# Organizational Capital, Learning-by-Doing and Investment Volatility

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**Abstract**
This paper addresses the issue of plant-level investment volatility in the context of a purely convex model, where fluctuations are driven by technological shocks. The aim is to assess the role of learning-by-doing in reproducing the well-documented non-smooth investment dynamics at the plant-level, instead of relying on typical non-convexities (fixed costs or indivisibilities) used to account for lumpy investment behavior. The concept of organizational capital is essential in the analysis, and it provides the channel through which learning affects production. Our results indicate that learning-by-doing constitutes a potentially important source of investment volatility at the plant-level, and that one should not believe that convex models of investment necessarily deliver smooth dynamics.

*Keywords:* Organizational Capital, Investment Volatility, Learning-by-Doing

*JEL Classification*: C63, D21, E22,

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**Resumo**
A alta volatilidade nas taxas de investimento das firmas é tipicamente modelada como resultado de não-convexidades (custos fixos ou indivisibilidades). Neste artigo, investigamos até que ponto um modelo de decisão ótima de investimento puramente convexo, porém acrescido de *learning-by-doing* e capital organizacional, é capaz de gerar alta volatilidade nas decisões de investimento. Os resultados demonstram que não é correto necessariamente identificar modelos de investimento convexos com dinâmicas de investimento suaves, uma vez que a combinação de capital organizacional e *learning-by-doing* é capaz de gerar considerável volatilidade na taxa de investimento.

*Palavras-Chave:* Capital Organizacional, Volatilidade do Investimento, Efeito Aprendizado

*Classificação JEL*: C63, D21, E22

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## 1. Introduction

The standard model of investment with *ad hoc* convex-adjustment costs is unable to account for the investment dynamics observed at the plant-level.[1] Several empirical studies – Doms e Dune (1998), Sakellaris (2000), and Caballero et alii (1995) – provide clear evidence that investment decisions are much less smooth than convex-adjustment costs alone would imply. Non-convexities and irreversible investment are listed in the literature as important factors underlying such evidence.

In order to better assess the role of such factors, Cooper e Haltiwanger (2000) look deeper into the nature of investment adjustment costs. They implement an indirect inference procedure to recover structural parameters for a hybrid investment model, obtaining estimates that support a mix of irreversibility, convex and non-convex adjustment costs. Hence, the authors are able to demonstrate that convex adjustment costs do play a role in explaining investment dynamics.

In some sense, our paper tries to push this notion even further by investigating what are the limits of a purely convex investment model, that is, what else it can accomplish before we have to introduce non-convex features. Combining the ideas of Rosen's (1972) and Cooper e Johri (1999), we write down a model advancing the message that learning-by-doing can work as an endogenous mechanism for the propagation of technological shocks and account for non-smooth investment behavior. The concept of firm-specific organizational capital is also brought to light, as it becomes crucial for motivating the increased responsiveness of the firm in our formulation.

An essential point should be made clear from start though. Whereas, for instance, Cooper e Haltiwanger (2000) are fundamentally concerned with formulating a model rich enough to match several moments of the data (investment inactivity, asymmetric response to shocks and the occurrence of investment spikes), we are interested in evaluating if firm-specific learning-by-doing can induce high volatility in the investment behavior.[2] Thus, we are interested in investigating the possibility of matching one aspect of the data, namely the investment spikes, without relying on fixed costs or irreversibilities which are so often used when one needs to account for non-convexities.

We set up a dynamic partial-equilibrium model in which a maximizing-profit firm faces constant returns to scale technology, market power in its output market, and competitive input markets. Organizational capital is treated as firm-specific capital and it captures learning effects stemming from the

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[1] We use the terms *plant* and *firm* interchangeably as referring to one single production unit.
[2] Inactivity, for instance, cannot be accounted for in our model.

repetitive use of physical capital as in Rosen (1972). We augment Rosen's formulation by allowing for depreciation of the organizational capital and by introducing a temporary negative effect of newly added units of physical capital. We then parameterize the model and perform a numerical simulation exercise. The results have mainly qualitative significance and they are used to illustrate the promises and limitations of firm-specific learning in accounting for the volatility of the investment behavior at the plant-level.

The paper is structured as follows. Section 2 briefly sketches the central idea of Rosen's (1972) model and draws on it to suggest a new specification. We then set up the maximization problem of the firm and obtain the associated first-order conditions. Section 3 describes the numerical approach used to calculate the policy functions and discusses the parameterization of the model. Section 4 simulates the model and presents the results. Section 5 summarizes the paper.

## 2. The Model

### 2.1. *Rosen's framework*

Rosen (1972) models knowledge as a firm-specific capital good ($H$), which is accumulated through experience during the use of a composite market input ($C$). The jointly production process of market good ($Y$) and firm-specific knowledge ($H$) is formally described as:

$$Y_t = Q\left(C_t, H_t\right) \tag{1}$$

$$H_{t+1} - H_t = \phi C_t, \quad \phi > 0 \tag{2}$$

Equation (1) makes explicit the role of knowledge as an input, whereas (2) describes its evolution as a byproduct of experiences related to the use of the composite input $C$. The parameter $\phi$ is a positive constant and it affects the rate of learning from experience as well as the marginal product of knowledge. Product and factor markets are assumed to be competitive and the production function $Q$ displays all usual properties of continuity and differentiability. Given positive initial stocks of $C$ and $H$, the optimizing firm maximizes the present value of its profits by allocating inputs over its lifetime.

### 2.2. *Modifying Rosen's model*

We draw on this basic framework to study the investment dynamics at the firm-level. In order to do so, some modifications of Rosen's model are made. Clearly, the first one is to break down the composite input ($C$) into physical capital ($K$) and labor ($L$). We also move away from the non-stochastic environment of Rosen's Model, allowing for random technological shocks. The production of the market good is then characterized by:

$$Y_t = e^{A_t} F(H_t, K_t, L_t) \tag{3}$$

where $A$ denotes random (non-observable) technological shocks. Our next modification augments the process according to which the firm-specific knowledge is produced. Its motivation is twofold.

Firstly, as Rosen himself points out, the specification (2) does not yield a stationary solution since H can grow forever. This fact restricts the implementation of his model to finite horizon economies. By introducing a depreciation rate to the stock of knowledge we overcome this problem. From an economic perspective, postulating a negative aging effect over the stock of knowledge makes sense if one believes that parts of this stock become useless along the time. [3] Thus, depreciation of firm-specific knowledge and learning from experience are opposite forces acting simultaneously over the production process.

Secondly, Rosen's model implicitly assumes that increases in the use of inputs instantaneously lead to higher firm-specific knowledge. This assumption is consistent with learning effects but it overlooks the possibility that, in the short-run, changes in the level of input may cause temporary reduction in the stock of firm-specific knowledge. Along the lines of the organizational capital literature, one may argue that changing the ratio in which inputs are combined has the short-run effect of disrupting the way production is organized, causing a partial, though immediate, destruction of the firm-specific knowledge stock. As time goes by, such disruption eventually dies out and learning from experience pays off.

Alternatively, one could also argue that the process of capital adoption implies first-time costs for new investment. In this case, there would be an additional learning story going on according to which newly added units of capital would embody technological change and would require time to be fully productive. This reasoning is consistent with the work of Parente (1994) and Jovanovic e Nyarko (1996) on costly adoption of new technologies. Then, there would be learning effects in capital adoption together with the learning effects coming from experience. In order to address such possibilities, we adopt the following law of motion for $H$:

$$H_{t+1} - H_t = -\delta_H H_t - \gamma I_t + \phi K_t, \quad \gamma > 0, \quad \phi > 0, \quad \phi > \gamma \delta_K \tag{4}$$

[3] This is the case when employees develop expertise over certain procedures that must be abandoned or substantially modified for reasons exogenous to the firm. For instance, skills on DOS syntax acquired over the eighties were rendered virtually useless by the widespread use of operational systems with graphic interfaces over the nineties. Alternatively, Benkard (2000) rationalizes this phenomenon as an *organizational forgetting feature* typical of long production lines and provide supporting empirical evidence for the case of aircraft production.

where $\delta_H$ , $\gamma$ and $I_t$ denote, respectively, the depreciation rate of $H$, a positive constant that parameterizes the degree of short-run disruption caused by investment (or the costly adoption of embodied technology), and investment itself. The positive constant $\phi$ is the same used previously and the last inequality above will be explained later.

Equation (4) augments equation (2) by introducing a depreciation rate to $H$ and allowing for a one-period disruption effect of investment over the stock of knowledge. Note that any investment decision leads to two conflicting forces. The first one is long-lasting and it operates through a higher stock of physical capital, which leads to higher learning effects as in the Rosen's Model. The other one is effective only during the immediate subsequent period of the investment decision and it is responsible for a partial destruction of the firm-specific stock of knowledge, reflecting the costs of reorganizing production or, alternatively, learning effects in capital adoption.

As pointed out by Cooper e Johri (1999), the introduction of knowledge and learning-by-doing enriches the propagation mechanism of the technological shock. This fact brings important consequences for the firm's investment decision in response to shocks and, in this context, we investigate to what extent a richer formulation can compensate for the lack of non-convexities when explaining spikes in investment behavior.

### 2.3. *The firm's problem*

Before writing down the firm's maximization problem, we further specialize our formulation by assuming the following constant returns to scale technology for the market good:

$$Y_t = e^{A_t} H_t^{\alpha_H} K_t^{\alpha_K} L_t^{\alpha_L}, \quad \alpha_H + \alpha_K + \alpha_L = 1 \tag{5}$$

We also assume that the firm has some degree of market power and that it faces the following downward demand curve:

$$D_t = \lambda_t^{\theta}, \quad \theta < 0 \tag{6}$$

where $D$ stands for demand, $\lambda$ for the price of the market good and $\theta$ for the corresponding demand elasticity. The relevant market clearing condition allows us to write the total revenue function as: [4]

[4] Total revenue is given by price times quantity ($\lambda_t Y_t$). Solving the demand curve (equation 6) for prices and using the fact that, in equilibrium demand equals production ($D_t = Y_t$), the total revenue can be written as

$$(Y_t)^{1/\theta} Y_t = Y_t^{(1+\theta)/\theta}$$

.

$$R(A_t, H_t, K_t, L_t) = [e^{A_t} H_t^{\alpha_H} K_t^{\alpha_K} L_t^{\alpha_L}]^{\frac{\theta+1}{\theta}} \tag{7}$$

Finally, the firm maximizes its discounted stream of profits taking as given the factor prices, the demand elasticity for the market good and the evolution of its state variables.

$$\begin{aligned}
\underset{\{H_t,K_t,L_t,I_t\}_{t=0}^{\infty}}{Max} \quad & E_0 \sum_{t=0}^{\infty} \beta^t \left[R(A_t, H_t, K_t, L_t) - pI_t - wL_t\right] && (8a) \\
& st \quad K_{t+1} = (1-\delta_K)K_t + I_t && (8b) \\
& H_{t+1} = (1-\delta_H)H_t - \gamma I_t + \phi K_t, \gamma > 0, \phi > 0 && (8c) \\
& A_{t+1} = \rho A_t + \epsilon_t, |\rho| < 1, \epsilon_t \sim iid\, N(0,\sigma^2) && (8d) \\
& \phi > \gamma\delta_H && (8e) \\
& K_0 > 0, \quad H_0 > 0 && (8f)
\end{aligned} \tag{8}$$

As it is clear in the formulation above, we adopt a standard law of motion for the physical capital stock (8b) and a first-order autoregressive process for the technological shock (8d). Equation (8c) describes the evolution of the organizational capital and it provides the channel through which learning and disruption effects affect the firm. Initial conditions are given by (8f).

The inequality (8e) is important to ensure a well-behaved solution to the model by avoiding negative values for the value function. Its economic interpretation is that the amount of disruption caused by new additions of physical capital (or alternatively, the learning costs associated with capital adoption) is bounded by the amount of learning stemming from experience. If this was not the case, the organizational capital could converge to zero, and the firm's production would collapse.

In order to solve this problem, we set up the Bellman Equation associated with (8a–f): [5]

$$\begin{aligned}
V(A,H,K) = \underset{I,L}{Max} \quad & \{R(A,H,K,L) - pI - wL + \beta EV(A',H',K')\} \\
st \quad & K' = (1-\delta_K)K + I \\
& H' = (1-\delta_H)H - \gamma I + \phi K \\
& A' = \rho A + \epsilon, \quad |\rho| < 1, \quad \epsilon \sim iid\, N(0,\sigma^2) \\
& \phi > \gamma\delta_H, \quad K_0 > 0, \quad H_0 > 0
\end{aligned}$$

[5] In what follows, time subscripts are omitted and one-period-ahead variables are denoted with a prime.

The first-order conditions with respect to investment ($I$) and labor ($L$) are, respectively:

$$\beta \left[EV_K(A', K', H') - EV_H(A', K', H')\gamma\right] = p \tag{9}$$

$$R_L(A, H, K, L) = w \tag{10}$$

The envelope conditions associated with the state variables $H$ and $K$ are, respectively:

$$V_H(A, H, K) = R_H(A, H, K, L) + \beta EV_H(A', H', K')(1 - \delta_H) \tag{11}$$

$$\begin{aligned} V_K(A, H, K) = R_K(A, H, K, L) + \beta \Big[ & EV_K(A', H', K')(1 - \delta_K) \\ & + EV_H(A', H', K')\phi \Big] \end{aligned} \tag{12}$$

## 3. Model Evaluation and Parameterization

In order to evaluate the implied investment dynamics, we obtain the optimal policy function for investment by implementing a linear-quadratic approximation of the model. The first step of this approach is to numerically calculate a second-order Taylor approximation of the objective function around the steady state of the model.[6] After that, we obtain the first-order conditions by again numerically evaluating the relevant derivatives. This procedure yields a convenient linear policy function of the form:[7]

$$I_t = \lambda_0 + \lambda_1 A_t + \lambda_2 K_t + \lambda_3 H_t \tag{13}$$

Unfortunately, the variable $H$ is non-observable, making the identification of parameters like $\gamma$ and $\phi$ a non-trivial issue. Since the coefficients of the optimal policy function depend on the parameters of the model, we have to be careful about the generality of our statements. Ideally, one should turn to econometric techniques capable of producing estimates of these parameters. Though this seems to be a promising route, we believe that pursuing it would take us deep into econometric issues and far from our main theoretical point.

Hence, instead of directly estimating the parameters of the model, we assign sensible values for them. By sensible values we mean estimates found in the literature that, even though not fully consistent with the specification of our model, provide some sense as to what is reasonable to assume.

[6] The term steady state refers to the equilibrium values obtained analytically from the system (9)-(12), when the stochastic technological shock is set equal to its unconditional mean, which is zero – see Appendix.

[7] Obviously, this model has two policy functions: one for investment and the other for labor demand. In this paper, we are focusing solely on the investment decision.

The discount factor $\beta$ is set to 0.93, which is consistent with an annualized interest rate of 6.5%. The input shares for physical capital ($\alpha_K$), labor ($\alpha_L$), and organizational capital ($\alpha_H$) are set to 0.18, 0.72 and 0.04, respectively. These values were calculated by Atkeson e Kehoe (2001), and they were obtained for the U.S. manufacturing sector during 1959-99. The demand elasticity ($\theta$) is assumed to be $-4.8$ and it is based on estimates of Cooper e Haltiwanger (2000) using LRD plant-level data. The depreciation rate of physical capital ($\delta_K$) is assumed to be 0.07. We set the depreciation rate of organizational capital ($\delta_H$) and the learning rate ($\phi$) to 0.39 and 0.35, respectively. These numbers are based on estimates of Benkard (2000).

As to the technological shock, we set its persistence ($\rho$) and standard deviation ($\sigma$) to 0.71 and 0.09, respectively.[8] Finally, the investment disruption rate ($\gamma$) is left as a free parameter and we use it to investigate the ability of our model to match the occurrence of investment spikes (defined as a investment to capital ratio around 20%).

## 4. Computational Experiment

We focus on the investment to physical capital ratio ($I/K$) in order to study the investment dynamics implied by our model. As a direct consequence of our stochastic environment in which the firm is hit by a technological shock each period, this ratio will be always fluctuating. We illustrate our results by simulating the model and graphing the behavior of the variable $I/K$ over time.

The simulation of the model can be briefly described as follows. First we generate 145 observations of the technological shock ($A$) and assume initial conditions for the endogenous state variables $K$ and $H$.[9] Once this is done, the state-space for period 1 is completely determined and the policy functions will pin down the optimal investment and labor demands in that period. Following that, the state-space of period two will be also completely determined and the optimal behavior for that period is once again easy to calculate given the policy functions. This process goes on until the entire path of $K, H, I$ and $L$ is obtained for the 145-time period.

In order to simulate the model, we make use of the parameterization carried out in the last section. As the reader might recall, we left the disruption rate ($\gamma$) as a free parameter, and in this simulation exercise we consider three different values for it. Thus, we perform three distinct simulation exercises out of the same draw of innovations $\epsilon$, encompassing some interesting polar cases. This approach is helpful for qualitatively assessing the promises and limitations of firm-specific learning in accounting for investment spikes at the firm-level. Table

[8] Theses numbers were kindly provided by John Haltiwanger and correspond to typical values found in plant-level data for the US.

[9] To mitigate spurious dynamics introduced by setting bad initial conditions, we simulate the model for 245 periods and then throw away the first 100 periods. This procedure is usually justified by assuming that the economy (firm in this case) is not far away from its stationary equilibrium.

1 ahead brings the values of $\gamma$ we used, all other parameters are the same as given in the last section.

Table 1

| | |
|---|---|
| Simulation 1 | $\gamma = 0$ |
| Simulation 2 | $\gamma = 1.3$ |
| Simulation 3 | $\gamma = 3$ |

Figure 1 in the Appendix depicts the first simulation and it corresponds to the situation in which there is no disruption coming from investment (or alternatively, there are no costs involved in capital adoption). In this case, there is excessive volatility in the investment to capital ratio. Indeed, Cooper e Haltiwanger (2000) and Sakellaris (2000) present evidence that the investment spikes observed in the data are much smaller (around 20%).

It is interesting to mention that we adopted the same standard deviation for the technological shock that Cooper e Haltiwanger (2000) used, and the authors showed that the standard convex adjustment cost model would generate an excessively smooth investment dynamics under sets of parameters commonly assumed in the literature. In particular, the investment to capital ratio would not go higher than 8% in the standard *ad hoc* adjustment formulation, while our model can generate spikes of almost 80%. This suggests the importance of firm-specific learning in amplifying the volatility of investment decisions even when no departure from convexity is allowed.

The fact that our model is able to produce such high and counter-factual investment spikes highlights the relevance of the disruption effect. In simulation 2 (see Figure 2 in the Appendix) the disruption channel is turned on and we pick a value for $\gamma$ which makes the size of the investment spikes fairly consistent with the data. Thus, our model suggests that learning effects alone (without allowing for the disruption channel) generate an excessively volatile dynamics, and that a positive value for $\gamma$ seems to be crucial for matching the dynamics observed in the data.

Simulation 3 (see Figure 3) illustrates a polar case by picturing an extremely non-responsive investment dynamics when the disruption effect is set to be sufficiently high. Its interesting to mention that this case fairly replicates the volatility of the standard *ad hoc* adjustment cost model, but it has the advantage of making explicit the source of the costly adjustment in the capital stock.

The results indicate that our model can produce high volatility in the firm's investment behavior without resorting to non-convexities. This high volatility stems from the combination of learning-by-doing and organizational capital, but it is important to understand precisely how these two assumptions interact. In any model where technological shocks are present, a positive draw induces firms to demand higher levels of inputs. However, in our formulation, the presence of learning effects creates an additional benefit of investing in physical capital. In particular, such investment directly increases the stock of two production factors:

(i) the physical capital stock itself and

(ii) the organizational capital.

This fact amplifies the effects of the technological shock over the firm's investment decision and leads to the higher volatility observed in our model.

## 5. Conclusions and Extensions

We combined learning-by-doing and organizational capital within a purely convex investment model. Our intention was to evaluate how much investment volatility at the plant-level could be generated by the learning-by-doing hypothesis regardless of any underlying non-convexity. The results indicated that learning-by-doing can be particularly powerful in producing non-smooth investment behavior. This conclusion should not be taken to mean that non-convex costs or indivisibilities are not relevant, but rather that one should not naively believe that convex investment models necessarily imply smooth dynamics. In this context, a meaningful extension of the research presented here would be to devise empirical identification strategies capable of isolating the true role of non-convexities (net of learning effects) in explaining investment spikes at the plant-level.

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## Appendix

Because the firm is hit by a technological shock every period, this model does not present a "resting-point" steady state. Instead, it converges to a stationary distribution in which the firm responses are equilibrium fluctuations naturally emerging from the stochastic environment. Thus, the term steady state used in the paper refers to the steady state of the "certainty version" of the model – that is, when the technological shock is set to its unconditional mean (which is zero). This steady state is used in the numerical approximations and it can be analytically calculated from the following expressions (which are derived from the first-order conditions and the law of motion for the state variables):

$$\Omega_1 R_K(\bar{H}, \bar{K}, \bar{L}) + \Omega_2 R_H(\bar{H}, \bar{K}, \bar{L}) = p$$

$$R_L(\bar{H}, \bar{K}, \bar{L}) = w$$

$$\bar{K}\delta_K = \bar{I}$$

$$\bar{H}\delta_H = (\phi - \gamma\delta_K)\bar{K}, \quad \phi > \gamma\delta_K$$

where

$$\Omega_1 = \frac{\beta}{1 - \beta(1 - \delta_K)}$$

$$\Omega_2 = \frac{\beta(\phi\beta - \gamma(1 - \beta(1 - \delta_K)))}{(1 - \beta(1 - \delta_K))(1 - \beta(1 - \delta_H))}$$

$$R(\bar{H}, \bar{K}, \bar{L}) = [\bar{H}^{\alpha_H} \bar{K}^{\alpha_K} \bar{L}^{\alpha_L}]^{\frac{\theta+1}{\theta}}$$

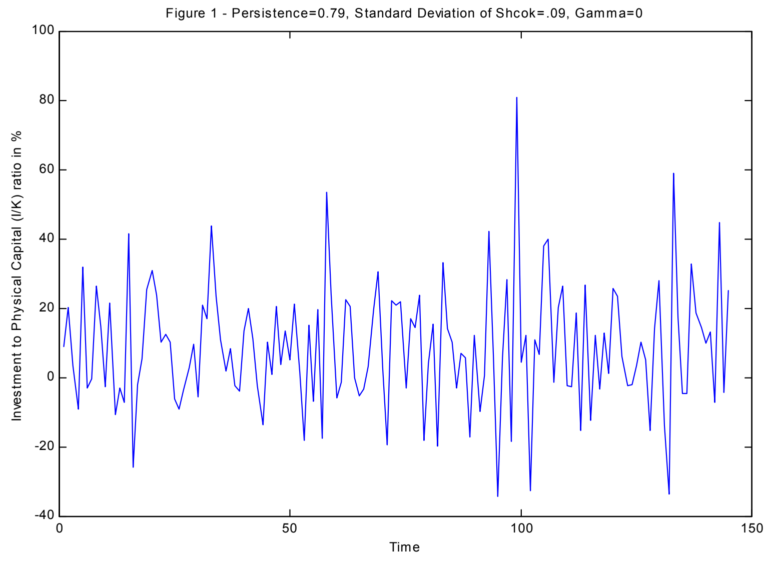
Figure 1 - Persistence=0.79, Standard Deviation of Shcok=.09, Gamma=0
Investment to Physical Capital (I/K) ratio in %
Time
100
80
60
40
20
0
-20
-40
0
50
100
150

Fig. 1.

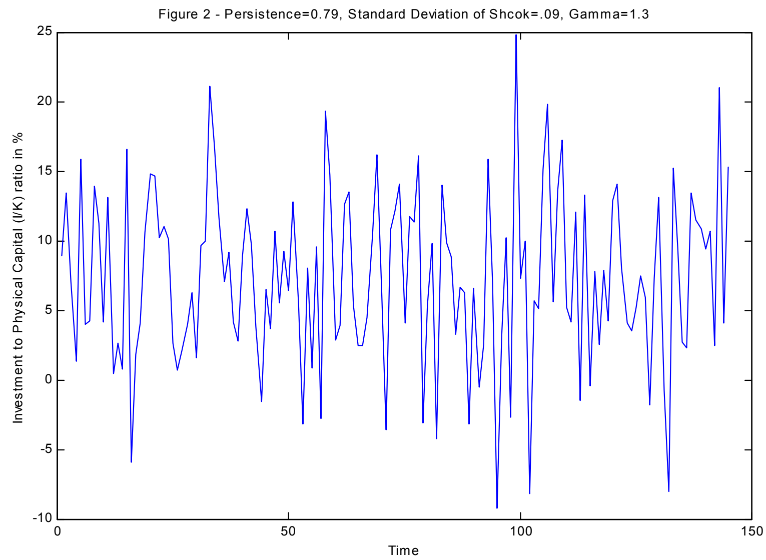
Figure 2 - Persistence=0.79, Standard Deviation of Shcok=.09, Gamma=1.3
Investment to Physical Capital (I/K) ratio in %
Time
25
20
15
10
5
0
-5
-10
0
50
100
150

Fig. 2.

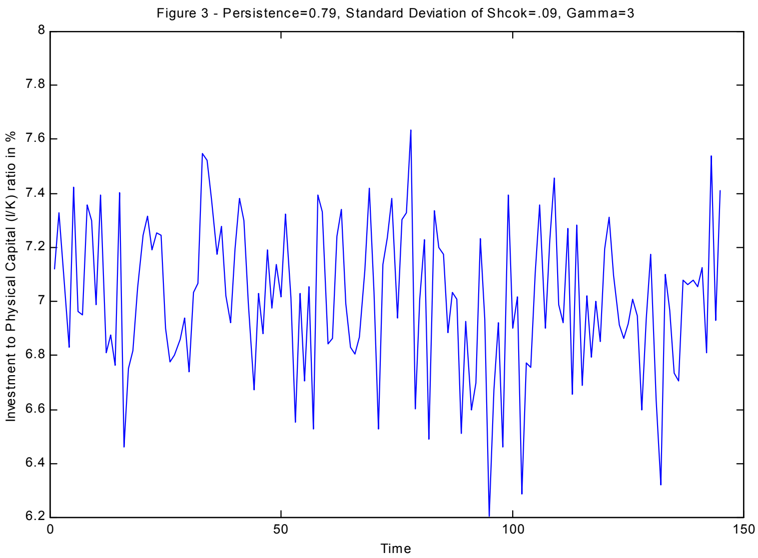
Figure 3 - Persistence=0.79, Standard Deviation of Shcok=.09, Gamma=3
Investment to Physical Capital (I/K) ratio in %
Time
8
7.8
7.6
7.4
7.2
7
6.8
6.6
6.4
6.2
0
50
100
150

Fig. 3.