption is that our instruments $z_t(i)$ are independent of any *relative* industry pattern in technology shocks:

$$\lim_{M\to\infty} \frac{\sum_{i=1}^{M} z_t(i)'[\Delta \ln A_t(i) - \Delta \ln A_t]}{M} = 0 \quad \text{for all } t, \tag{8}$$

where $\Delta \ln A_t$ denotes average growth across industries $i = 1, \ldots, M$ at date t. Below we show for each model that (8) is sufficient to yield consistent estimates of the parameters of interest from regressions involving relative industry growth in TFP and prices.

Given (5), the growth in relative industry technology, $\Delta \ln A_t(i) - \Delta \ln A_t$, equals $[\eta(i) - \eta]\, a_t + \epsilon_t(i)$, where η is the average value for $\eta(i)$ across industries. The idiosyncratic technology shocks, $\epsilon_t(i)$, are by construction orthogonal to aggregate technology shocks, which implies that they are orthogonal to variations in aggregate consumption. We obtain (8) by assuming additionally that the luxury and durability parameters $\sigma(i)/\sigma$ and $\delta(i)$ are uncorrelated across i with the parameter $\eta(i)$, which dictates the responsiveness of technology in the industry to aggregate technology shocks.

Our approach complements prior work, such as Ramey (1991) and Hall (1988), that estimates production parameters by instrumenting with time series on government spending, oil prices, and so forth. Note that the conditions that would violate exogeneity of such time-series instruments are unrelated to the exogeneity of our instruments.

Constant Returns and Fixed Capital Utilization

With sufficiently rising disutility from working undesirable shifts, capital utilization s does not vary and we normalize it to one. Because $\gamma = 1$ and s is fixed, the growth in the Solow residual for industry i

in period t is the change in technology, $\Delta \ln A_t(i)$. Consider an aggregate expansion created by a common improvement in technology. Identifying assumption (8) then implies that the behavior of Solow residuals across industries is unrelated to the luxuriousness or durability of the good produced by the industry. Therefore, regressing an industry's relative growth in TFP on its relative growth in inputs (or output) instrumented by $z_t(i)$ yields a population coefficient of zero.

Aggregate capital is predetermined, but industry capital can move across industries within a period. With fixed s, the wage schedule reduces to a common hourly wage w faced by all firms. A firm's optimal choice of labor and capital implies

$$\frac{n_t(i, j)}{k_t(i, j)} = \frac{\alpha r_t}{(1 - \alpha) w_t}. \tag{9}$$

As the right-hand side does not vary by industry or firm, the optimal labor/capital ratio is the same for all firms. Combining (9) with first-order conditions for the optimal choice of labor input reveals that relative prices are determined solely by relative productivities:[3]

$$\Delta \ln p_t(i) - \Delta \ln p_t(l) = -[\Delta \ln A_t(i) - \Delta \ln A_t(l)]. \tag{10}$$

Industries with high productivity growth display declining relative prices. Note that luxury and durability parameters do not affect relative productivities or relative prices. So identifying assumption (8) implies that regressing an industry's relative price change on its relative growth in inputs instrumented by $z_t(i)$ yields a population coefficient of zero.

Finally, consider the behavior of quantities. Substituting productivities for prices using (10) into the first-order condition (6) for choosing nondurable goods i and l and taking log first differences, we obtain

$$\Delta \ln c_t(i) = \frac{\sigma(i)}{\sigma(l)} \Delta \ln c_t(l) + \sigma(i)[\Delta \ln A_t(i) - \Delta \ln A_t(l)]. \tag{11}$$

Given assumption (8), (11) implies that relative output growth in industry i depends on the luxuriousness of good i. More exactly, consider an aggregate expansion created by an increase in the aggregate technology parameter a_t. If this expansion is associated with no relative technology shock between industries i and l, then $c_t(i)$ will

[3] For ease of exposition, (10) pertains to the case in which labor's share α is the same in the two industries. If α varies across industries, then changes in factor prices affect relative output prices. In all estimation below we generalize to industry-specific factor shares.

display an elasticity of $\sigma(i)/\sigma(l)$ with respect to $c_l(l)$. Because this shock creates no relative shifts in TFP, it is associated with a like-size shift in relative inputs across the two sectors.

Cyclical Capital Utilization

We drop two assumptions from the previous model. The first is the assumption that capital is costlessly mobile across industries. We now assume that each industry's capital stock is determined before shocks are realized. This means that industries can differ in their labor/capital ratios because an industry cannot draw capital away from other industries during a period.

Second, we drop the assumption of a fixed rate of capital utilization. We follow Lucas (1970) in tying capital utilization to disutility from working inconvenient times: s enters disutility (1) because households must work less desirable times of the day, days of the week, and weeks of the year in order for the capital stock to be used more intensively.[4]

The preference parameter $\phi > 0$ controls how disutility rises with the inconvenience of the shift time. If ϕ is sufficiently high ($\geq 1 - \alpha$), there are no variations in capital utilization. As a result, the Solow residual for the industry correctly measures the industry's technol-

[4] The "time microfoundations" of utilization in disutility (1) and production (4) are as follows. Household disutility and firm production for each good are sums over moments τ ranging from zero to s, with $\tau = 0$ being the most desired time:

$$\tilde{\lambda} \int_0^s n_\tau \tau^\phi d\tau \tag{1'}$$

and

$$y = \tilde{A} \int_0^s n_\tau^\alpha k^{1-\alpha} d\tau - \mu sk, \tag{4'}$$

where n_τ is the number of people working in the industry at moment τ. As $\phi > 0$, disutility rises from working less than ideal times. When the optimal allocation of labor across times τ is used, (1′) and (4′) reduce to (1) (its disutility component) and (4) with

$$n = \int_0^s n_\tau d\tau,$$

$$\lambda = \tilde{\lambda} \frac{1 - \alpha - \phi}{1 - \alpha - \alpha\phi},$$

$$A = \tilde{A} \frac{1 - \alpha}{1 - \alpha - \alpha\phi} \left(\frac{1 - \alpha - \phi}{1 - \alpha} \right)^\alpha .$$

Note that total hours worked $n(i)$ and capital hours $s(i)$ can move independently and that capital hours are not synonymous with hours worked per worker in the industry.

ogy shock and, by (8), will not depend systematically on the luxuriousness or durability of the good produced. The change in an industry's relative price will, however, depend on the luxuriousness and durability of the good. Consider a common, positive technology shock. If firms in industry i raise output more than in other industries, then given fixed capital, its labor/capital ratio must rise relative to that of other industries. This reduces the relative marginal product of labor in industry i, which drives up the relative marginal cost and price of good i. If parameter ϕ is not too high ($< [1 - \alpha]/\alpha$), a general expansion does lead to higher relative capital utilization in more cyclical industries. Since $\mu > 0$ in (4), greater utilization also sacrifices output because of the added maintenance required on the capital stock.

Household and firm optimization equates the ratio of marginal utilities to the ratio of marginal products for hours n and shifts s in each industry i, yielding

$$s_t(i) = \left\{\frac{A_t(i)[1 - (1 + \phi)\alpha]}{\mu}\right\}^{1/\alpha} \frac{n_t(i)}{k_t(i)}. \tag{12}$$

When industry technology is held fixed, utilization is proportional to the labor/capital ratio in the industry. Calculating a Divisia index of TFP growth for industry i (using factor growth weighted by factor shares) for production function (4) given (12) yields

$$\Delta \ln \mathrm{TFP}_t(i) = \frac{\Delta \ln A_t(i)}{\alpha} + \frac{\phi}{1 + \phi}[\Delta \ln n_t(i) - \Delta \ln k_t(i)]. \tag{13}$$

Here measured TFP growth is linked to unmeasured changes in capital utilization through changes in $n_t(i)/k_t(i)$. Under our identifying assumption, regressing relative $\Delta \ln \mathrm{TFP}_t(i)$ on relative $\Delta \ln n_t(i) - \Delta \ln k_t(i)$ instrumented by $z_t(i)$ yields a population coefficient of $\phi/(1 + \phi)$.

Combining (12) with first-order conditions for labor and capital reveals that an industry's relative wage and price reflect its relative labor/capital ratio. If firms in an industry increase capital utilization, they must pay higher wages to compensate workers for shifting to less desirable work schedules, thereby boosting industry marginal cost and price. When variables that vary only with respect to time, not industry, are suppressed, the growth in industry i's relative wage equals

$$\Delta \ln w_t(i) = \phi\Delta \ln s_t(i) = \frac{\phi}{\alpha}\Delta \ln A_t(i) + \phi\Delta \ln \frac{n_t(i)}{k_t(i)}. \tag{14}$$

Recall that $\phi > 0$ is the preference parameter governing how disutility rises with the inconvenience of the shift time. When variables that do not differ across industries are again suppressed, the growth in industry i's relative price is

$$\Delta \ln p_t(i) = -(1 - \alpha\phi)\Delta \ln A_t(i) + \phi\Delta \ln \frac{n_t(i)}{k_t(i)}. \quad (15)$$

An industry with a rising labor/capital ratio, and, by (12), therefore a rising capital utilization, will have a rising relative output price (with relative technologies controlled for). With fixed capital utilization, the elasticity of relative industry prices with respect to relative labor/capital ratios is $1 - \alpha$, compared to ϕ in (14). Because variable utilization requires $\phi < 1 - \alpha$, it results in smaller movements in relative prices. Variable utilization gives firms another margin (in addition to labor) for increasing output.

What are the implications for a common, positive technology shock? This raises the relative output of luxuries and durables, raising those industries' relative labor/capital ratios. For example, consider two nondurable goods: good i with associated luxury parameter $\sigma(i)$ and good l with parameter $\sigma(l)$. The relative responses of n_t/k_t across the two industries to such a shock can be represented as

$$\Delta \ln \frac{n_t(i)}{k_t(i)} - \Delta \ln \frac{n_t(l)}{k_t(l)} = \frac{\dfrac{\sigma(i) - \sigma(l)}{\sigma(l)}}{\alpha + \dfrac{\phi}{1 + \phi} + \phi\sigma(i)} \Delta \ln c_t(l).$$

Suppose that we choose good l with parameter $\sigma(l)$ such that $c_t(l)$ exhibits a consumption expansion path of one with respect to total nondurable consumption. This implies that $\Delta \ln c_t(l)$ and total nondurable consumption will respond the same to a common aggregate shock. This rationalizes our instrumenting for relative industry responses of n_t/k_t by interacting a good's $\sigma(i)$ with the growth rate of total nondurable consumption, $\Delta \ln c_t$. Equations (12)–(15) then tell us that the more cyclical industries producing durable luxuries will display greater cyclicality in their capital utilization, TFP, wages, and prices in proportion to the greater cyclicality of their labor/capital ratios.

Increasing Returns to Scale

If firm production exhibits increasing returns, competitive output markets cannot be sustained. We consider two forms of imperfect competition: Cournot competition and Dixit-Stiglitz monopolistic competition.

In the Cournot version, free entry ensures zero pure profits period by period. Given utility function (1), equating marginal revenue to marginal cost for a Cournot competitor j producing nondurable i yields

$$p_t(i)\left[1 - \frac{y_t(i, j)}{\sigma(i)x_t(i)}\right] = mc_t(i, j). \tag{16}$$

Note that the elasticity of market demand is $\sigma(i)$, which comes from preferences (1). The ratio y/x is the firm's market share, which given symmetry equals the inverse of the number of firms N. Zero profits and cost minimization subject to technology (4) produce a markup equal to the degree of returns to scale γ:

$$\frac{p_t(i)}{mc_t(i, j)} = \gamma. \tag{17}$$

Combining (16) and (17), we obtain the number of firms producing consumer good i:

$$N(i) = \frac{\gamma}{\sigma(i)(\gamma - 1)}.$$

The number of firms decreases with returns to scale and elasticity of industry demand.

Because the number of firms in each industry is constant over time, when the scale of an industry expands, each firm in the industry does so by the same proportion. This means that TFP growth for the entire industry takes the simple form

$$\begin{aligned}\Delta \ln \mathrm{TFP}_t(i) = {} & \Delta \ln A_t(i) + (\gamma - 1) \\ & \times [\alpha\Delta \ln n_t(i) + (1 - \alpha)\Delta \ln k_t(i)].\end{aligned} \tag{18}$$

Recall that common shocks induce greater changes in output of luxuries and durables than of necessities and nondurables. Because greater changes in production entail greater changes in inputs, (18) implies that TFP growth will change more for luxuries and durables in response to aggregate shocks. Furthermore, given (8), regressing relative industry TFP growth on the relative industry growth of inputs, instrumenting with z_t, yields a population coefficient of $\gamma - 1$.

What does this model imply for relative prices? By assumption the scale parameter γ is equal across industries. Because the markup equals γ, the relative price of good i is its relative marginal cost. By the cost-minimizing choice of hours, each firm's marginal cost is the hourly wage divided by the marginal product of labor:

$$mc_t(i) = \frac{w_t}{\alpha\gamma A_t(i)\, n_t(i)^{\gamma\alpha-1}\, k_t(i)^{\gamma(1-\alpha)}}.$$

Note that the hourly wage is common to all industries because the labor market is competitive and shifts are constant. Growth in relative prices can be expressed as

$$\begin{aligned} &\Delta \ln p_t(i) - (1-\alpha)\Delta \ln \frac{n_t(i)}{k_t(i)} \\ &= -\Delta \ln A_t(i) - (\gamma - 1)[\alpha\Delta \ln n_t(i) + (1-\alpha)\Delta \ln k_t(i)], \end{aligned} \tag{19}$$

with variables that do not differ across industries at time t again suppressed. If industry capital is predetermined, common shocks push up labor/capital ratios more in luxury and durable good industries. Equation (19) shows that if returns to scale are sufficiently high ($\gamma > 1/\alpha$), the relative price of luxuries and durables will actually fall. In this case increasing returns *amplify* the relative growth of luxuries and durables. For lower returns to scale the relative price of luxuries and durables rises ($\gamma < 1/\alpha$) or remains unchanged ($\gamma = 1/\alpha$). If industry capital is not predetermined, then equation (19) simplifies since n/k is not industry specific. Then $\gamma > 1$ is sufficient to generate a fall in the relative price of luxuries and durables in expansions. Instrumental variable estimation of (19), under our identifying assumption, yields a population coefficient of $-(\gamma - 1)$.

These implications of Cournot competition carry over to Dixit-Stiglitz monopolistic competition. Each variety is produced by a single firm, with each "industry" consisting of many monopolistic competitors producing symmetric varieties. With the number of varieties and hence firms fixed for each industry, industry TFP growth looks the same as in the Cournot case. As each firm's market share is one, equation (16) reduces to

$$p_t(i)\left[1 - \frac{1}{\sigma(i)}\right] = mc_t(i, j).$$

Instead of the markup being fixed at γ, it is fixed by preferences for the good. Markups, being constant over time, do not affect growth in relative prices. So, for our purposes, Dixit-Stiglitz and Cournot competition are observationally equivalent.[5]

III. Calibrating Durability and Engel Curves

We quantify the cyclicality predicted for 57 consumer goods by calibrating values for parameters δ and σ governing their durability and luxuriousness. The goods are those categories in the Consumer Expenditure Surveys (CEX) that closely match four-digit industries in the Census Bureau standard industrial classification (SIC). The 57 goods and their SIC numbers appear in table 1. Table 1 also presents expenditure shares for the goods based on the 1984–90 CEX. (The sample is described more fully below.) They are shares of total nondurable consumption and sum to 84 percent.

Durability

Our calibrated values for durability are presented in table 2. We treat 11 of the goods as truly nondurable, that is, having a service life of less than 1 year. These goods are listed as ND in table 2. We use two data sources to establish durability for the remaining 46 goods. The primary source is life expectancy tables for consumer possessions employed by insurance adjusters in responding to claims for fire and theft damage. For other items, such as autos, we use the service lives reported in the Bureau of Economic Analysis (BEA) publication *Fixed Reproducible Tangible Wealth, 1925–89*. Appropriately for our purposes, both sources aim to capture obsolescence as well as physical depreciation.

More specifically, most of our depreciation rates are based on an interoffice memorandum, dated 1972, from a major U.S. property-casualty insurance company. For videocassette recorders, microwave ovens, and phone answering machines, we supplemented the 1972 memo through personal contacts with insurance adjusters. Our sources assure us that these rates remain in use today. In table 2 this source is denoted IC for insurance company. For those cases in

[5] We have treated the elasticity of demand as constant. For nondurables our specification of preferences implies a constant elasticity. For durables this is questionable. Under Cournot competition the demand elasticity for the flow of expenditures depends on future prices and hence future output of firms. If the elasticity of demand changes, the number of firms changes, altering the TFP and price predictions. Under Dixit-Stiglitz with a constant number of firms, the TFP predictions carry through. But, again, the elasticity of demand is not necessarily constant. This can create cyclicality of markups. Thus for durables our TFP predictions are good approximations if cyclical entry is not too important. Our pricing predictions are good approximations if cyclical entry and markups are not too important.

TABLE 1

SIC Industries and Expenditures by Good

	SIC Codes (1)	Expenditure Share* (2)	Percentage Buying (3)
Food bought at stores	2010, 2020, 2030, 2040, 2050, 2060, 2070, 2086, 2090	31.32	100.0
Pet supplies	2047	.31	33.7
Beer and wine	2082, 2084	1.16	60.0
Other alcohol	2085	.43	37.5
Cigarettes	2111	2.64	46.4
Other tobacco	2121, 2131	.21	11.1
Women's stockings	2251	.29	66.1
Men's stockings	2252	.12	50.8
Carpets and rugs	2271, 2272, 2279	.59	17.4
Men's suits and coats	2311	.79	46.7
Men's shirts and night wear	2321	.63	65.1
Men's underwear	2322	.12	43.9
Men's pants	2327, 2328	.74	65.4
Women's blouses	2331	.61	63.4
Women's dresses	2335	.76	50.1
Women's coats	2337	.80	44.5
Women's underwear	2341, 2342	.47	67.3
Girls' dresses and blouses	2361	.11	17.7
Curtains and drapes	2391	.26	17.1
Furniture	2511, 2512, 2514	1.86	38.3
Mattresses and springs	2515	.37	10.7
Blinds and shades	2591	.11	9.8
Newspapers	2711	.85	86.9
Magazines	2721	.42	70.2
Books	2731, 2732	.44	55.5
Prescription drugs	2834	2.00	76.8
Fuel oil and gasoline	2911	10.64	93.1
Motor oil	2992	.21	63.3
Tires	3011	1.61	64.8
Men's footwear	3143	.45	51.0
Women's footwear	3144	.73	68.4
Luggage	3161	.08	11.5
Glassware	3229	.06	15.7
China	3262	.11	15.9
Cookware	3263	.09	20.6
Lawn mowers	3524	.41	14.3
Stoves and ovens	3631	.39	11.7
Refrigerators and freezers	3632	.40	7.8
Washers and dryers	3633	.32	8.1
Portable heaters	3634	.10	12.3
Vacuums	3635	.14	8.8
Lamps	3645	.12	16.1
TVs, VCRs, and stereos	3651	1.62	46.7
Records and tapes	3652	.35	50.3
Telephones	3661	.13	19.3
New cars	3711	9.47	8.8
Trucks or vans	3713	3.15	2.9
Trailer campers	3792, 3716	.56	1.4
Boats	3732	.56	.9

TABLE 1 (*Continued*)

	SIC Codes (1)	Expenditure Share* (2)	Percentage Buying (3)
Motorcycles	3751	.21	9.8
Eyeglasses and contacts	3851	.50	31.7
Film and photographic	3861	.38	60.8
Clocks and watches	3873	.28	35.9
Jewelry	3911	.93	44.2
Silverware	3914	.05	8.6
Musical instruments	3931	.20	8.5
Games and toys	3944	1.05	58.1

* Relative to total nondurable spending.

which the memo indicates a range, we chose the midpoint. The depreciation rates for 43 goods are actually based on a finer classification for 66 goods obtained from IC. As examples, there are separate rates for carpets and rugs, washers and dryers, four different types of furniture, and six different types of video equipment. We use CEX expenditure shares as weights to aggregate the depreciation rates for the 66 goods into the broader categories of 43 goods in table 2. We define the depreciation rate δ for each good to be one over its expected life in table 2 (for nondurables it equals one).

Engel Curves

Our Engel curve estimates are based on cross sections of household spending in the CEX. The Bureau of Labor Statistics conducts two separate surveys of consumer expenditures, an interview survey and a diary survey. Our data are based on a reorganization carried out by Julie Nelson (1992) linking households across interview surveys. Our sample consists of 25,204 households from the 1984–90 surveys. Each household has up to four consecutive quarterly surveys. (One-fourth of the sample departs and is replaced each quarter. Households missing more than one interview are excluded from our sample.)

The CEX provides little information on stocks of consumer durables. Therefore, we must base our estimates of Engel curves on expenditures. Expenditure by a household on good i, with depreciation rate $\delta(i)$, can be written as

$$x_t(i) = \delta(i)c_t(i) + [1 - \delta(i)][c_t(i) - c_{t-1}(i)].$$

An index for household is implicit. We substitute for $c_t(i)$ from equation (7), which expresses consumption of durable i with respect to

TABLE 2

EXPECTED LIVES OF CONSUMER GOODS

	Expected Life (in Years)	Data Source*
Food bought at stores	ND	
Pet supplies	ND	
Beer and wine	ND	
Other alcohol	ND	
Cigarettes	ND	
Other tobacco	ND	
Women's stockings	1.0	IC
Men's stockings	1.7	IC
Carpets and rugs	11.1	IC
Men's suits and coats	4.1	IC
Men's shirts and night wear	2.7	IC
Men's underwear	2.2	IC
Men's pants	2.7	IC
Women's blouses	2.3	IC
Women's dresses	4.0	IC
Women's coats	4.3	IC
Women's underwear	1.8	IC
Girls' dresses and blouses	2.3	IC
Curtains and drapes	4.2	IC
Furniture	8.1	IC
Mattresses and springs	15.0	IC
Blinds and shades	10.9	IC
Newspapers	ND	
Magazines	ND	
Books	11.0	IC
Prescription drugs	ND	
Fuel oil and gasoline	ND	
Motor oil	ND	
Tires	3.0	BEA
Men's footwear	2.5	IC
Women's footwear	2.6	IC
Luggage	17.5	IC
Glassware	10.0	IC
China	17.5	IC
Cookware	17.5	IC
Lawn mowers	7.5	IC
Stoves and ovens	14.1	IC
Refrigerators and freezers	15.0	IC
Washers and dryers	11.0	IC
Portable heaters	11.3	IC
Vacuums	9.5	IC
Lamps	16.7	IC
TVs, VCRs, and stereos	11.9	IC
Records and tapes	5.0	IC
Telephones	7.1	IC
New cars	10.0	BEA
Trucks or vans	8.0	BEA
Trailer campers	8.0	IC
Boats	10.0	IC
Motorcycles	8.6	IC, BEA
Eyeglasses and contacts	10.0	IC

TABLE 2 (*Continued*)

	Expected Life (in Years)	Data Source*
Film and photographic	6.7	IC
Clocks and watches	15.5	IC
Jewelry	5.5	IC
Silverware	27.5	IC
Musical instruments	13.0	IC
Games and toys	5.0	IC

* IC refers to an interoffice memo of a major property-casualty insurance company; BEA refers to the BEA publication *Fixed Reproducible Tangible Wealth, 1925–89.*

nondurable l. For convenience we drop the index l so that c_t, p_t, and σ refer to $c_t(l)$, $p_t(l)$, and $\sigma(l)$:

$$\ln \hat{x}_t(i) = \ln \delta(i) + \frac{\sigma(i)}{\sigma} \ln c_t - \sigma(i) \ln \tilde{p}_t(i) - \sigma(i) \ln[E_t v_{t+1}(i)]$$
$$+ \ln\left(1 + \frac{1-\delta(i)}{\delta(i)}\left\{1 - \left(\frac{c_{t-1}}{c_t}\right)^{\sigma(i)/\sigma}\left[\frac{\tilde{p}_{t-1}(i)E_{t-1}v_t}{\tilde{p}_t(i)E_t v_{t+1}}\right]^{-\sigma(i)}\right\}\right) + \epsilon_t(i), \tag{20}$$

where $\tilde{p}_t(i) = p_t(i)/p_t$, and

$$v_{t+1}(i) = 1 - \beta[1 - \delta(i)]\frac{\tilde{p}_{t+1}(i)}{\tilde{p}_t(i)}\left(\frac{c_{t+1}}{c_t}\right)^{-1/\sigma}.$$

In recognition that the CEX measures expenditures with error, $\hat{x}_t(i)$ denotes measured household expenditure on good i; ϵ_t equals the discrepancy between measured and actual log expenditures. We assume that ϵ_t is distributed independently across households with mean zero. (For this reason we ignored it in developing TFP and price predictions in Sec. II.)

We define consumption c_t to be a household's total nondurable consumption. We then estimate elasticities of household consumption for each of the 57 goods with respect to total nondurable consumption by sequentially letting each good be good i. The choice of total nondurable consumption as the reference good is arbitrary, but what matters is the relative, not absolute, magnitudes of our 57 elasticities.

Equation (20) can be presented as

$$\ln \frac{\hat{x}_t(i)}{c_t} = \frac{\sigma(i) - \sigma}{\sigma} \ln c_t + \omega_t(i), \tag{21}$$

where

$$\omega_t(i) = \ln \delta(i) - \sigma(i) \ln \tilde{p}_t(i) - \sigma(i) \ln[E_t v_{t+1}(i)]$$

$$+ \ln\left(1 + \frac{1-\delta(i)}{\delta(i)}\left\{1 - \left(\frac{c_{t-1}}{c_t}\right)^{\sigma(i)/\sigma}\left[\frac{\tilde{p}_{t-1}(i) E_{t-1} v_t}{\tilde{p}_t(i) E_t v_{t+1}}\right]^{-\sigma(i)}\right\}\right) + \epsilon_t(i).$$

For a nondurable good, ω_t reduces to the relative price of good i, which we assume does not vary across households, and the measurement error ϵ_t. For a durable good, however, ω_t also reflects household growth and expected growth in nondurable consumption, as well as expectations of the relative price of good i. We assume that price expectations for the relative price of good i do not vary across households. But current consumption, c_t, is clearly correlated with v_t because the latter contains the growth in consumption from $t - 1$ to t. Therefore, to consistently estimate $[\sigma(i) - \sigma]/\sigma$, we need to instrument for $\ln c_t$ with variables orthogonal to household consumption growth from $t - 1$ to t or its expected growth from t to $t + 1$. Instrumenting for $\ln c_t$ also corrects for measurement error in household responses for total nondurable consumption.

For each household we construct spending on all nondurables and on each of the 57 goods in table 1 from the second through fourth interviews. They represent our cross-household measures for c_t and $\hat{x}_t(i)$. We exclude from our measures of spending a household's spending in the first quarterly interview in order to use that datum to instrument for a household's total nondurable consumption in the second through fourth quarters. We instrument for $\ln c_t$ with nondurable consumption and durable expenditures in quarter 1, after-tax income in the previous year, plus time period dummies and several household characteristics. These time dummies and household characteristics are also included as regressors along with $\ln c_t$ in (21). The household characteristics are average age of the household head and spouse, that age squared, number of children, and dummy variables for single male–headed households, for single female–headed households, for the presence of children, for residence in a city, and for home ownership. According to the permanent-income hypothesis, purely cross-sectional differences in consumption growth from $t - 1$ to t and from t to $t + 1$ should be orthogonal to lagged consumption and income variables. Therefore, these variables are valid instruments for $\ln c_t$ in equation (21).

For some goods, particularly very durable goods, expenditures are zero for many households. (Column 3 of table 1 presents the fraction of households purchasing each good over a 12-month period.) This means that we cannot take logs of expenditures to estimate consumption elasticities from (21). We deal with this problem in several ways.

Our first approach is to approximate the left-hand side of (21) by the deviation of a household's expenditure on good i from the mean expenditure in the sample. This yields an estimated elasticity relative to average expenditure on good i rather than relative to a household's own expenditure on the good. Results for this exercise, with estimation by two-stage least squares, are presented in column 1 of table 3. The elasticities vary considerably. The steepest Engel curve pertains to luggage. A 1 percent increase in nondurable spending is associated with a roughly 2 percent increase in spending on each of luggage, jewelry, and china. At the other extreme, tobacco products (excluding cigarettes) exhibit an elasticity with respect to total nondurables of only about .20. Spending on food, motor oil, washers and dryers, and heaters each exhibits an elasticity of about .65. Overall, 41 of the 57 good elasticities are significantly different from one. Across the 57 goods there is a positive correlation (.32) between these estimated Engel curves and the measure of durability in table 1. That is, durable goods are more likely to be luxuries.

To avoid zero expenditures and still use functional form (21), we estimated a second set of Engel curves based on first grouping the data according to nondurable consumption. We created 50 equal-sized cells according to nondurable consumption in each household's first quarterly survey. For each cell we calculated mean nondurable consumption in the first survey quarter, mean nondurable consumption in quarterly surveys two through four, and mean expenditure on each of the goods.[6] Two-stage least-squares estimation is used. We instrument for a cell's mean ln c_t, based on nondurable consumption in the second through fourth surveys, on the cell's mean ln c_t in the first quarterly survey. (The R^2 in this first step is typically .99.)[7] Results are presented in column 2 of table 3. In most cases the estimates are similar to those from column 1.[8] When exe-

[6] We combine new cars, trucks and vans, campers, boats, and motorcycles into a single category. For household furnishings we control for whether the household owns or rents its home. For these goods we create separate cells by nondurable consumption for both home owners and renters. Similarly, for men's clothing we control for the presence of an adult male, for women's clothing for the presence of an adult female, and for toys and girls' dresses for the presence of children.

[7] Both the first- and second-stage estimations use weighted least squares. In the first stage the weights are the inverse of the coefficient of deviation for c within group j. In the second stage the weights are the inverse of the coefficient of deviation for $x(i)$ within group j. These weights correspond to minimum χ^2 methods for grouped data (Maddala 1983).

[8] We also estimated the elasticities by Tobit. Many of the Engel curves became much steeper, sharply departing from our other estimates and from estimates in the literature. Tobit estimation requires a smooth distribution of demands across the point of censoring; but for some goods, persons with zero expenditures might be drawn from a distinct population. For example, households not spending on tobacco and alcohol may have health concerns or moral convictions that cause them

cuting TFP and price regressions in Section IV, we consider both sets of Engel curve estimates reported in table 3. Our results are not sensitive to this choice.

IV. Testing the Competing Models with Industry Panel Data

In Section II we outlined each model's predictions for the cyclical behavior of TFP and prices for luxuries and durables relative to necessities and nondurables. In Section III we used micro evidence to calibrate the luxuriousness and durability of 57 consumer goods. We can now test the predictions of the competing models with industry panel data. To this end we employ the NBER Productivity Database, which contains data for 450 SIC four-digit U.S. manufacturing industries over 1958–91. This database derives from establishment data collected in the Census Bureau Surveys of Manufactures.[9] We use those 57 industries in the NBER database that closely match categories in the CEX (see table 1). Our sample has 1,881 observations reflecting a panel of 57 industries for 33 years (1959–91). We proceed to test first the cyclical utilization model and then the model with increasing returns. The baseline, constant-returns, constant-utilization model is a special case of both of these models.

Testing for Cyclical Capital Utilization

In the cyclical utilization model, relative industry movements in TFP, wages, and prices vary predictably with an industry's relative movement in n/k according to equations (13)–(15). Each of these equations yields an estimate of the preference parameter ϕ, which reflects how disutility rises by working less ideal times. We estimate these equations first without instrumenting, estimating by seemingly unrelated regressions (SUR). We then instrument using our instrument set $z_t(i)$, defined above, which interacts the estimated durability and

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to view these goods as "bads." Therefore, Tobit estimates may overstate the market elasticity of demand with respect to nondurables consumption.

[9] The NBER Productivity Database measures labor hours for production workers but only employment for nonproduction workers. For the estimation we present in tables 4 and 5 below, we set the workweek for nonproduction workers at 40 hours. We constructed an alternative measure of labor hours by assuming instead that the workweek for nonproduction hours varies in the same manner as that for production workers. The results for growth equations of TFP and prices are very similar to those we present in tables 4 and 5. But the estimate of ϕ based on relative wage growth (table 4, eq. [14]) becomes even larger. It goes from .569 to .945 (standard error .043) when the first set of σ's is used and from .539 to .923 (standard error of .041) when the second set of σ's is used.

TABLE 3

ESTIMATES OF ENGEL CURVES

	Elasticity 1 (with Respect to the Mean) (1)	Elasticity 2 (Grouped) (2)
Food bought at stores	−.346	−.188
	(.007)	(.012)
Pet supplies	.518	.468
	(.070)	(.062)
Beer and wine	.324	.140
	(.031)	(.030)
Other alcohol	.598	.302
	(.048)	(.047)
Cigarettes	−.274	−.179
	(.030)	(.046)
Other tobacco	−.806	−.515
	(.095)	(.070)
Women's stockings	.380	−.060
	(.035)	(.027)
Men's stockings	.034	.269
	(.036)	(.038)
Carpets and rugs	.562	.624
	(.110)	(.122)
Men's suits and coats	.782	.545
	(.047)	(.056)
Men's shirts and night wear	.369	.315
	(.029)	(.033)
Men's underwear	.007	.012
	(.045)	(.046)
Men's pants	.137	.145
	(.029)	(.035)
Women's blouses	.363	−.040
	(.033)	(.027)
Women's dresses	.861	.257
	(.042)	(.045)
Women's coats	.978	.289
	(.058)	(.063)
Women's underwear	.329	−.028
	(.032)	(.031)
Girls' dresses and blouses	.132	.098
	(.072)	(.061)
Curtains and drapes	.432	.320
	(.144)	(.120)
Furniture	.301	.424
	(.064)	(.066)
Mattresses and springs	.320	.372
	(.108)	(.117)
Blinds and shades	.977	.618
	(.167)	(.161)
Newspapers	−.168	−.257
	(.020)	(.016)
Magazines	.310	.038
	(.034)	(.027)

TABLE 3 (*Continued*)

	Elasticity 1 (with Respect to the Mean) (1)	Elasticity 2 (Grouped) (2)
Books	.591	.334
	(.047)	(.036)
Prescription drugs	2.106	2.495
	(.035)	(.035)
Fuel oil and gasoline	2.059	.044
	(.012)	(.030)
Motor oil	2.352	2.129
	(.038)	(.048)
Tires	.068	.146
	(.037)	(.047)
Men's footwear	.068	2.197
	(.036)	(.039)
Women's footwear	.270	2.117
	(.032)	(.036)
Luggage	1.211	1.030
	(.095)	(.089)
Glassware	.753	.476
	(.155)	(.119)
China	.904	.682
	(.119)	(.091)
Cookware	.032	2.056
	(.114)	(.085)
Lawn mowers	2.479	2.423
	(.143)	(.137)
Stoves and ovens	2.200	2.039
	(.101)	(.092)
Refrigerators and freezers	2.121	2.166
	(.121)	(.093)
Washers and dryers	2.356	2.158
	(.109)	(.110)
Portable heaters	2.341	2.350
	(.149)	(.109)
Vacuums	.072	.137
	(.142)	(.116)
Lamps	.719	.647
	(.098)	(.103)
TVs, VCRs, and stereos	.081	.076
	(.064)	(.040)
Records and tapes	.370	.205
	(.052)	(.049)
Telephones	.262	.179
	(.077)	(.053)
New cars	.661	.560*
	(.091)	(.070)
Trucks or vans	.158	.560*
	(.158)	(.070)
Trailer campers	.625	.560*
	(.347)	(.070)
Boats	.725	.560*
	(.530)	(.070)

TABLE 3 (*Continued*)

	Elasticity 1 (with Respect to the Mean) (1)	Elasticity 2 (Grouped) (2)
Motorcycles	.280	.560*
	(.203)	(.070)
Eyeglasses and contacts	−.074	−.043
	(.050)	(.040)
Film and photographic	.516	.554
	(.064)	(.054)
Clocks and watches	.452	.339
	(.083)	(.062)
Jewelry	.991	.638
	(.074)	(.064)
Silverware	.846	.481
	(.167)	(.133)
Musical instruments	.291	.710
	(.227)	(.181)
Games and toys	−.011	−.049
	(.043)	(.042)

NOTE.—The slope of the Engel curve for each good is 1 + the coefficient.
* The elasticities for new cars, motorcycles, trucks and vans, campers, boats, and motorcycles were constrained to be the same in col. 2.

Engel curve for an industry's good with rates of growth in aggregate nondurable consumption. The equations are estimated jointly by generalized method of moments (GMM).

The SUR results appear in column 1 of table 4. In the presence of technology shocks, these estimates of ϕ in the TFP and price equations are inconsistent. Therefore, the SUR results are presented primarily for descriptive purposes. The results show that relative TFP increases markedly with an industry's relative n/k. The estimate of ϕ from the TFP equation, .48, is consistent with an increase of 0.33 percent in an industry's relative TFP for each 1 percent increase in an industry's relative n/k. Relative wages and prices, by contrast, do not increase with an industry's relative n/k.[10]

Before we examine the instrumental variable results, it is important to demonstrate that our instruments $z_t(i)$ are in fact relevant predictors of industry cyclicality. Regressing relative industry movements in n/k (first removing the impact of industry dummies) on $z_t(i)$ yields a first-stage R^2 of .085. Multiplying this by the number of

[10] For comparison purposes, we ran an ordinary least squares regression of relative industry TFP growth on relative industry n/k growth (after removing industry means) for the entire panel of 448 industries in the NBER Productivity Database over 1959–91. The resulting coefficient was .315 (.005), very close to the 0.33 percent SUR estimate for our 57 goods.

TABLE 4

Estimates of ϕ for the Cyclical Utilization Model

Equation	Dependent Variable	SUR (1)	GMM: 1st Set of σ's (2)	GMM: 2d Set of σ's (3)
(13)	$\Delta \ln TFP_t(i)$	.481	.294	.362
		(.031)	(.077)	(.088)
(14)	$\Delta \ln w_t(i)$	.040	.569	.539
		(.012)	(.055)	(.052)
(15)	$\Delta \ln p_t(i)$	.010	.217	.160
		(.011)	(.042)	(.042)
(13), (14), and (15)	Common ϕ		.300	.296
			(.028)	(.028)
(13) and (15)	Common ϕ		.243	.230
			(.028)	(.027)

Source.—NBER Productivity Database.
Note.—All variables are relative to yearly averages for all 57 industries. Each regression includes industry dummies. The industry panel pertains to t = 1959–91; i = 1, . . . , 57 (the 57 industries in table 2). Number of observations is 1,881 (33 years times 57 industries).

observations produces a Nelson-Startz (1990) statistic for instrument relevance equal to 160 (p-value .00), far above their threshold of two, below which bias becomes serious because the instrument is poor.

We now turn to the GMM results. They appear in columns 2 and 3 of table 4. These columns correspond to choosing either the first or second set of estimates for relative industry Engel curves, $\sigma(i)/\sigma$ from Section III. The results are not very sensitive to this choice.[11] We first discuss the results in column 2. Instrumenting does reduce the cyclicality of TFP substantially, though it remains very procyclical. The estimate of ϕ from the TFP equation, .29 (with standard error .08), implies that a 1 percent cyclical increase in an industry's n/k, predicted by our instruments, is associated with a 0.23 percent increase in TFP. Note that this finding is a rejection of the baseline model with constant returns and constant utilization (p-value .00 for the baseline model).

The utilization model predicts that both relative wages and prices move by an elasticity of ϕ with respect to relative movements in n/k. In fact, instrumenting dramatically increases the estimated response in wages and prices. The estimate of ϕ from the price equation goes from .01 to .22 and is statistically very significant. This estimate is

[11] We also examined estimates by three-stage least squares for both the varying utilization and increasing returns models. The results are qualitatively very similar to those by GMM.

quantitatively similar to the estimate of ϕ from the TFP equation of .29. The data do not reject a common estimate of ϕ, equal to .24 (with standard error .03), for the TFP and price equations (p-value .54). Instrumenting raises the response of wages to n/k from .04 to a very economically and statistically significant value of .57. This estimate for ϕ is substantially larger than the estimate based on TFP and prices. Estimating a common ϕ across the three equations yields a value of .30, but the data firmly reject this constraint (p-value .00).

In modeling we assumed a completely integrated labor market across industries. The only source of relative wage changes is a compensating differential for working less ideal hours. If industries face industry-specific supply curves, this provides an additional rationale for relative wage increases for the more cyclical industries producing durable luxuries (see, e.g., Bils and McLaughlin 1997). This would imply that the wage equation estimate of ϕ is potentially biased upward. Note, however, that any bidding up of industry wages should still be reflected in an industry's price. Thus this might rationalize the higher value for ϕ from the wage than from the TFP equation, but not the differential between the wage and price equations.

Overall, however, we view the results as consistent with the predictions of the utilization model. They also clearly highlight the importance of instrumenting. Adopting the second set of estimates for the industry Engel curves yields the GMM estimates in column 3. They are qualitatively very similar to the results in column 2. The TFP equation does now yield a slightly higher value for ϕ, and the price equation yields a slightly lower value. The data continue to accept a common estimate of ϕ for the TFP and price equations (p-value .16), which now takes the value .23 (with standard error .03).

Testing for Increasing Returns to Scale

For the increasing returns model, relative industry movements in TFP and prices vary predictably with relative movement in total inputs according to equations (18) and (19). Each of these equations yields an estimate of the technology parameter $(\gamma - 1)$, that is, returns to scale minus one. Again for descriptive purposes, we first estimate these equations by SUR. We then estimate the equations jointly by GMM, instrumenting with $z_t(i)$.

The SUR results are presented in column 1 of table 5. The TFP equation estimate for $\gamma - 1$ shows that relative TFP increases by 0.23 percent for each percentage increase in an industry's rate of growth in relative inputs. By contrast, the pricing equation generates a slightly negative estimate for $\gamma - 1$. This is driven by the result that relative prices for durable luxuries do not decline in recessions. This

TABLE 5

ESTIMATES OF $\gamma - 1$ FOR THE INCREASING RETURNS TO SCALE MODEL

			GMM	
EQUATION	DEPENDENT VARIABLE	SUR (1)	1st Set of σ's (2)	2d Set of σ's (3)
(18)	$\Delta \ln \mathrm{TFP}_t(i)$	.228	.185	.206
		(.021)	(.055)	(.057)
(19)	$\Delta \ln p_t(i) - (1 - \alpha)$	−.013	−.185	−.153
	$\times \Delta \ln[n_t(i)/k_t(i)]$	(.025)	(.067)	(.068)
(18) and (19)	Common $1 - \gamma$		.167	.173
			(.040)	(.058)

SOURCE.—NBER Productivity Database.

NOTE.—All variables are relative to yearly averages for all 57 industries. Each regression includes industry dummies. The industry panel pertains to $t = 1959$–91; $i = 1, \ldots, 57$ (the 57 industries in table 2). Number of observations is 1,881 (33 years times 57 industries).

is true even though the very procyclical term $(1 - \alpha)\Delta \ln(n_t/k_t)$ is subtracted from the price changes to reflect the contribution of increases in the labor/capital ratio to marginal cost.

Before examining the GMM results, we first document the result of the Nelson-Startz test for relevance of the instruments. The regression of relative industry movements in total inputs on $z_t(i)$ yields a first-stage R^2 of .108. Multiplying by the number of observations produces a test statistic of 204, which rejects irrelevance of the instruments with a p-value of .00 and handily clears their hurdle of two.

The GMM results are presented in columns 2 and 3 of table 5. The two columns again correspond to whether the first or second set of Engel curve estimates is incorporated in the instrument set. The results, as can be seen, are not sensitive to this choice. The estimate of $\gamma - 1$ from the TFP equation is .185 (standard error .055) for the first instrument set and .206 (standard error .057) for the second. These estimates are not much below the SUR estimate of .23. These TFP results constitute a rejection of the baseline model with constant returns and constant utilization (p-value .00).

The increasing returns model predicts that, to the extent that we observe procyclical TFP growth in an industry, we should also see countercyclical growth in prices, once we correct for movements in an industry's labor/capital ratio by subtracting $(1 - \alpha)\Delta \ln(n_t/k_t)$ from price changes. This is not true, however, in the data. The estimate of $\gamma - 1$ from the price equation is .185 (standard error .067) for the first set of instruments and .15 (standard error .07) for the second. These estimates are opposite in sign to the estimates based on TFP and have approximately the same magnitude, actually suggesting decreasing returns to scale. We cannot, however, reject a common value of $\gamma - 1$ in the TFP and price equations of .17 using either instrument set. Thus we do not formally reject the increasing returns to scale model (*p*-values .31 and .15 for the two instrument sets).

The GMM estimates do reject, at standard significance levels, returns to scale on the order of 1.3 or above. A related point is that the estimates suggest that returns to scale are not sufficient to offset short-run diminishing returns to labor. Relative expansions in cyclical industries are associated with significant increases in their relative prices. To illustrate this point we reestimated the relative price equation (19) without netting off the diminishing returns effect $(1 - \alpha)\Delta \ln(n_t/k_t)$. We find a substantial increase in industry relative prices in response to increases in industry inputs predicted by our instruments. For each predicted percentage increase in inputs, relative prices increase by 0.33 percent for the first set of instruments and by 0.29 percent for the second set (both standard errors .05).

In modeling increasing returns to scale, we assumed integrated factor markets supplying labor and materials across the consumer industries. One might argue that the impact on prices of strong increasing returns is masked by the increase in the *relative* industry input prices for labor and materials as an industry expands. This requires industry-specific factor markets for labor and materials. In fact, input prices do vary substantially across industries cyclically, with cyclicality defined by our instruments. When the first set of instruments is used, relative industry wages increase by 0.707 percent (standard error .057) and materials prices by 0.529 percent (standard error .053) for each percentage increase in inputs predicted by our instruments. When the second set of instruments is used, the corresponding numbers are 0.681 percent (standard error .055) and 0.549 percent (standard error .055). The result that prices of materials supplied to durables and luxuries increase in expansions is consistent with Shea's (1993) finding that industry prices predictably increase in response to expansions in downstream industries. This defense of increasing returns is somewhat problematic, however, since it fails to explain why relative prices rise for more cyclical materials industries. Furthermore, regardless of whether marginal costs rise because of diminishing returns or increased factor prices, this provides a potentially stabilizing influence on fluctuations.

V. Conclusion

Consumer theory tells us that luxuries and durables should be more cyclical than necessities and nondurables. We use these features to instrument for relative industry movements in inputs over the business cycle. Armed with micro evidence on luxuriousness and durability for 57 consumer goods, we use U.S. industry data to test predictions of three distinct business cycle models: a standard constant-returns-to-scale real business cycle model, a model with cyclical utilization of capital, and a model with increasing returns.

We find the following. First, industry productivity is more procyclical for industries producing goods that are durables or luxuries. This finding is consistent with (unmeasured) cyclical utilization and with increasing returns. Second, industry prices are also more procyclical for industries that produce luxuries and durables. The pricing behavior favors models with cyclical utilization and is not consistent with models built on substantial increasing returns.

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