A DYNAMIC CHARACTERIZATION OF EFFICIENCY

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Abstract:

The definition and measurement of dynamic economic performance has been addressed obliquely in the literature with the notions of scope economies and capacity utilization measures, but little work has focused on develop the static theory analogs of efficiency measures into the dynamic context. This paper is an attempt to identify some of the conceptual and methodological issues to be addressed. A model allowing for dynamic production decisions in the face of inefficiency is presented to illustrate some of the issues and the extensions necessary to identify truly dynamic performance measures.

A Dynamic Characterization of Efficiency

I. INTRODUCTION

The issue of dynamic efficiency is an important component in assessing capital accumulation patterns and growth. Early characterizations of efficiency over time focus on how the capital stock relates to the Golden Rule level (Phelps, 1961; Diamond, 1965). Others focus on how the presence of dynamic efficiency facilitates intergenerational transfer of assets (Weil, 1987) and can eliminate the prospect of speculative bubbles (Tirole, 1985). Abel et al. (1989) investigate if capital accumulation levels of OECD economies operate above or below Golden Rule levels. Most of these studies have a distinctly macroeconomic policy orientation. However, the extent of inefficient behavior in the management of dynamic assets at the firm level has not been clearly characterized or modeled.

The determination of efficient behavior discussed here is temporal in nature by describing the degree of efficiency of the firm at a particular point of its adjustment path. The firm's optimal adjustment path over time and the steady-state may vary with temporal efficiency. This paper initiates a discussion of conceptual and methodological issues revolving around the measurement of economic performance when firm make decisions linked over time. A model allowing for dynamic production decisions in the face of inefficiency is presented to illustrate some of the issues and the extensions necessary to identify truly dynamic performance measures.

II. CONCEPTUAL ISSUES

When addressing the dynamic efficiency we need to distinguish between a) tracking efficiency over time (which involves modeling exogenous versus endogenous forces and the impact of covariates/environmental variables on econ performance), and b) persistence which involves identifying the contributions of structural (deterministic) sources and the stochastic sources. The sources of economic dynamics are:

- economic forces (for example, adjustment cost and financial constraint models),
- technological characteristics (for example, physical/biological nature of production, and vintage investment/stock nonconvexities like we see with lumpy investment), and
- cognitive capacity.

To date, our models do not separate our these forces, and thus, can confound the results reported in the literature.

The economic forces can relate largely to adjustment processes which has been classically presented in the literature as a dichotomy between the short and long runs. The distinction between the short and long run becomes a prime consideration in determining the appropriate time scale of economic decision making strategies. These strategies focus on the choice of production factors assumed to be fixed when factor allocation decisions are to be made. All economic activity occurs in the short-run to the extent a factor (or factors) of production are taken as fixed. The long run refers to the firm planning ahead to select a future short-run production situation. The problem with the classical description of the short- and long-run is that the story of the envelope curve is not entirely consistent with the story motivating the distinction between the short and

long run.[1] The long run consists of a range of possible short run situations available to the firm. As such, the firm always operates in the short run but plans for the long run. A more complete description of producer behavior in the long-run theory of cost concentrates on the planning problem involving the minimization of the discounted stream of costs. Such a characterization focuses on long-run costs as a stock rather than a flow concept.

The classical approach characterizes both short- and long-run cost functions as flows. The long-run is merely the case where the fixed factor is now variable -- presumably because the time span under consideration is now long enough to view the problem as a short-run planning problem. This could entail describing the short-run to last 5 or 10 years given capital adjustment rates estimated in the empirical literature. Viner's (1931) idea of some factors being "freely adjusted" while others are "necessarily fixed" is sufficiently vague to allow long-run costs to be considered a flow. Freely adjusted implies that altering the input levels of these factors does not impose a penalty on the firm other than a constant acquisition cost.

The application of non-freely adjusted inputs presumably occurs because some additional costs must be absorbed by the firm beyond the acquisition cost. The introduction of adjustment costs can capture this phenomenon. Some factors are considered "fixed" in the short run, not because the operator is physically prevented from removing or introducing more of the factor, but because the economic environment places a high cost on adjusting the factor level. For example, it may be more profitable

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[1] Alchian (1959) and De Alessi (1967) recharacterize long-run costs as a discounted flow of costs that involve a sequence of production targets as represented by the volume of production over the time horizon. Stefanou (1989) recasts these formulations into a dynamic adjustment framework to create long- and short-run value functions.

at the margin to under or over utilize a given set of quasi-fixed factors rather than renting the services of those factors (external adjustment costs). In addition, additional costs may arise from the adjustment in the technical relationships (internal adjustment costs).

Temporal Efficiency and the Steady-State

The adjustment cost hypothesis states current additions to the stock of capital are output decreasing at the time of investment but output increasing in the future by increasing the future stock of capital. Thus, the firm's current investment decisions involve a trade-off between instantaneous cost and the gains arising from future production possibilities. The firm's optimal adjustment path over time and the steady-state are likely to vary with the degree of temporal efficiency. Temporal efficiency is a flow notion of dynamic efficiency in that the firm's decisions are assumed to be made in the short run with a view to the long run.

Characterizing Dynamic Efficiency: Functional or Function?

The notion of efficient allocation of variable and quasi-fixed inputs in the long run can take on a criterion based on stock efficiency or temporal efficiency. The stock-, or functional-based notion of efficiency focuses on a capital trajectory that is a decision path where perfectly efficient decisions are made at each decision point over the time horizon. This is the efficiency characterization implied by Diamond (1965), Abel et al. (1989) and Thalmann (1996). Focusing on this definition of dynamic efficiency is extremely restrictive and not reflective of how decisions are made. If decisions are always made in the short run with a view to the long run, then efficiency is a temporal issue and not a comparison of trajectories. The temporal notion is also conditioned on

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past decisions but reflects dynamic linkages of past decisions to future prospects. The temporal notion of allocative efficiency reflects the operator making the right current decisions towards long-run equilibrium.

Both characterizations of dynamic efficiency are conditional notions. Temporal efficiency is a conditional notion in that current decisions are efficient given all past (efficient or inefficient) investment decisions. A stock-based efficiency measure is also conditional since the decision trajectory from, say, t_o to T is efficient given all (efficient or inefficient) investment decisions previous to $t=t_o$. Assuming k_o is not long-run efficient due to unexpected price changes, for example, there is an inefficient trajectory at some point previous to the initial period, t_o. However, if investment decisions are made in the short run with a view to the long run, dynamic efficiency is a temporal notion and does not involve an explicit comparison of trajectories. As a result, the stock notion of dynamic efficiency does not reflect how investment decisions are made.

III. METHODOLGOICAL ISSUES

The approaches to measuring efficiency levels over time can be broadly classified as those emanating from data-driven empirical approaches and those based on structural models reflecting dynamic behavioral decisions permitting dynamic efficiency impacts. The value of both approaches is substantial. The data driven approaches can provide evidence and direction on where to look for inefficiency effects that the structural models may assume away. Rarely are the structural models so all-encompassing as to nest all sources of inefficiency. As the area of dynamic efficiency measurement gains greater

attention, the interplay emerges between theory-driven applications as well as applications-drive theory.

There are two issues on the agenda of dynamics and efficiency measurement: 1) what is the evidence of inefficiency behavior over time (e.g., do firms get better, stay the same, get worse, get better then worse, …)?, and 2) what structural models of economic decision making combined with the technological characteristics and cognitive capacity can be developed to explain the patterns of efficiency behavior? An important question of interest is if we must deal with the two issues simultaneously, or can we sequentially address the two issues. Just measuring the efficiency level at each time point in isolation will surely yield biased results. The production technology exhibits no technological forces suggesting dynamic linkages over time. Since there is no behavioral resource allocation model addressed, the choices of input use over time are taken exogenously.

In general, endogeneity issues are rarely addressed by decisions taken in an earlier period influencing the distribution of the long-run efficiency level. Of course, it depends on the factors z that one specifies, and this is a cautionary note that should be sounded loudly. Surely, there are forcing factors and choices the decision maker can execute to influence the long-run inefficiency level and these are the variables you would include as covariates, z.   A true unifying model should take into account the decision processes and choices associated with choosing the levels of these forcing factors influencing efficiency levels over time.

Dynamic versus Time-Varying Efficiency Measures:

Estimating the efficiency and productivity patterns over time is being revisited in the literature as the data sets become richer. Recent studies in the analysis of productivity changes find that there are serious problems in dealing with aggregate measures of productivity. These studies indicate that the analysis of a sector or an industry focusing only on aggregate productivity measures may be misleading, presenting a simplistic explanation of the process. Dhrymes and Bartelsman (1998) and Dhrymes (1991) find that two-digit industry wide productivity, and its growth over time, may be reduced considerably upon addressing the four-digit industry composition of the sample. Hence, a disaggregated analysis can provide a more detailed perspective of the dynamics of total factor productivity (TFP) growth when compared with the aggregate level analysis of TFP growth. Pakes and colleagues[2] refine the effort by taking on micro-level panel data sets to model the economic interactions leading to productivity gains and some efficiency impacts. Exploiting the heterogeneity in the micro-level data (plants or firms) leads to identifying the weakness of the theory developed with a macro view of behavior. One example, is where the aggregate modeling suggests capital adjustment is smooth process, the micro-level evidence strongly suggests the presence of discontinuous (or lumpy) capital adjustment (Nilsen and Schiantarelli, 2003; Celikkol and Stefanou, 2004). The presence of discontinuous capital changes can lead to much different characterizations of efficiency since capital adjustment patterns may lead a firm to appear to be overcapitalized in some periods and under capitalized in others.

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[2] Important references include Pakes and McGuire (1994), Ericson and Pakes (1995), Olley and Pakes (1996).

The modeling of time-varying efficiency historically appears as the specification of time as a regressor which leads to the challenge of disentangling the two roles time plays; namely, time as a proxy for technical change in the deterministic kernel of the stochastic production frontier versus time as an indicator of technical efficiency change in the composite error term. Historically, three popular specifications are present in the literature, historically (Kumbhakar and Lovell, 2000):

- $u_{it} = u_i \gamma(t)$, where $\gamma(t)$ is a parametric function of time and u_i is a nonnegative random variable (Kumbhakar, 1990, and Battese and Coelli, 1992);

- $u_{it} = u_i \gamma_t$, where γ_t are the time effects represented by time dummies and the u_i term can be either fixed or random producer-specific effects (Lee and Schmidt, 1993); and,

- $u_{it} = \Omega_{1i} + \Omega_{2i} t + \Omega_{3i} t^2$ where the Ω's are producer-specific parameters (Cornwell, Schmidt and Sickles, 1990).

A new generation of specifications is emerging that present themselves as dynamic frontier approaches and have the goal of sorting out the long-run from the short-run inefficiency levels. Ahn, Good and Sickles (2000) allow for the future arrival of unexpected inefficiency sources by focusing on an autoregressive specification of technical efficiency. This error structures intended to capture the sluggish adoption of technological innovations that relate to long- and short-run dynamics rather than incorporating a structural model of sluggish adoption. Tsionas (2006) allows for a stochastic and unknown long-run efficiency level by taking a Bayesian perspective on generating the short- and long-run efficiency distributions. The basic proposition is that

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long-run inefficiency cannot be a deterministic limiting point when you start off with a stochastic measure of short-run (or instantaneous) inefficiency.

Structural Modeling Approaches

The structural approaches to modeling dynamic efficiency involve both primal and dual specifications. The earliest efforts go back to Shephard and Färe (1978) that evolved into the Dynamic DEA models in Färe and Grosskopf (1996). This approach takes on a network theory orientation addressing an intertemporal substitution among inputs, outputs and intermediate outputs, and is particularly well-suited for multistage production processes. By preserving the time-ordered sequence of decisions, the timing of decisions permits the impact of technical inefficiency at one stage to be transmitted to later stages. Sengupta (1995, 1997) take a primal perspective with the explicit specification of a smooth adjustment cost function. Working with a linear-quadratic specification, closed form solutions are presented at the cost of modeling additional production flexibility. Nemoto and Giro (1999, 2003) take on a primal focus as well by building a discrete time mathematical programming model as it related to dynamic optimization theory. The fundamentals of this approach builds on Kleindorfer et al. (1975) which constructs the discrete time variants of the optimal control theory's Pontryagin Principle.

Two new directions build on the dynamic production analysis frameworks found in the same issue of the *Journal of Productivity Analysis*. Silva and Stefanou (2007) develop a myriad of efficiency measures associated with the dynamic generalization of the dual-based revealed preference approach to production analysis found in Silva and

Stefanou (2003). Vaneman and Triantis (2003) take on a system dynamics approach to specify the axioms of dynamic production and then build off this foundation in Vaneman and Triantis (2004) to measure a form of dynamic technical efficiency. By focusing on system performance, they explicitly take into account the interactions and feedback mechanisms that explain the causes of efficiency behavior, the dynamic nature of production, and non-linear combinations of the input/output variables.

Another tack builds on the shadow value function approach pioneered by Toda (1967) and Atkinson and Halvorson (1980), and then extended by Stefanou and Saxena (1988), Atkinson and Cornwall (1994), and Kumbhakar (1997). In this context both actual and behavioral value functions are constructed to capture how inefficiency leads to deviations from optimal decisions. The next section develops a model to illustrate the generalization of the shadow value function from an intertemporal perspective.[3]

IV. SHADOW VALUE FUNCTION MODEL

Consider the profit-maximizing firm facing adjustment costs with the objective to maximize the discounted flow of net revenue

$$(1) \quad J^a(k_o) = \max_I \int_0^\infty e^{-r\tau} \left[\pi(w, K) - qK - C(I) \right] dt$$

subject to

$$K = I - \delta K, K(0) = k_o$$

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where $\pi(w, K)$ is the short-run profit function defined as

$$\pi(w, K) = \max_x f(x, K) - wx$$

with w being the price of variable input, x, normalized by the output price; $f(x, K)$ is the production function conditional on capital stock, K; $C(I)$ represents the adjustment cost characterized by $I \cdot C_I \geq 0$ and $C_{II} > 0$ for all I. This leads to the dynamic programming equation

$$(2) \quad rJ^a(k_o) = \max_I \left[\pi(w, k_o) - qk_o - C(I) + (I - \delta k_o)J_k^a \right]$$

This equation presents the opportunity cost of the production plan, rJ^a, equals the instantaneous cash flow, $\pi(w, k_o) - qk_o - C(I)$, plus the instantaneous change in long-run profit, $dJ^a / dt = \dot{K}^a J_k^a$. The necessary condition for intertemporal profit maximization is

$$(3) \quad C_I(I) = J_k^a$$

or the marginal adjustment cost equals the shadow value of the capital stock.

In the event of a misallocation of capital, the equality in (3) does not hold. Figure 1 indicates the regions where the behavioral investment differs from the actual (profit maximizing) investment. To create an optimization structure for the behavioral investment behavior, we define an implicit (or behavioral) relationship where the shadow value of capital is augmented to create an equality; i.e.,

$$(4) \quad C_I(I^b) = \mu J_k^a = J_k^b$$

This suggests the dynamic programming equation for the behavioral problem is

$$(5) \quad rJ^b = \pi(w, k_o) - qk_o - C(I^b) + (I^b - \delta k_o)J_k^a$$
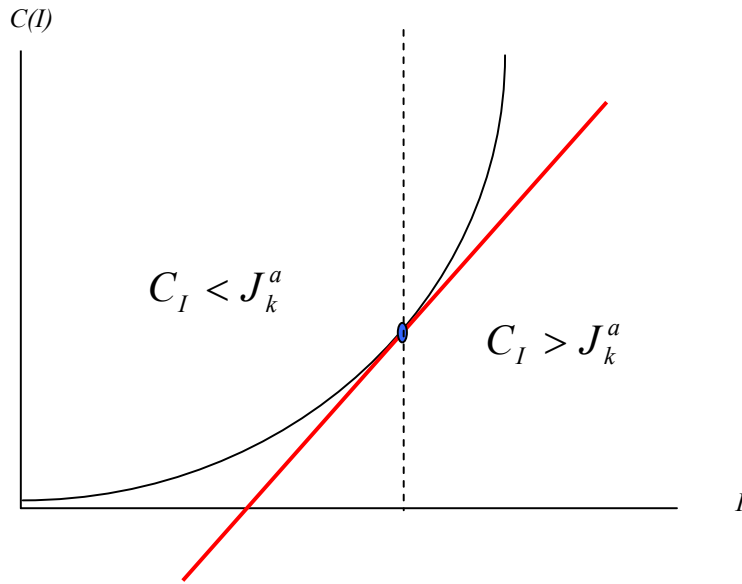
Consider the two stage problem where from period (o, τ) the firm makes mistakes such that $\mu \neq 1$ in stage I and then is perfectly efficient in allocating capital thereafter. The optimization problem in (1) can be partitioned into two segments such that

$$(6) \quad J(k_o) = \max_I \int_0^\tau e^{t\tau}\{\pi(w,K) - qK - C(I)\}dt + e^{-rt}\int_\tau^\infty e^{r\tau}\{\pi(w,K) - qK - C(I)\}dt$$

Using Bellman's Principle of Optimality, we can rewrite this as

$$(7) \quad J(k_o) = \max_I \int_0^\tau e^{r\tau}\{\pi(w,K) - qK - C(I)\}dt + e^{r\tau}V(k_\tau)$$

where k_τ is the capital stock consistent with the optimal capital accumulation up to time period τ, and

$$(8) \quad V(k_\tau) = \max_I \int_\tau^\infty e^{-r\tau}\{\pi(w,K) - qK - C(I)\}dt$$

$V(k_\tau)$ can be expressed in the form of a flow as

(9) $\quad V(k_\tau) = \max_I \int_\tau^\infty e^{-r\tau} \{\pi(w, K) - qK - C(I)\} dt$

or

$$V(k_\tau) = V(k_o) + \int_0^\tau dV = V(k_0) + \int_0^\tau \dot{K} V_k dt$$

Hence, we can rewrite (7) as

(10) $\quad J(k_0) = e^{-r\tau} V(k) + \max_I \int_0^\tau e^{-r\tau} \{\pi(w, K) - qK - C(I) + e^{-r\tau} \dot{K} V_k\} dt$

The dynamic programming equation is

(11) $\quad rJ^a(k_o) = \max_I \left[\pi(w, k_o) - qk_o - C(I) + \dot{K}(J_k^a + e^{-r\tau} V_k) \right] + e^{-r\tau} V(k_\tau)$

where the superscript a implies the actual value function. The term $J_k^a + e^{-r\tau} V_k$

presents the shadow value of capital into components attributable to stage I, J_k, and to

stage II, $e^{-r\tau} V_k$. The necessary condition for optimality in the presence of allocative

inefficiency (i.e., $\mu \neq 1$) is

(12) $\quad C_I(I^b) = \mu \left[J_k^a + e^{-r\tau} V_k \right] = J_k^b + \mu e^{-r\tau} V_k$

We can express the optimized behavioral value function, J^b, as

(13) $\quad rJ^b(k_o) = e^{-r\tau} V(k_0)\mu + \pi(w, k_0) - qk_0 - C(I^b) + \dot{K}^b(J_k^b + \mu e^{-r\tau} V_k)$

and the actual behavioral function, J^a, as

(14) $\quad rJ^b(k_o) = e^{-r\tau} V(k_0)\mu + \pi(w, k_0) - qk_0 - C(I^b) + \dot{K}^b(J_k^b + \mu e^{-r\tau} V_k)$

Equations (13) and (14) together imply

$$J^a(k_o) - J^b(k_o) = \frac{1}{r} \left[C(I^b) - C(I^a) + \dot{K}^a(J_k^a + e^{-r\tau} V_k) - \dot{K}^b(J_k^b + \mu e^{-r\tau} V_k) + (1-\mu)e^{r\tau}(k_o) \right] \geq 0$$

When the decision maker consistently over-invests ($\mu > 1$) the gap between the actual and behavioral value functions is dominated by the differences in the instantaneous adjustment costs which is the current period cost. When the decision maker consistently under-invests ($\mu < 1$), the gap between the actual and behavioral value functions is dominated by the difference in the instantaneous capital gain between the actual and behavioral decisions and the value potential in stage II starting undercapitalized.

Table 1.
Signing the Within and Between Periods Costs of Allocative Inefficiency

	$C(I^b) - C(I^a)$	$\dot{K}^a(J_k^a + e^{-r\tau}V_k)$ $- \dot{K}^b(J_k^b + \mu e^{-r\tau}V_k)$	$(1-\mu)e^{-r\tau}V(k_o)$
$\mu < 1$	**POSITIVE**	**INDETERMINATE**	**POSITIVE**
$\mu > 1$	**NEGATIVE**	**INDETERMINATE**	**NEGATIVE**

The signs of the components are presented in table 1. The first term, $C(I^b) - C(I^a)$, reflects an instantaneous cost reflecting the difference in the current period adjustment cost arising from under- or over-investment.[4] The next two terms reflect the distribution in costs over time. The first of these terms,

$$\dot{K}^a(J_k^a + e^{-r\tau}V_k) - \dot{K}^b(J_k^b + \mu e^{-r\tau}V_k),$$

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[4] The use of Figure 1 illustrates the relative magnitudes of these marginal adjustment costs. When $\mu > (<)1$ the firm is over- (under-) investing, which implies $C_I(I^a) > (<)C_I(I^b)$.

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reflects the change in the instantaneous capital gain (or loss) associated with an adding

(or not allocating) another unit of capital. We can decompose this term further to reflect

the impact of the instantaneous capital gain/loss in stage I, $\dot{K}^a J_k^a - \dot{K}^b J_k^b$, and impact of

an investment mistake in stage I the instantaneous capital gain/loss in the stage II,

$(\dot{K}^a - \dot{K}^b)(1-\mu)e^{-r\tau}V_k$. The second of these terms, $(1-\mu)e^{-r\tau}V(k_o)$, reflects the impact

of stage I inefficiency on the value function in stage II.

     A simple graphical illustration is presented in Figure 2. The optimal capital

trajectory is the blue line, $K_0\,A_0\,A_1$. Consider the case a mistake is made at time t_1 where

$\mu = \mu_1 > 1$ leading to overinvestment in that period. If this overinvestment is expected to

persist indefinitely, then the capital trajectory continues from B_0 to B_1. The problem

with this characterization of inefficiency is that it is implicitly assumes that there will be

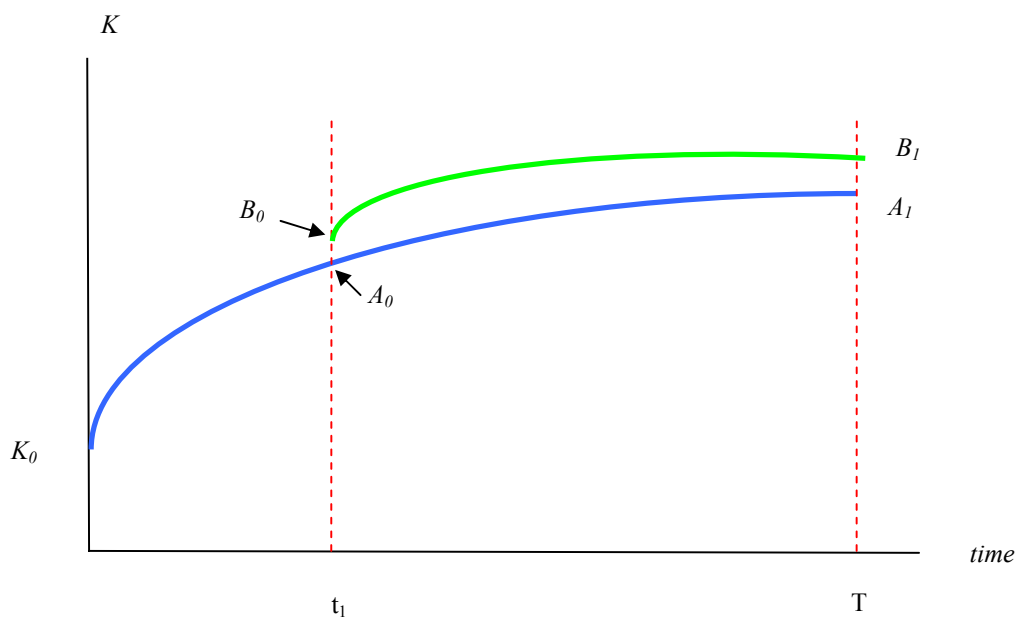no more mistakes between t_1 and the terminal time.

Figure 2

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V. FUTURE DIRECTIONS

Distribution of Trajectories

The shadow value function model starkly illustrates the need to generate the distribution of trajectories associated with the distribution of inefficiencies over time. On this score, the approach of Tsionas (2006) can offer a useful starting point. The fuller extension should also account for the decision processes and choices associated with choosing the levels of these forcing factors influencing efficiency levels over time. The first steps in addressing the structural model with a distribution of inefficiency-influenced trajectories is to specify an equation of motion on how the inefficiency changes over time. The approach of Ahn, Good and Sickles (2000) can be augmented to include the structural nature of adjustment and the distributed impact of present inefficiency into the future. At present, the Ahn, Good and Sickles approach specifies two of the three essential elements of a structural model: a) production feasibility with the production function specification, and b) an equation of motion on efficiency change with the autoregressive error specification. The element that is missing is the behavioral constraints relating to optimization problem endorsed by the decision maker.

Learning and Efficiency

When looking at the cognitive capacity, the notions of learning and efficiency come together. Identifying the dynamic-based costs of inefficiency in table 1 is only half of the story. There are benefits associated with making mistakes and when the benefits are realized there is evidence of learning taking place.

Focusing on learning as an accumulation of knowledge, the acquisition of additional knowledge necessarily draws on information acquisition. Knowledge plays an important role in the process of growth by choosing the right things to do (supporting the selection systems of technologies) and by doing the right things better (the understanding and execution of an implemented technology). Knowledge has value if one can translate it into actions or decisions that lead to enhanced cognitive or economic value. Two fundamental challenges to the process are: a) how does one acquire more knowledge and b) how does one translate the knowledge gained into action. Unlike most studies of information and technology decisions which take a recursive approach to modeling information acquisition then action on that information, Saha et al (1994) and Genius, Pantzios and Tsouvelekas (2006) jointly model the degree of technology adoption as a process jointly determined with the decision maker's information acquisition processes. The joint determination of these decisions reflects movement toward a long-run structural measurement of learning and technological decisions, which can then translate into measuring efficiency gains and innovation gains.

Firm decision makers react to competitive pressures by balancing the trade off between exploiting the full productive potential of their systems and technologies and adopting innovations. Both avenues can lead to enhanced profitability. Sustaining competitiveness over the long run involves attention to both growth prospects: (i) innovations are needed to keep pushing the competitive envelope, and (ii) efficiency gains are needed to ensure that implemented technologies can succeed. The effective management of knowledge and its acquisition (i.e., learning) contributes to both sources of profitability growth.

An emerging direction is to consider the directional distance function approach in a dynamic context. The start to this conceptualization can be found in Silva and Stefanou (2007)

$$F_g(y_t, x_t, I_t, k_t) = \min\{\gamma_{gt} : (\gamma_{gt} x_t, \gamma_{gt}^{-1} I_t)) \in V(y_t : k_t)\},$$

where this measure computes the maximum equiproportionate variable input reduction and gross investment expansion in the input requirement set, $V(y_t: k_t)$, to itself and $0 < F_g(y_t, x_t, I_t, k_t) \leq 1$. Silva and Oude Lansink (2006) present a first venture into this entirely new area and demonstrate how efficiency measures can be additive measures of efficiency measures rather than ration measures and allow the separation of the contribution of individual variable and dynamic factors to inefficiency.

But how learning is modeled in this context needs to be clearly specified. Is the firm *Planning to Learn vs. Planning to Execute.* This can influence the inefficiency measure in terms of modeling decisions as exogenous or endogenous. When the resources and efforts to mount a significant increase in the base of knowledge are considerable, the there is also the option value to learn, which can lead to modeling learning-based adjustment paths.

VI. CONCLUDING COMMENTS

The multiple directions observed in the literature to date to a great extent reflect a trade off between power of the theory and power of the data. The theory imbedded in structural models offers power in terms of informing our model specification of behavioral constraints and error structures as we look to rationalize the data. A theoretically founded structural model offers the further advantage of extending our

models to address related issues in the area of dynamic economic performance such as productivity growth, capacity utilization, the impact of multiple output production scenarios and the scope economies they imply. However, the data can often get in the way and our results can point out some disturbing shortcomings in the power of the theory-based models.   With the emergence of longer panels at the enterprise and plant levels, we are observing a phenomenon of the persistence of inefficiency; that is, firms are not necessarily doing things better. We can try to rationalize these results by focusing on the structural foundations of decisions making or the data-driven modeling building. For example, is the persistence of inefficiency:

- an artifact of the data in terms of the variable constructions and definitions (a notorious problem when considering the efficiency of capital assets and whether they are valued at book value or market value);

- an artifact of the model that is not able to capture all the sources driving inefficiency; or,

- a shortcoming in our characterization of decision making protocols which related to the behavioral objectives, or finally, if the cost of inefficiency of some small level $\alpha > 0$ is not offset by benefit of being perfectly efficient.

The static modeling of inefficiency has made great strides on both theoretical and methodological fronts over the past 30 years and these efforts are directing future attention to the measurement of dynamic economic performance. This paper has tried to lay out some perspectives on the dynamic case, but the landscape is still in need of clear articulation.

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