NBER WORKING PAPERS SERIES

TECHNOLOGY COMMITMENT AND THE COST OF ECONOMIC FLUCTUATIONS

Garey Ramey

Valerie A. Ramey

Working Paper No. 3755

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 1991

For helpful comments we are grateful to John Cochrane, Robert Engle, James Hamilton, Clive Granger, Andrew Levin, Robert Lucas, James Rauch and seminar participants at U.C. Berkeley, U.C. San Diego, the 1990 NBER Summer Institute and the February 1991 NBER Economic Fluctuations Research Meeting. We are also grateful to Subir Bose for expert assistance and to the UCSD Committee on Research for financial support. This paper is part of NBER's research program in Economic Fluctuations. Any opinions expressed are those of the authors and not those of the National Bureau of Economic Research.

NBER Working Paper #3755
June 1991

TECHNOLOGY COMMITMENT AND THE COST OF ECONOMIC FLUCTUATIONS

ABSTRACT

When firms must make technology commitments, economic fluctuations impose costs in the form of ex post inefficiency in production technology. We present a general equilibrium model in which, due to the presence of technology commitment, greater volatility of productivity shocks leads to *lower mean output.* When learning-by-doing is incorporated, mean output becomes *permanently lower* as a consequence of higher volatility. The negative and persistent relationship between mean and variance of output implied by our model is strongly verified by the data. We estimate that observed volatility has imposed a cost amounting to almost two percentage points of U.S. GNP growth.

Garey Ramey
Department of Economics, D-008
University of California,
San Diego
9500 Gilman Drive
La Jolla, CA 92093-0508

Valerie A. Ramey
Department of Economics,
D-008
University of California,
San Diego
9500 Gilman Drive
La Jolla, CA 92093-0508
and
NBER

In a Keynesian world of involuntary unemployment and Okun's gap, economic fluctuations impose substantial costs on individuals. Likewise, the attention given to business cycle concerns in the popular press suggests important welfare costs. Recently, however, Robert Lucas (1987) estimated that the cost of U.S. business cycles is very small. In particular, using a representative consumer framework, he calculated that each person would be willing to pay only a miniscule amount to eliminate all variability in consumption attributable to business cycles. Hence, he concluded that the gains from stabilization policy in the post-World War II economy are small.

In this paper we present a model that leads to very different conclusions. We embed Lucas' representative consumer in a simple general equilibrium model in which firms must make *technology commitments* in advance. These may include both long-run commitments, such as the determination of the scale of a new factory, and shorter-run commitments, such as the size of the attached labor force. Each technology corresponds to a different minimum efficient scale, i.e. a different level of output at which average costs are minimized. In the absence of economic fluctuations, firms would choose their technology to bring minimum efficient scale into line with the equilibrium output level. If economic conditions fluctuate, however, equilibrium output levels may depart from minimum efficient scale, and firms may end up with average costs above the minimum level.

While profit-maximizing firms will make their technology commitments in a manner that minimizes expected costs ex ante, volatility in realized production causes firms' production plans to be suboptimal ex post. Planning errors thus lead to dissipation of resources in the form of ex post inefficient technology choices. These production inefficiencies imply that economic instability will lead to *lower mean output*, which we refer to as the *first moment effect* of volatility. This cost of economic fluctuations is entirely distinct from consumer aversion to consumption risk.

In this paper we posit a simple general equilibrium model in which the firm must fix its mimimum efficient scale before it knows the realization of a stochastic labor productivity parameter. We show that with this structure, an increase in the volatility of the shocks leads, under reasonable assumptions, to lower mean output; thus, our model implies a negative relationship between mean and variance of output. The negative effect of an increase in volatility can be decomposed into an *inefficiency effect*, generated by less efficient utilization of a given technology, and a *planning effect*, whereby the firm chooses a smaller-scale technology in anticipation of the reduced mean output. Because of the smaller planned scale, output is made lower *for each realization* of the productivity shock. We also show that a one-time increase in volatility has a *permanent* negative effect on output, when current output is linked to future output via learning-by-doing.

The implications of our theory are borne out strongly by the data on output in the U.S, which reveal a strong negative contemporaneous correlation between the mean and variance of GNP growth rates. Further, an increase in volatility does have a permanent negative effect on the level of GNP: we find that the real output level is cointegrated with the cumulation of past output volatility, as measured by the cumulative sum of squared forecast errors, and that output growth rates are Granger-caused by volatility. Thus the data indicate a clear causal link running from volatility to growth. Our estimates indicate that eliminating volatility would lead the average annual growth rate of real GNP to be 1.8 percentage points higher, as a result of greater production efficiency. This translates into a gain of over $380 per capita in the first year alone.

Further, the negative relationship between mean and variance of output is not explained by an asymmetrically large effect of negative shocks. Our estimates indicate that the cumulative sums of squared positive and negative forecast errors each have negative effects on output, of about the same magnitude, which is consistent with our technology commitment theory. We also show that the asymmetries in forecast variances discussed by Hamilton

(1989) are statistically insignificant in estimates formed from actual forecast errors, perhaps because the forecasters take into account the nonlinearities that Hamilton emphasized. These data nevertheless indicate a strong and persistent negative effect of volatility on output.

It is important to note that our theory and empirical results do not contradict recent work on increasing returns (e.g. Murphy, Schleifer and Vishny (1989), V. Ramey (1991)), which suggests that firms might voluntarily introduce volatility into their production schedules to exploit concavities in their cost functions. The key point is that the latter effect is linked to *planned* output decisions, while the inefficiencies associated with technology commitment emerge from *unplanned* variations in output. Moreover, deviations from planned output result from expectation errors that are incorporated into the error term of regressions involving planned output; thus, empirical evidence of decreasing marginal costs in planned output is entirely consistent with the presence of significant costs of variations from planned output.

The ideas and results of this paper are related to several strands of literature. First, several earlier papers have analyzed theoretical linkages between volatility and economic performance. Most closely related to our work is Rothenberg and Smith (1971), who analyze the effect of capital immobility in a two-sector model. They show that greater volatility of the labor endowment reduces mean national income, when capital is allocated according to a plausible rule of thumb.[1] Greenwood and Huffman (1989) consider the interaction of distortionary taxes and volatility, and they find that volatility becomes lower, and mean output somewhat higher, when the tax rate on distortionary taxes is reduced during recessions. Imrohoroglu (1989) extends Lucas' analysis of the risk costs of volatility by introducing heterogeneous agents and incomplete insurance markets. She concludes that the costs of volatility, while larger than those calculated by Lucas, are still surprisingly small.[2]

---

[1]Black (1987, pp. 109-10,163) argues informally that factor immobility makes unanticipated fluctuations costly, and this cost represents a major component of the cost of business cycles.

[2]Jovanovic and Rob (1990) present a model of research and development in which it is possible to cycle between phases of high-mean, low-variance invention and low-mean, high-variance

Second, a number of papers have uncovered empirical evidence of a negative relationship between mean output and volatility. For example, in their study of cyclical behavior during the last century, Zarnowitz and Moore (1986) point out that the standard deviation of GNP growth tends to be higher during periods of lower growth. Zarnowitz and Lambros (1987) also find that an increase in uncertainty about inflation has a short-run negative effect on GNP growth. Similarly, using his two-state Markov model, Hamilton (1989) demonstrates that the forecast error from an AR(4) is larger if the economy was in a recession in the previous period. Using cross-country comparisons, Kormendi and Meguire (1985) show that countries with high monetary volatility have lower growth rates. Thus, the negative relationship has appeared in several contexts, although none has linked the results with technology commitment or analyzed the persistence of the relationship.[3]

Third, our focus on rigidities in technology is related to ideas in the the literature on investment under uncertainty. Depending on the specification of the investment model, uncertainty has been shown to have a positive or negative effect on investment (see, for example, Hartman (1972), Abel (1983), Bernanke (1983), Pindyck (1988), and Caballero (1991)). All of the models in this literature concentrate on the problem of the individual firm, and our work may be viewed as a first attempt at addressing this issue in a general equilibrium setting.

The first section of this paper lays out our general equilibrium model and demonstrates that greater volatility of productivity shocks leads to lower mean equilibrium output. The final part of the section develops an endogenous growth model and shows how volatility can lead output to be permanently lower. In the second section of the paper, we give empirical

---

invention.

[3]Delong and Summers (1987) develop a technique for measuring the costs of volatility that associates peak GNP with full employment. They find a negative relationship between volatility and mean output, but in essence their technique establishes such a relationship by definition.

evidence indicating a strong negative contemporaneous relationship between mean and variance of U.S. GNP, and we present results showing that the level of GNP depends on the entire history of volatility. Evidence distinguishing the inefficiency and planning effects is presented next, followed by discussions of business cycle asymmetry and increasing returns. Section three concludes.

1. Theoretical Analysis

A. A General Equilibrium Model with Technology Commitment

We will develop our ideas in the context of a stylized model in which (1) all prices are determined by general competitive equilibrium; (2) economic volatility emerges from fluctuations in the productivity of inputs; and (3) agents' expectations derive from the true distributions of economic variables, i.e. the rational expectations hypothesis prevails. Two goods are traded, a nonstorable consumption good Q and labor L. There is a representative price-taking consumer who derives utility from the consumption good and leisure, according to the following function:

$$U(Q,\mathcal{L} - L) = \ln(Q) + \ln(\mathcal{L} - L)$$

where $\mathcal{L} > 0$ gives the labor endowment.[4] There is also a representative price-taking firm, whose production technology depends on its technology choice. Let K indicate the technology choice, which is required to be nonnegative. The production technology is specified as follows. When the firm produces Q units under technology K, its minimum labor requirement is:

---

[4]Our analysis can be easily extended to incorporate the slightly more general utility function $\ln(Q) + \psi\ln(\mathcal{L} - L)$ with positive constant ψ.

(1) $$L(Q,K) = \alpha Q + \beta(Q - K)^2$$

where α and β are positive parameters.[5]

Average labor requirement curves associated with (1), which measure average cost in terms of labor input, are illustrated in Figure 1 for the technology choices K and K′. Note that minimum efficient scale occurs where Q is equal to the technology choice parameter, and that minimum average cost is constant at α. As β rises, the curves shift upward for every $Q \neq K$ and become more sharply convex; thus β serves to index the costs of departing from minimum efficient scale, with higher β representing higher costs.

The technology choice is intended to capture the quasi-fixed aspects of technology. It is clear, for example, that K may be thought of as an index of the minimum efficient scale of operation of a plant in terms of output per hour. Deviations from K decrease the average productivity of labor. Alternatively, K could be proportional to the labor force attached to the firm, and deviations of Q from K impose overtime and short-week costs, as well as rescheduling costs; in this case we may interpret the quadratic term in (1) as an adjustment cost.[6]

Under our specification of production technology, there arises the possibility that no feasible output-leisure combinations exist, e.g. K may be so large relative to $\bar{L}$ that adjustment

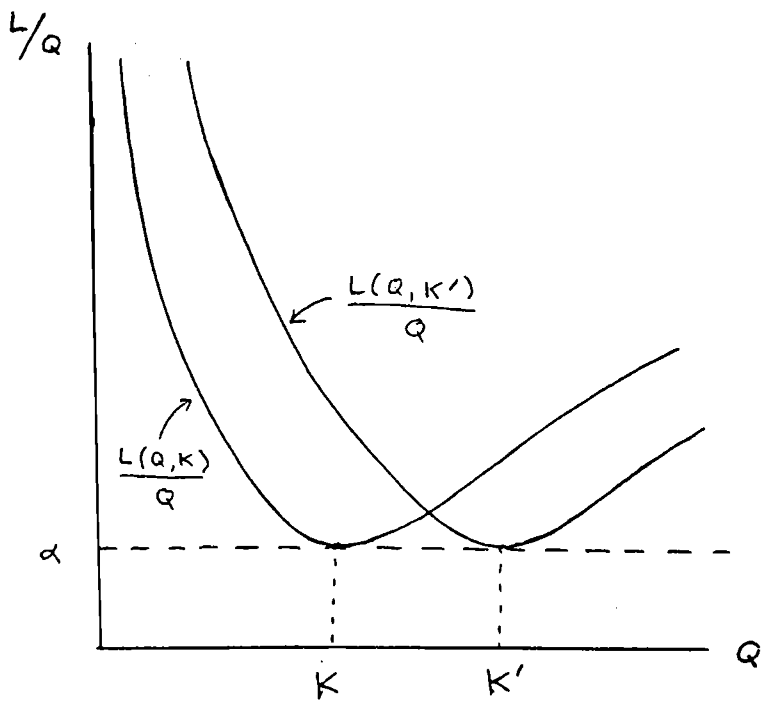
---

[5]If there are n price-taking firms, then (1) will represent the aggregate production function if each firm is endowed with the technology $C(q,k) = \alpha q + n\beta(q - k)^2$, where q is the firm's output and k is its technology choice. In a symmetric equilibrium we have $Q = nq$ and $K = nk$. Note that as the number of firms rises, the firm-level adjustment parameter needed to achieve a given aggregate β must rise. This is caused by the fact that under the specification (1), marginal adjustment costs decline as Q and K are scaled down proportionately.

[6]This cost function is similar to the ones analyzed by Holt, Modigliani, Muth and Simon (1960) in the context of production planning and inventories. Our propositions would continue to hold in a repeated version of our model, if output were assumed to be nonstorable. If firms could store their goods, however, then inventories could be used to offset the effects of technology commitment. In this case, inventory holding costs would to some extent replace the costs of technical inefficiency that we emphasize, but our basic conclusions would remain the same.

Figure 1

Average Labor Requirement Curves



costs completely exhaust the labor endowment before any units of output can be produced. This possibility is ruled out under the following condition:

Feasibility Condition: Production possibilities are nondegenerate if and only if:

(a) $\alpha^2 + 4\beta(\bar{L} - \alpha K) > 0$; and

(b) If $K < \alpha/2\beta$, we must also have $\bar{L} - \beta K^2 > 0$.

The feasibility condition is illustrated in Figures 2a and 2b, which depict production possibility frontiers (PPF's) for $\beta = 0$ and $\beta > 0$. Note that at $Q = K$ the $\beta > 0$ PPF's are tangent to the $\beta = 0$ PPF, and the former lie strictly inside the latter for $Q \neq K$. Part (a) of the feasibility condition is needed to ensure that the $\beta > 0$ PPF crosses into the $\bar{L} - L > 0$ half-plane. From Figure 2a it is clear that this is sufficient to ensure nondegenerate production possibilities if $K \geq \alpha/2\beta$; otherwise we must add the condition $\bar{L} - \beta K^2 > 0$, as illustrated in Figure 2b.

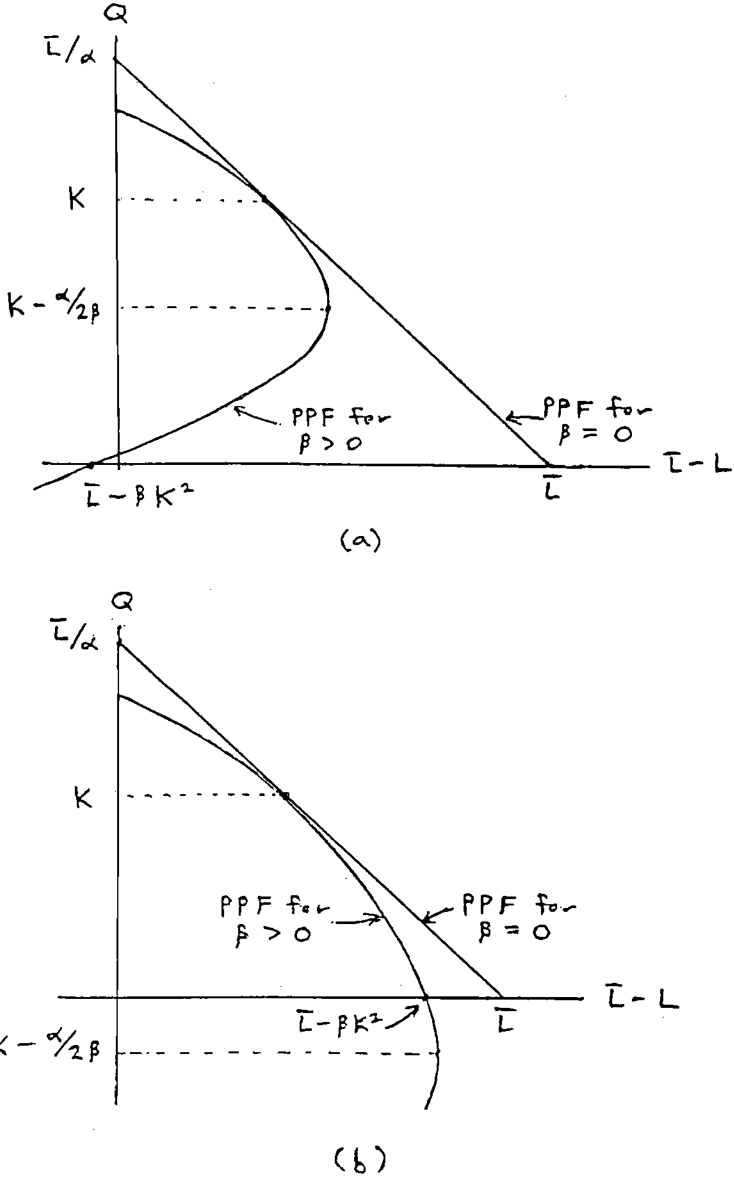
To capture the idea of technology commitment, we assume that K is chosen before equilibrium prices are determined, so that it becomes a fixed parameter of the production technology. For values of the parameters $\bar{L}$, α, β and K that satisfy the feasibility condition, there exists a unique competitive equilibrium, as shown in the following lemma (the proofs of all lemmata are given Appendix 1).

Lemma 1: If the feasibility condition holds, there exists a unique competitive equilibrium, with the equilibrium price of output in terms of leisure given by:

$$P = \frac{1}{3}(\alpha - 2\beta K + 2[(\alpha - 2\beta K)^2 + 3\beta(\bar{L} - \beta K^2)]^{1/2}), \qquad (2)$$

Figure 2.

Production Possibilities Frontiers



and equilibrium output given by:

(3) $$Q = \frac{1}{3\beta}(2\beta K - \alpha + [(\alpha - 2\beta K)^2 + 3\beta(L - \beta K^2)]^{1/2})$$

Using Lemma 1, we may recover Lucas' (1987) analysis of volatility costs as a special case of this model. When $\beta = 0$, technology commitment effects disappear, and equilibrium output and leisure become:

$$Q = \frac{\bar{L}}{2\alpha}, \quad \bar{L} - L = \frac{\bar{L}}{2}$$

Note that output is proportional to $1/\alpha$, which is the productivity of labor. It follows that as long as mean labor productivity remains the same, random fluctuations in α will not affect mean output. We will henceforth assume that the fluctuations of α are generated by a random variable $\tilde{\theta}$, whose realization determines $1/\alpha$; thus in the absence of technology commitment, a mean-preserving spread of $\tilde{\theta}$ has no effect on mean output. Lucas' specification emerges when we set $\bar{L} = 2$ and:

$$\tilde{\theta} = \exp(-\frac{1}{2}\sigma_z^2)\tilde{z}$$

where $\ln(\tilde{z}) \sim N(0,\sigma_z^2)$. Calibrating σ_z^2 to the variance of U.S. consumption, Lucas finds that the representative consumer would be willing to give up only 0.00008 per cent of consumption to eliminate all volatility, which amounts to \$1.71 per capita in 1990 dollars.

B. Equilibrium Technology Choice

Suppose now that $\beta > 0$, so that K has a nontrivial effect on the competitive equilibrium. We make the following key assumption: the firm must choose K *before* it observes the realization of $\tilde{\theta}$. This means that the firm must commit to its technology prior to observing all information that is relevant to its choice. To be precise, the timing of our model is given by:

Stage 1: The firm chooses K prior to observing $\tilde{\theta}$.

Stage 2: $\tilde{\theta}$ is realized.

Stage 3: The agents observe $\tilde{\theta}$, and a competitive equilibrium ensues under the predetermined values of K and $\alpha = 1/\tilde{\theta}$.

To solve this model, we first derive the equilibria that arise in Stage 3 for each possible set of predetermined variables, which has already been done in Lemma 1. It remains to consider the choice of technology in Stage 1. From the point of view of Stage 1, the equilibrium price is a random variable determined from $\tilde{\theta}$ according to (2) and $\alpha = 1/\tilde{\theta}$, which we write $\tilde{P}$. In Stage 1 the firm is assumed to form rational expectations about $\tilde{P}$, and it believes that the distribution of $\tilde{P}$ is fixed independently of its choice of K (since the firm is a price taker). In a rational expectations equilibrium (REE), the firm's choice of K maximizes its expected profit, subject to the distribution of $\tilde{P}$ determined from (2) by that choice of K. We have:

Lemma 2: K gives a REE if and only if $E[\tilde{Q}] = K$, where equilibrium output $\tilde{Q}$ is determined from $\tilde{\theta}$ according to (3) and $\alpha = 1/\tilde{\theta}$.

In the proof of Lemma 2, it is shown that in a REE the output supply function takes the following form:

$$Q_S = E[\tilde{Q}] + \frac{\tilde{P} - 1/\tilde{\theta}}{2\beta}$$

where $E[\tilde{P} - 1/\tilde{\theta}] = 0$, i.e. fluctuations of supply around mean output are induced by shocks to the "net price" $\tilde{P} - 1/\tilde{\theta}$. This "Lucas-type" supply behavior does not emerge from imperfect perceptions of nominal variables, sustained by information lags (Lucas (1972, 1973)). Rather, the optimality of technology choice forces the net price to be zero on average, and output fluctuations arise as a consequence of *ex post* volatility.

To assure satisfaction of the feasibility condition for $\beta > 0$, we will need to restrict the support of $\tilde{\theta}$ lie in a compact interval $[\underline{\theta},\bar{\theta}]$, with $\underline{\theta} > 0$. Existence and multiplicity of REE are discussed in the following proposition, whose proof is given in Appendix 1:

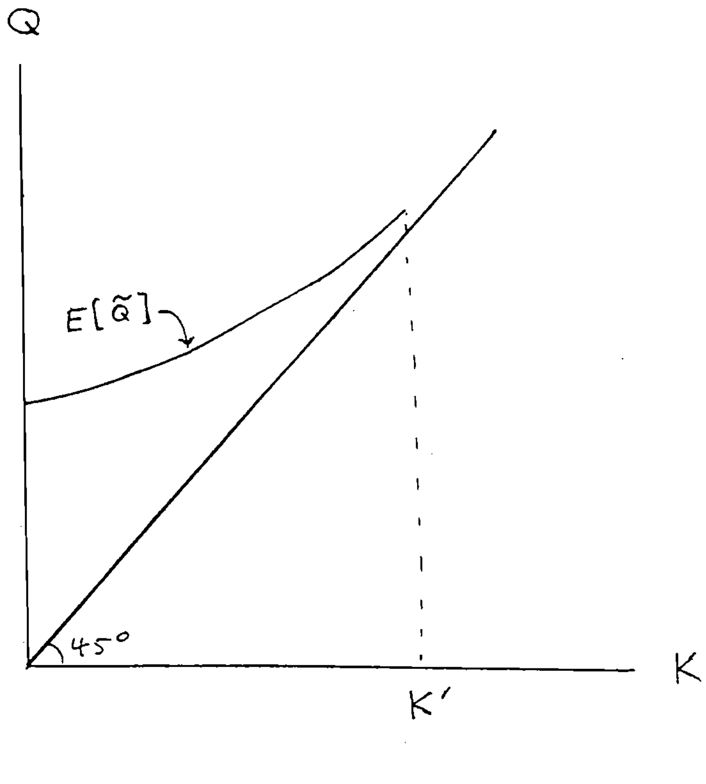
Proposition 1: (a) A REE exists if $\underline{\theta}$ is sufficiently close to $\bar{\theta}$, i.e. the length of the support of $\tilde{\theta}$ is sufficiently small;

(b) There can exist at most one REE.

Possible nonexistence of REE is related to failure of the feasibility condition for $\tilde{\theta}$ near the bottom of its support. This is illustrated in Figure 3, which depicts $E[\tilde{Q}]$ as a function of K. A REE exists wherever $E[\tilde{Q}]$ intersects the 45° line. As K rises, however, a point K' is reached such that feasibility is violated for $\tilde{\theta} = \underline{\theta}$, and K cannot be further increased. It follows that no REE will exist if $E[\tilde{Q}]$ remains above the 45° line at this point, as shown. To guarantee existence, we must restrict the support of $\tilde{\theta}$ sufficiently to ensure that feasibility is maintained at $\tilde{\theta} = \underline{\theta}$, for all potential REE values of K which might arise as $\tilde{\theta}$ ranges over $[\underline{\theta},\bar{\theta}]$. Finally, uniqueness is obtained from the fact that the feasibility condition implies

Figure 3

Nonexistence of REE



$\partial E[\tilde{Q}]/\partial K < 1$.

C. Mean Output and Volatility

Introducing technology commitment significantly alters the nature of volatility costs, for a mean-preserving spread of $\tilde{\theta}$ will lead to *lower mean output.* The key step in demonstrating this result is contained in the following lemma:

Lemma 3: Suppose $\beta > 0$.

(a) In a REE, $\tilde{Q}$ is a strictly concave function of $\tilde{\theta}$ for $\tilde{Q}$ sufficiently close to $E[\tilde{Q}]$;

(b) If β is sufficiently large, then $\tilde{Q}$ is strictly concave in $\tilde{\theta}$ for all $\tilde{\theta}$.

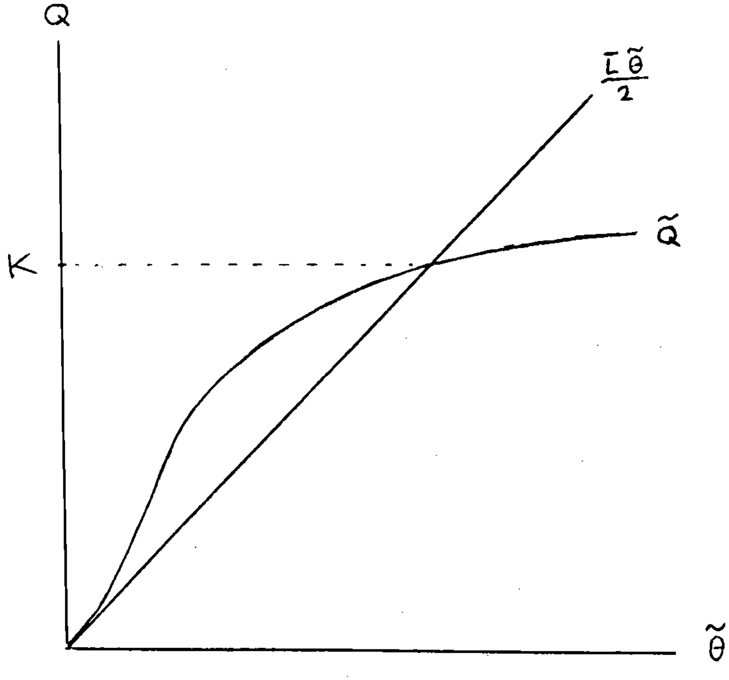
The intuition underlying the concavity of $\tilde{Q}$ is straightforward: since $\tilde{Q}$ is strictly increasing in $\tilde{\theta}$, it follows that extreme realizations of $\tilde{\theta}$ give rise to extreme realizations of $\tilde{Q}$. Further, $\beta > 0$ implies that (1) is convex in output, i.e. marginal labor requirement is increasing, and this translates into decreasing marginal increments of $\tilde{Q}$ as $\tilde{\theta}$ rises. This technology-based effect outweighs any preference-based effects when $\tilde{Q}$ is in the neighborhood of K. As illustrated in Figure 4, $\tilde{Q}$ will fail to be concave only when β is small and $\tilde{\theta}$ is in the neighborhood of zero; in this case the behavior of preferences as output is squeezed to zero serves to offset the effect of technology commitment.

Part (b) of the lemma demonstrates that $\tilde{Q}$ becomes globally concave once β is sufficiently large, i.e. once the costs of technology commitment are sufficiently high. It is important to note that the concavity introduced by technology commitment does not hinge on our particular scaling of the random variable: the proof of the lemma establishes that for *any* function $\alpha = \alpha(\tilde{\theta})$ with $\alpha'' \geq 0$, $\tilde{Q}$ will be concave in $\tilde{\theta}$ for β sufficiently large.

From Lemma 3 it follows that by taking $\underset{\sim}{\theta}$ sufficiently close to $\bar{\theta}$, the largest and smallest realizations of $\tilde{Q}$ can be made as close to $E[\tilde{Q}]$ as desired; in particular, we can ensure

Figure 4

Equilibrium Output in the Small β Case



that $\tilde{Q}$ is strictly concave in $\tilde{\theta}$ for every $\tilde{\theta} \in [\underline{\theta},\bar{\theta}]$. A mean-preserving spread of $\tilde{\theta}$ within this interval must then lead to a lower value of $E[\tilde{Q}]$ for every given K, as illustrated in Figure 5, and the resulting equilibrium value of K will be strictly lower. Thus we have proven:

<u>Proposition 2</u>: If $\underline{\theta}$ is sufficiently close to $\bar{\theta}$, then a mean-preserving spread of $\tilde{\theta}$ will lead to strictly lower $E[\tilde{Q}]$ in the ensuing REE.

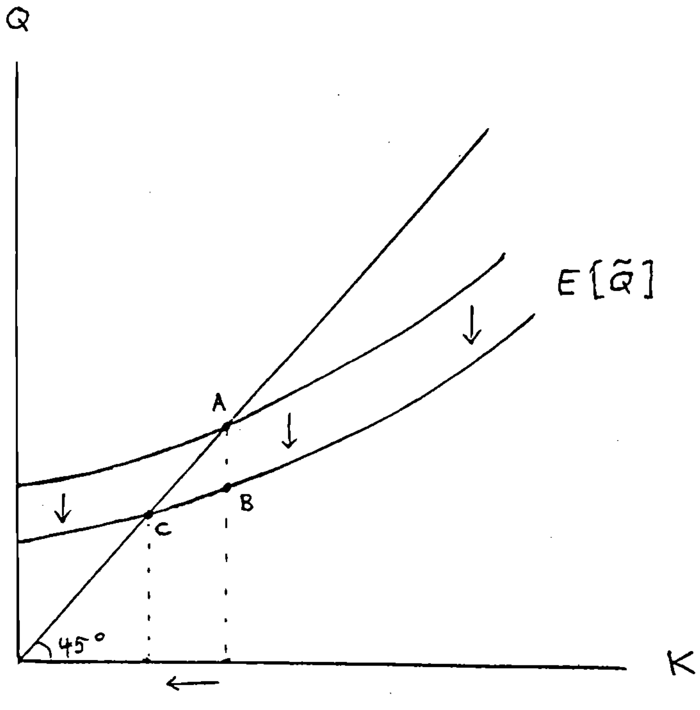
Proposition 2 establishes a negative relationship between mean output and volatility, which we will refer to as the *first moment effect* of volatility. The first moment effect may be decomposed into two components. First, for a fixed technology parameter K, a rise in volatility reduces mean output by driving up the marginal losses associated with ex post technical inefficiency; this *inefficiency effect* is reflected by the movement from A to B in Figure 5. Profit-maximizing technology choice introduces a second component: the firm recognizes that higher volatility will reduce mean output, and it plans for this by choosing smaller scale. This *planning effect* moves the outcome from B to C in Figure 5.

The planning effect in fact exerts an independent influence on output, in that smaller scale will tend to reduce the level of realized output regardless of volatility. This may be seen in the following lemma:

<u>Lemma 4</u>: If $\underline{\theta}$ is sufficiently close to $\bar{\theta}$, then $\tilde{Q}$ is strictly increasing in K for all $\tilde{\theta} \in [\underline{\theta},\bar{\theta}]$ and all K that might arise in a REE.

The support restriction is needed in this case to rule out the possibility that K is very large relative to $\underline{\theta}$, so that reducing K would raise output when $\tilde{\theta}$ is close to $\underline{\theta}$. Combining Lemma 4 with Proposition 2, we may conclude that an increase in volatility will lead not only to lower mean output, but also to lower output *for each realization* of $\tilde{\theta}$, as a consequence of

Figure 5
Effect of a Rise in Volatility



the reduction in planned scale. It should be noted that the planning effect operates as long as the firm merely perceives higher volatility, whether or not the perception is actually correct.

The potential importance of the first moment effect is readily illustrated by means of simulation. Here we specify two-point distributions of the labor productivity parameter $\tilde{\theta}$, and volatility is varied by moving the points symmetrically around a fixed mean of $E[\tilde{\theta}] = 1$. We set $\bar{L} = 2$, so that expected equilibrium output in the $\beta = 0$ case is normalized to unity for all levels of volatility. Results are illustrated in Figure 6, which shows the relationship between mean and variance of REE output for various levels of β; the expected value of equilibrium output is graphed on the vertical axis, and the variance of equilibrium output is graphed on the horizontal axis. Observe that higher β generates a steeper tradeoff between mean and variance of output.

Point x in Figure 6 is an estimate of the average position of U.S. GNP over the period 1953 to 1989, based on the empirical evidence presented below. Given the calibration $\beta = 2.4$ and $Var[\tilde{Q}] = 0.0015$, it follows that $E[\tilde{Q}] = 0.983$, meaning that mean output is about 1.7 per cent below what it would be if all volatility were eliminated; that is, the cost of observed economic fluctuations, in terms of reduced output only, is just under two percent of GNP. This estimate implies a per capita loss of over $380 of output in 1990 dollars. This number, which ignores risk effects, is still sufficiently large to suggest that economic volatility may impose important costs in the presence of technology commitment.[7]

D. Long-run Costs of Volatility

Thus far we have shown that in the presence of technology commitment, volatility

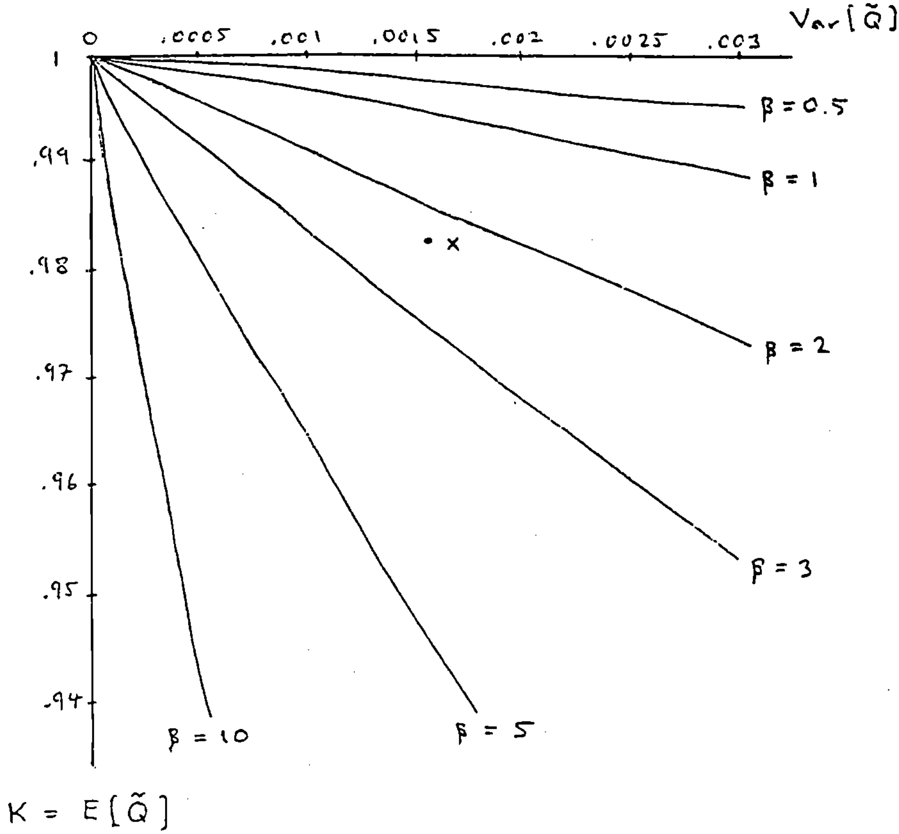
---

[7]Details of the calibration are given in Appendix 3. For the indicated calibration, the consumer would require an increase in output of 2.1 per cent as compensation for volatility, which figures at $450 per capita. This number includes both the reduction in mean output and the added loss in welfare due to consumption and leisure risk. Risk costs are much higher than under Lucas' calibration because having $\beta > 0$ serves to reduce the volatility of output relative to the volatility of the productivity parameter; thus the added $70 reflects the cost of *latent risk* associated with high volatility of the productivity parameter.

Figure 6

Simulation of Equilibrium Model with Two-Point Distributions of $\tilde{\theta}$

$\bar{L} = 2, \ E[\tilde{\theta}] = 1$



within a period will impose a cost in terms of lost output in that period. Output will be lost in future periods as well, however, to the extent that current output provides the resources needed for economic growth. In this section we demonstrate that volatility can impose long-term costs in the context of our two good model, where we use a simple "learning-by-doing" specification to connect current output with future output.

Let there now be infinitely many periods indexed by $t = 1,2,\ldots$. In each period the activities of the representative consumer and firm are just as in the preceding model: at the start of each period t the firm chooses K_t, the random productivity parameter for that period is then realized, and a competitive equilibrium ensues. The preferences, labor endowments and form of the labor requirement function are the same in each period. The distribution of the productivity parameter shifts over time, however, as a reflection of technical progress. Let $[\underline{\theta}_1,\bar{\theta}_1]$ denote the support restriction of the period one productivity parameter $\tilde{\theta}_1$, with $\underline{\theta}_1 > 0$, and let $F(\tilde{\theta}_1)$ give its distribution function.

We assume that technical progress leaves the form of the distribution function unchanged, and simply shifts the support upward by a given amount. Thus $\tilde{\theta}_2$ has support restriction $[\underline{\theta}_2,\bar{\theta}_2]$, with $\underline{\theta}_2 > \underline{\theta}_1$ and $\bar{\theta}_2 - \underline{\theta}_2 = \bar{\theta}_1 - \underline{\theta}_1$, and distribution function $F(\tilde{\theta}_2 - (\underline{\theta}_2 - \underline{\theta}_1))$. Further, the amount of the shift depends on the output level of the preceding period; in particular, $\underline{\theta}_2 = A(Q_1)\underline{\theta}_1$, where Q_1 is period one output and $A(0) = 1$, $A' > 0$. We interpret this as learning by doing that accrues from operation of the production technology.[8] For periods $t > 2$, the distribution function of $\tilde{\theta}_t$ is given by $F(\tilde{\theta}_t - (\underline{\theta}_t - \underline{\theta}_1))$, and $\underline{\theta}_t$ and $\underline{\theta}_{t-1}$ are defined recursively by $\underline{\theta}_t = A(Q_{t-1})\underline{\theta}_{t-1}$ for a given output sequence $Q_1,Q_2,\ldots$.

The next lemma gives conditions that facilitate analysis of equilibrium trajectories of the growth model.

---

[8]This specification is similar to that used by Backus, Kehoe and Kehoe (1990), based on empirical evidence by Argote and Epple (1990).

Lemma 5: (a) For any scalar $D > 0$, there exists $\theta_0 > 0$ such that a REE exists when the support restriction satisfies $\bar{\theta} - \underline{\theta} = D$ and $\underline{\theta} > \theta_0$;

(b) If $\underline{\theta} \geq 2(L\beta)^{-1/2}$, then $\partial^2\tilde{Q}/\partial\tilde{\theta}^2 < 0$ and $\partial\tilde{Q}/\partial K > 0$ for all $\tilde{\theta} \in [\underline{\theta},\bar{\theta}]$ and all K that might arise in a REE.

Part (a) ensures that for a given length of the initial support restriction $[\underline{\theta}_1,\bar{\theta}_1]$, a REE will exist in period one if $\underline{\theta}_1$ is sufficiently large. Under our growth technology, the support restrictions $[\underline{\theta}_t,\bar{\theta}_t]$ for $t > 1$ will continue to have the same length, and $\underline{\theta}_t > \underline{\theta}_1$ implies that a REE will exist in period t. Thus by taking $\underline{\theta}_1$ sufficiently large we can be sure that each realized trajectory $\tilde{\theta}_1,\tilde{\theta}_2,\ldots$ generates a path of REE. Part (b) gives properties of the equilibrium output function that we will apply along equilibrium trajectories.

Now consider the following experiment: in period one the distribution function shifts to $G(\cdot)$ that is a mean preserving spread of $F(\cdot)$, and then shifts back to $F(\cdot)$ for periods $t = 2,3,\ldots$. Let K_1^F and K_1^G give the period one equilibrium technology choices under distribution functions $F(\cdot)$ and $G(\cdot)$, respectively, and assume $\underline{\theta}_1 \geq 2(L\beta)^{-1/2}$. The concavity condition of Lemma 5(b) implies $K_1^G < K_1^F$ just as in Proposition 2, and Lemma 5(b) also implies that output will be lower for each realization of $\tilde{\theta}_1$. If we write the equilibrium outputs as $\tilde{Q}_1^F$ and $\tilde{Q}_1^G$, then we have $\tilde{Q}_1^G < \tilde{Q}_1^F$ for all $\tilde{\theta}_1$.

From the latter fact it follows that the technology parameter is sure to grow by a smaller amount when period one volatility is increased, since for any realization $\tilde{\theta}_1$ we have $\underline{\theta}_2^G = A(\tilde{Q}_1^G)\underline{\theta}_1 < A(\tilde{Q}_1^F)\underline{\theta}_1 = \underline{\theta}_2^F$. Consequently the distribution $F(\tilde{\theta}_2 - (\underline{\theta}_2^F - \underline{\theta}_1))$ first order stochastically dominates $F(\tilde{\theta}_2 - (\underline{\theta}_2^G - \underline{\theta}_1))$, and expected second-period output becomes strictly lower for every given K_2. The period two equilibrium must therefore satisfy $K_2^G < K_2^F$ for every $\tilde{\theta}_1$, despite the fact that the form of the distribution function shifts back to $F(\cdot)$.

Since $\underline{\theta}_2^G > \underline{\theta}_1$ for every $\tilde{\theta}_1$, we may proceed inductively to establish that $E[K_t^G|\tilde{\theta}_1] < E[K_t^F|\tilde{\theta}_1]$ for $t = 3$, and so on for larger t; thus the one-time increase in volatility reduces expected output in all future periods. This suffices to prove:

Proposition 3: If $\underline{\theta}_1$ is sufficiently large, then a mean-preserving spread of $\tilde{\theta}_1$ will lead to strictly lower expected output in every future period, conditional on any realization of $\tilde{\theta}_1$.

This analysis demonstrates that periods of high volatility may have adverse consequences for economic productivity that extend into the distant future; mean output levels may be permanently lower due to a one-time volatility increase.[9]

2. Empirical Evidence

A. Empirical Implementation

The theory developed above yields several striking testable implications. First, the static analysis predicts that in the presence of technology commitment, periods of greater volatility will be associated with lower mean output, while the growth analysis predicts that an increase in current volatility will lead future output to be permanently lower. Second, the theory demonstrates that output can be depressed by both the anterior perception of volatility, which we will call *ex ante uncertainty*, and the actual presence of volatility, or *ex post volatility*; the former operates through the planning effect, while the latter operates through the inefficiency effect.

Our empirical tests of these predictions will be developed in terms of a reduced form version of the model, rather than the model's explicit structure. The advantage of the reduced

---

[9]This does not necessarily imply that the growth *rate* of output is permanently lower following a one-time increase in volatility, since the lower output base will tend to raise the growth rate. It is easy to specify plausible sufficient conditions under which volatility does reduce output growth rates, however. One simple specification is to let F be degenerate at $(\bar{\theta} + \underline{\theta})/2$ and to suppose $A'' \geq 0$; in this case $Q_t^F - Q_t^G$ is strictly increasing in t, and the increase in period one volatility assures strictly lower output growth rates once t is sufficiently large.

form approach is that it does not restrict the source of volatility to technology shocks exclusively; the disadvantage is that the results are potentially consistent with alternative models, albeit models in which volatility has adverse consequences for output.

We summarize the theoretical predictions in the following equation:

$$\tilde{Q}_t = h_t(\tilde{\theta}_t, \mathrm{Var}(\tilde{\theta}_t), E_{t-1}\mathrm{Var}(\tilde{\theta}_t), \mathrm{Var}(\tilde{\theta}_{t-1}), E_{t-2}\mathrm{Var}(\tilde{\theta}_{t-1}), \ldots) \tag{4}$$

$\mathrm{Var}(\tilde{\theta}_t)$ denotes the variance of $\tilde{\theta}_t$, conditional on information through period t-1, while $E_{t-1}\mathrm{Var}(\tilde{\theta}_t)$ denotes agents' expectations of the conditional variance. If agents are fully informed as to the underlying distribution of $\tilde{\theta}_t$, then in a REE we have $E_{t-1}\mathrm{Var}(\tilde{\theta}_t) = \mathrm{Var}(\tilde{\theta}_t)$, and $E_{t-1}\mathrm{Var}(\tilde{\theta}_t)$ will not have an independent effect. If, on the other hand, agents' perceptions of the distribution differ from the true distribution, then both variables will have an effect, with $\mathrm{Var}(\tilde{\theta}_t)$ working through the inefficiency effect and $E_{t-1}\mathrm{Var}(\tilde{\theta}_t)$ working through the planning effect. Our theory predicts that both effects should be negative. The lagged values should have a negative impact as well if the effects of volatility are permanent.

In estimating (4) we face the key problem that the actual and perceived variances of $\tilde{\theta}_t$ are difficult to measure, and further there may be other sources of volatility in the economy that are important in determining output. To handle this problem, we will use the conditional variance of output as a proxy for these measures of underlying volatility; thus, we test the relationship between the log of real GNP (or the log differences) and the variance of the forecast errors for the log of real GNP. The latter measure of volatility is a good proxy for $\mathrm{Var}(\tilde{\theta}_t)$ in the context of our model, since the variance of forecast errors is approximately proportional to $\mathrm{Var}(\tilde{\theta}_t)$ under the null hypothesis of $\beta = 0$.[10] Below we will introduce a second

---

[10]In particular, $E[(\ln\tilde{Q}_t - \ln E[\tilde{Q}_t])^2] \cong 2\mathrm{Var}(\tilde{\theta}_t)/L\, E[\tilde{\theta}_t^2]$ when $\beta = 0$. Our test is structured in terms of logs rather than levels due to the time series properties of GNP. When $\beta > 0$, the proportionality factor becomes dependent on K_t, and concavity of output in $\tilde{\theta}_t$ introduces an

proxy that distinguishes perceived from actual variances.

We use two different series for the forecast errors, taking their squares as a measure of the variance.[11] Our preferred series is based on the American Statistical Association - National Bureau of Economic Research (ASA-NBER) forecast survey. We view the errors based on the survey data as the best measure of the errors actually made at the time, but the ASA-NBER data begin only in 1969. Thus we also employed a rolling regression procedure using an AR(2) in GNP growth rates to generate one-quarter-ahead forecast errors over the period 1953:1 to 1989:4; this specification gives forecast errors that are highly correlated with the ASA-NBER forecast errors for the subsample. Appendix 2 contains details on the construction of both series.

As discussed above, our theory also makes predictions concerning agents' ex ante uncertainty, to the extent that it differs from the actual variance. Ideally, one would estimate the effect of ex ante uncertainty on output with an ARCH-M model (Engle, Lilien, and Robins (1987)). Unfortunately, there is no evidence of ARCH in real GNP growth, as the estimates presented in later sections will show. Instead we will use a measure of ex ante uncertainty first studied by Zarnowitz and Lambros (1987), based on probability distributions reported by individual forecasters in the ASA-NBER survey. Because the series is very short (1968:4 to 1981:2), most of our analysis will use the squared forecast errors. Section 2D will discuss the construction and analysis of the probability distribution data.

---

additive term that also depends on K_t.

[11]In constructing measures of the variance of forecast errors, we must fix the relevant length of the forecast horizon. Multi-year forecast variances would matter if technology commitment were embodied in the capital stock; on the other hand, if the commitment effect stemmed primarily from labor force decisions, then one-quarter ahead forecast variances might be more relevant. In order to maximize the degrees of freedom, we use one-quarter ahead forecast errors. In any case, the longer-term errors are likely to be correlated with the short-term errors.

B. Correlation between Growth and Volatility

This section addresses the contemporaneous relationship between output and volatility by analyzing the simple correlation between $E[\tilde{Q}_t]$ and $Var(\tilde{\theta}_t)$ over different sample periods. We use the variance of forecast errors from the rolling regressions as proxies for $Var(\tilde{\theta}_t)$, and for comparison we also report correlations with the unconditional variance of GNP growth rates.[12] Following Ball and Cecchetti's (1990) analysis for inflation, we split the data into non-overlapping periods, and calculate the sample means and variances of GNP growth for each sub-period. The results for the period 1953 to 1989 are presented in Table 1.

Table 1

Mean versus Variance of U.S. GNP, 1953-1989

		Correlation with the Mean	
Length of subperiods in years	Number of subperiods	Unconditional Variance	Conditional Variance
1	37	-0.278	-0.300
2	18	-0.529	-0.449
3	12	-0.746	-0.627
4	9	-0.828	-0.674
5	7	-0.769	-0.754
6	6	-0.941	-0.783
7	5	-0.956	-0.987
8	4	-0.567	-0.800
9	4	-0.676	-0.464
10	3	-0.820	-0.823

Both the conditional and unconditional variance display strong negative correlations with average growth; periods of high volatility are periods of low growth. Further, the

[12]Growth rates rather than levels are used because of the nonstationarity of real GNP.

correlation tends to be stronger as the length of the subperiod increases. When the subperiods cover three years, the correlation between the mean and conditional variance is -0.63, while it is -0.75 for the unconditional variance.

Figure 7 shows a graph of the mean and conditional variance of GNP for nine four-year subperiods, corresponding to presidential terms. The graph demonstrates that the clear negative relationship between mean and variance is not accounted for by a few outliers. The periods of high volatility were the late 1950's, the 1970's, and the early 1980's. These periods were also low growth periods. On the other hand, the main periods of low volatility were the 1960's and mid-1980's; these periods were relatively high growth periods.

Does the negative relationship between volatility and growth also hold for earlier periods? To answer this question we use annual data on real GNP growth rates from 1870 to 1989. The pre-1929 data consists of Romer's (1989) estimates of GNP. The sample is divided into 24 periods, each consisting of five years. Because of the difficulty of estimating a forecasting equation for the earlier periods, only unconditional variances are calculated.

Figure 8 shows the plot of points for the entire period. There are three obvious outliers in the graph: the point with the highest variance and the second lowest mean corresponds to the period 1945-49, which was the wind-down from World War II; the point with the lowest mean and second highest variance corresponds to 1930-34, the Great Depression; and the point with the highest mean corresponds to 1940-1944, World War II.

Table 2 shows the correlation between mean and variance for various sample periods. For the entire period, the correlation is -.5, but most of this negative correlation is caused by the three outliers. The correlation from the pre-Great Depression period is slightly positive. For the post-World War II period, the annual data support the high negative correlation found in the quarterly data.

Our model gives a straightforward interpretation of these results. It is plausible that technology commitment was not as important during the first part of the sample for at least

Figure 7: Volatility and Growth

Three-Year Periods, 1953–1988

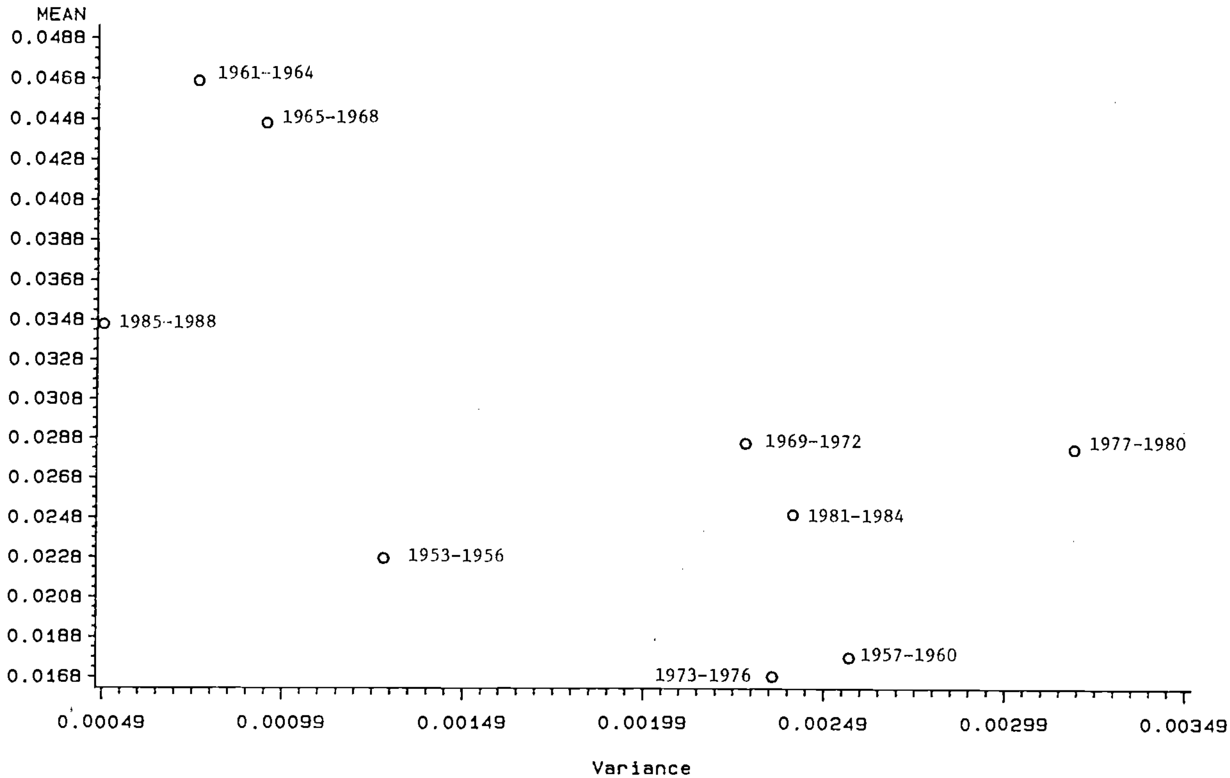


Figure 8: Volatility and Growth

Five-Year Periods, 1870–1989

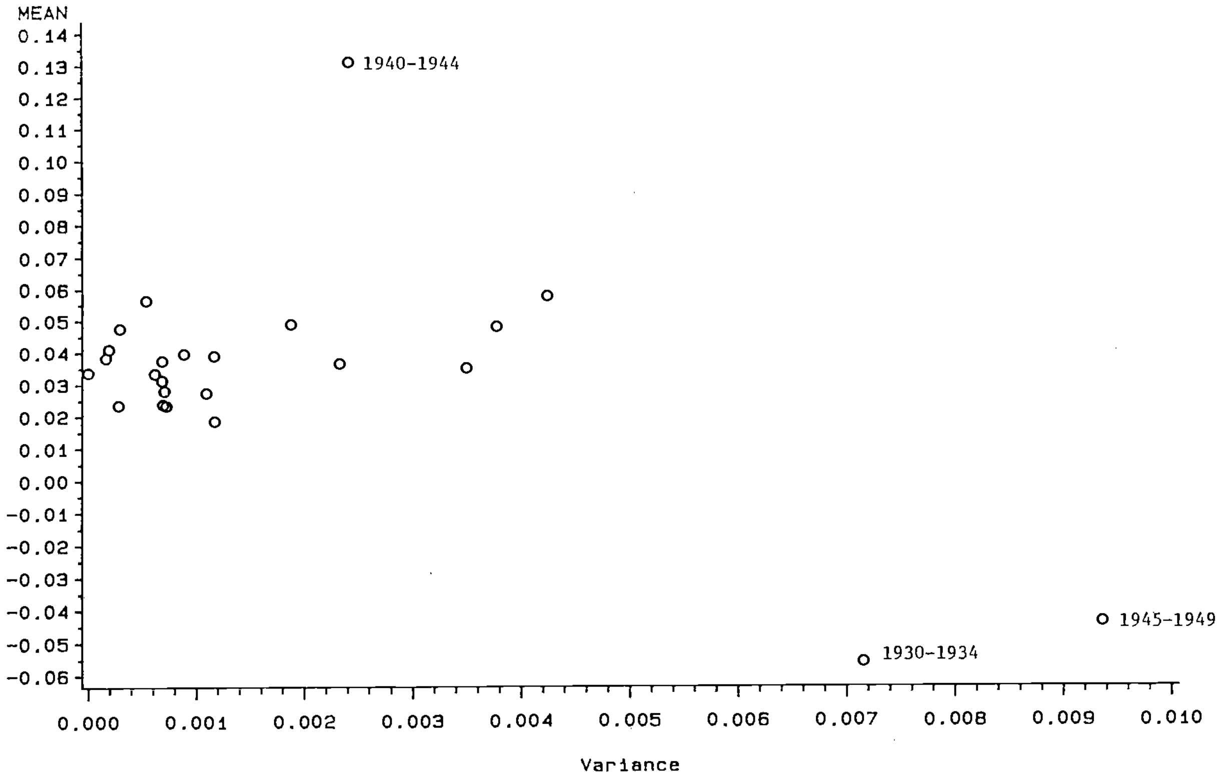


Table 2

Historical Correlations between Mean and Variance

1870-1989	-0.522
1870-1929	0.160
1870-1939	-0.578
1945-1989	-0.917
1955-1989	-0.878

two reasons. First, highly integrated production processes such as the assembly line were not adopted until after 1913 (Chandler (1977)), which would tend to make the scale of production more flexible. Second, firms faced much more flexibility in their labor force adjustments. Before World War I, when immigration rates were high, firms organized tasks so that little specific human capital was involved (Slichter (1929)). Thus, firms did not lose much in the way of human capital investment when they decreased their work forces. Further, internal labor markets and union contracts were virtually nonexistent, so firms were relatively unrestricted in their labor force adjustments. Thus, in the context of our model, one could argue that β was substantially lower before the Great Depression than after World War II, and so periods with high volatility did not suffer substantially slower growth.

This argument also highlights potential problems in comparing means and variances across countries or industries. Those countries or industries with higher inherent variance may at the same time have more flexible technologies, that is, technologies with a lower β. Therefore, a study of the effect of the variance on mean growth must also take into account the possibility of different β's. Such an analysis is saved for future research.

C. Persistence and Causality

We now turn to time series evidence on persistence. Our growth model predicts that in the presence of technology commitment, an increase in current variance has a permanent negative effect on output. While the preceding correlations indicate a negative contemporaneous relationship between variance and growth, they are not informative about the structure of the relationship nor about the long-run effects of volatility. In this section we test whether there is a long-run relationship between volatility and output, and we assess the direction of causality. The function h_t in (4) will be specified simply as the unweighted cumulative sum of past variances; thus past volatility exerts a permanent effect on output. The independent effect of ex ante uncertainty will be suppressed until the next section. As proxies for volatility, we first consider the squared forecast errors generated from the rolling regression.

It is generally agreed that real GNP is nonstationary. While the squared forecast errors should be stationary, the cumulative sum of the past squared forecast errors should be nonstationary. Augmented Dickey-Fuller (ADF) tests with two lags give test statistics of -0.435 for log GNP, -6.372 for the squared forecast error, and -0.155 for the cumulative sums of squared forecast errors for the period 1953:4 to 1989:4. It follows that one cannot reject the presence of a unit root in either log GNP or in the sum of the squared forecast errors, while the presence of a unit root in the squared forecast errors can be rejected.

In analyzing the relationship between real GNP and the cumlative sum of the squared forecast errors, the first step is to determine whether there is a cointegrating relationship. This step is essential for specifying the correct form of the vector autoregression for nonstationary time series (Engle and Granger (1987)). Table 3 presents evidence on cointegration between log of real GNP and the cumulation of the squared forecast errors.

The first part of Table 3 shows the estimates of the relationship between the log of real GNP, a time trend and the sum of the squared forecast errors. The second part of Table 3 tests whether the variables in the first equation are cointegrated by testing the stationarity of the error term in the first equation, denoted z. The test statistic using the Engle-Granger test is -4.03. The critical value for a bi-variate system with a trend, taken from MacKinnon (1990), is -3.85. Thus, one can reject noncointegration at the five percent significance level. The results imply that log of real GNP and the sum of the squared forecast errors share a common stochastic trend.

Table 3

Cointegration Relationships

Cointegrating Regression
1953:1 - 1989:4; n = 148
Estimated using OLS

$$\log Q_t = \underset{(1691.0)}{7.20} + \underset{(40.0)}{.0121}\, t - \underset{(-15.4)}{40.262} \sum \varepsilon^2_{t-j} + z_t$$

$R^2 = 0.995$, D-W = 0.208

Cointegration Test
1953:4 - 1989:4

$$\Delta z_t = \underset{(-4.04)}{-\,0.160}\, z_{t-1} + \underset{(3.08)}{0.297}\, \Delta z_{t-1} + \underset{(1.72)}{0.142}\, \Delta z_{t-2}.^{*}$$

Test statistic: -4.04 | 5% critical value: -3.85

(t-statistics are in parentheses; Q denotes real GNP and t denotes a trend.)

* Additional lags were not significant.

According to the estimates of the cointegrating equation, shown in the first part of the table, log GNP and the cumulated squared forecast errors have a negative long run relationship; the nonstationary deviations of GNP from the deterministic trend are in fact related to the history of squared forecast errors. The estimates imply that a temporary increase in the squared forecast error is associated with a downward shift of the entire path of future output, as our growth model predicts.

These statistical implications are actually much stronger than the predictions of our model, which states only that volatility has a permanent effect on the level of output. The cointegration results imply that all of the nonstationarity in the log of real GNP can be accounted for by the squared forecast errors. This result is striking because although many variables have an impact on output, few share a common stochastic trend with output.

Table 4

Cointegration Relationships for ASA-NBER Data

Cointegrating Regression
1969:1 - 1990:1; n = 85
Estimated using OLS

$$\log Q_t = \underset{(1536.8)}{7.76} + \underset{(11.4)}{.0108}\, t - \underset{(-4.6)}{77.502} \sum \varepsilon^2_{t-j} + z_t$$

$R^2 = 0.981$, D-W = 0.260

Cointegration Test
1970:2 - 1990:1

$$\Delta z_t = \underset{(-3.93)}{-\,0.261}\, z_{t-1} + \underset{(2.05)}{0.218}\, \Delta z_{t-1} + \underset{(1.96)}{0.212}\, \Delta z_{t-2} + \underset{(1.50)}{0.167}\, \Delta z_{t-3} + \underset{(1.37)}{0.155}\, \Delta z_{t-4}.$$

Test statistic: -3.93 5% critical value: -3.90

(t-statistics are in parentheses; Q denotes real GNP and t denotes a trend.)

In order to assess the robustness of the cointegration result, we performed similar tests using the ASA-NBER forecast error series as proxies for volatility. Table 4 presents evidence on cointegration using the ASA-NBER data for the period 1969:1 to 1990:1. The results using the ASA-NBER data also show cointegration between log GNP and the sum of squared forecast errors, indicating a long-run negative relationship between volatility and real GNP. Thus the cointegration relationship is not specific to our definition of forecast errors.[13]

Our finding of cointegration implies there is an associated error correction model (ECM) involving GNP growth and the squared forecast errors. Furthermore, this error correction system is the proper framework for studying the structure of the relationship, and, in particular, the causal relationships. As Engle and Granger (1987) discuss, cointegration implies Granger causality in at least one direction. Variable X is said to Granger cause variable Y if either the lagged values of X or the lagged value of the error correction term is significant.

We estimate the error correction system using full-information maximum likelihood (FIML), since the FIML estimator gives fully efficient estimates of both the cointegrating vector and the error correction parameters (Johansen (1988)). Furthermore, unlike the standard errors reported from the OLS estimate, the standard errors from the FIML estimate of the error correction model can be used for hypothesis testing (Johansen and Juselius (1988)). The estimates of the ECM for growth and volatility, using the ASA-NBER forecast errors in Table 5.

The EC equation for GNP growth ($\Delta \log Q_t$) shows that it depends on its own lags and also on the error correction term in parenthesis. Only the second lagged value of the squared forecast errors is marginally significant, but because the error correction term is significant, we conclude that the squared forecast errors Granger-cause GNP growth. On the other hand, neither the lagged GNP growth rates, nor the error correction term is significant in the EC equation for the squared forecast errors. The lack of significance of the lagged squared

---

[13]Jyotsna Jalan (1991) has conducted a preliminary investigation of the properties of the statistical model underlying our analysis. She has found that tests of cointegration between the first two moments are quite robust to misspecification, and do not seem to reflect spurious relations.

Table 5

FIML Estimation of VECM for ASA-NBER Data

1970:2 - 1990:1
(t-statistics in parentheses)

$$\Delta\log Q_t = \underset{(3.8)}{2.01} - \underset{(-3.7)}{.260}\,(\log Q_{t-1} - \underset{(-3.9)}{.0136}\,(t\text{-}1) + \underset{(2.1)}{125.0}\,\Sigma\,\varepsilon^2_{t-j-1})$$

$$+ \underset{(2.3)}{0.304}\,\Delta\log Q_{t-1} + \underset{(2.0)}{0.250}\,\Delta\log Q_{t-2} + \underset{(0.27)}{0.039}\,\Delta\log Q_{t-3} + \underset{(1.4)}{0.202}\,\Delta\log Q_{t-4}$$

$$+ \underset{(0.25)}{7.18}\,\varepsilon^2_{t-1} + \underset{(1.7)}{38.5}\,\varepsilon^2_{t-2} + \underset{(0.79)}{23.3}\,\varepsilon^2_{t-3} + \underset{(1.04)}{25.3}\,\varepsilon^2_{t-4}.$$

s.e. = 0.009, D-W = 2.09

$$\varepsilon^2_t = \underset{(.24)}{.0009} - \underset{(-.23)}{.0001}\,(\log Q_{t-1} - \underset{(-3.9)}{.0136}\,(t\text{-}1) + \underset{(2.1)}{125.0}\,\Sigma\,\varepsilon^2_{t-j-1})$$

$$+ \underset{(.44)}{.0004}\,\Delta\log Q_{t-1} - \underset{(-1.2)}{.0014}\,\Delta\log Q_{t-2} + \underset{(.69)}{.0005}\,\Delta\log Q_{t-3} + \underset{(.17)}{.0002}\,\Delta\log Q_{t-4}$$

$$- \underset{(-.40)}{.089}\,\varepsilon^2_{t-1} + \underset{(.49)}{.067}\,\varepsilon^2_{t-2} + \underset{(.45)}{.082}\,\varepsilon^2_{t-3} - \underset{(-.45)}{.093}\,\varepsilon^2_{t-4}.$$

s.e. = 0.00006, D-W = 1.98

LRT statistic for H_0: nothing predicts ε^2_t : 7.704.

(5 % critical value for χ^2_9 = 16.92.).

forecast errors is indicative that there is no ARCH in real GNP growth. Further, as shown at the bottom of the table, the null hypothesis that the squared forecast errors are unpredictable cannot be rejected at reasonable significance levels. It follows that GNP growth does not Granger-cause the squared forecast errors. One can conclude that the sum of the squared forecast errors is weakly exogenous, as defined by Engle, Hendry and Richard (1983), with respect to this model. The FIML estimates of the VECM using the rolling regression forecast errors, which are not reported for reasons of brevity, yield qualitatively similar results.[14]

The results of the Granger causality tests imply that it is not unreasonable to draw structural inferences from the estimates of the cointegration equation. In particular, we can ask how the path of output would have differed had the variance of forecast errors somehow been eliminated. To answer the question, we use the FIML estimate of -41.96 for the long-run relationship between the squared forecast errors and real output for the 1953 to 1989 sample period.[15] Comparing the path of actual output to what it would have been had the forecast variance been zero for the entire period, one finds that the implied average annual growth would have been 1.77 percentage points higher. That is, instead of experiencing growth just under three percent, the U.S. economy would have experienced 4.5 percent annual growth!

We can also conduct a more modest experiment by asking how the path of output would have differed had the squared forecast errors during the entire sample been equal to their average during the low volatility periods of 1961-1964, 1965-1968, and 1985-1988.

---

[14]The estimate of the cointegrating parameter on the sum of the squared errors is -41.96, with a t-statistic of 5.9; the estimate is close to the OLS estimate presented in Table 3. The only important difference from the Table 5 estimates is that while none of the lags in the equation explaining the squared forecast errors is individually significant, the lags are marginally significant jointly. The squared forecast errors, however, still appear to be weakly exogenous. It is likely that the ASA-NBER forecasts use a more complicated model, and hence the squared errors are not predictable. We will discuss this issue in more detail in Section 2E below.

[15]The coefficient estimate from the FIML estimation using the ASA-NBER data gives an even larger estimate of the effect on growth. We choose the estimates based on the rolling regression errors because they cover a longer period, and because they are estimated more precisely.

Recall from Figure 7 that these periods were characterized by the three lowest volatilities of all four-year presidential periods. In this case, one finds that the implied average annual growth rate would have been one percentage point higher. Thus, if all periods were as tranquil as these three periods, the estimates imply that growth would have averaged over four percent per year.[16]

This exercise, of course, says nothing of the feasibility of reducing variance, but it does call into question Lucas' dichotomy between the benefits of lower volatility and increased growth. In fact, the data indicate a critical link between volatility and growth. Further, while the theoretical model limits attention to productivity shocks that are presumably beyond the purview of policy authorities, the empirical results certainly do not rule out the possibility that there are other sources of volatility that policy could affect. A more detailed inquiry into these other sources would be of great interest, in view of the large negative impact of volatility.

D. The Effect of Ex Ante Uncertainty

The preceding section presents strong evidence that higher ex post volatility impedes economic growth. In this section we use the probability data from the ASA-NBER survey to study whether ex ante uncertainty has an independent negative impact. This serves as a powerful test of our technology commitment theory, as the theory predicts that ex ante uncertainty will exert an independent negative effect when beliefs about volatility differ from actual volatility.

One set of questions asked in the ASA-NBER survey involves the probabilities that individual forecasters assign to different growth rates of nominal GNP and the implicit price deflator from the current year to the next. Due to changes in the questionaire, a consistent series is available only from 1968:4 to 1981:2. Following Zarnowitz and Lambros (1987), we calculated the conditional variance for each forecaster based on his or her reported probability

[16]Actual growth averaged 4.2 percent during these three presidential periods.

distribution and took the average over all forecasters as our measure of ex ante uncertainty. Appendix 2 contains the details of the construction of the ex ante uncertainty variable. The forecast horizon varies from quarter to quarter because the survey is taken quarterly, while the probabilities reported are for growth rates from the current year to the next. Thus, in the empirical analysis we include quarterly dummy variables.

We first determined whether there was any relationship between the previously discussed squared forecast errors and the ex ante uncertainty measure. To our surprise, the correlation was essentially zero (-0.05). Further, lags of the squared forecast errors had no predictive power for the conditional variance, and the conditional variance had no predictive power for future squared forecast errors. Thus the conditional variance calculated from the probability distributions had no relationship to the squared forecast errors. These results could be due to the unpredictability of the squared forecast errors.

The conditional variance did, however, have additional explanatory power for the growth rate of GNP. The following equation shows the coefficient estimates of the OLS regression for the period 1969:2 to 1981:2:

$$\Delta\log Q_t = \text{quarterly dummies} - \underset{(-2.4)}{92.8}\, cvar_{t-1} - \underset{(-2.3)}{.154}\, z_{t-1} + \underset{(1.5)}{.201}\, \Delta\log Q_{t-1} + \underset{(1.5)}{.205}\, \Delta\log Q_{t-2}.$$

$R^2 = 0.301, \quad DW = 1.96$

(t-statistics in parenthesis)

$\Delta\log Q_t$ denotes the growth rate of real output, cvar is the conditional variance measure from the probability data, and z is the error correction term from the OLS relationship between the sum of the squared forecast errors and log Q estimated from 1969:1 to 1990:1. The cvar variable dated t-1 is the conditional variance measured during the second month of quarter t; we date it as t-1 because real GNP growth during quarter t is not known when the probability distribution is reported.

The estimates show that even after accounting for the effect of the squared forecast errors (through the error correction term z), the conditional variance measure has an additional negative impact on growth. Thus, both ex ante uncertainty and ex post volatility have an impact on growth. When lags of the squared forecast errors or lags of the conditional variance were added, they were not significant. For this shortened sample there was no evidence of cointegration for either the sum of the squared forecast errors or the sum of the conditional variance measures, so we did not attempt to make any inferences concerning persistence and the structure of the relationship. The results are, however, suggestive that volatility exerts both inefficiency and planning effects, as our theory suggests.

E. Statistical Asymmetries and Nonlinearities as Possible Explanations for the Results

Two arguments have been made suggesting that our finding of a negative relationship between volatility and growth may be a statistical artifact of the data. First, it is believed by many that business cycles are characterized by asymmetrically large effects of negative shocks, i.e. that recessions are "steeper" and "deeper" than booms. For example, Delong and Summers' (1987) associate the cost of business cycles with negative money shocks in the presence of nominal rigidities. Work by Falk (1986) and Sichel (1990), however, shows that although variables such as unemployment are asymmetric over the business cycle, there is little or no evidence that real GNP growth is asymmetric. Further, our data show that negative forecast errors do not exert an asymmetric effect. To establish this result, we re-estimate the error correction model for real GNP growth (using nonlinear least squares on the ASA-NBER forecast error data), and allow the squared negative forecast errors to have a different coefficient from the positive forecast errors. The results are as follows:

$$\Delta \log Q_t = \underset{(3.6)}{2.01} - \underset{(-3.6)}{.260} (\log Q_{t-1} - \underset{(-3.3)}{.0133} (t-1) + \underset{(3.3)}{128.7} \Sigma \varepsilon^2_{t-j-1} - \underset{(-.72)}{27.4} \Sigma n\varepsilon^2_{t-j-1})$$

$$+ \underset{(1.8)}{0.322} \Delta \log Q_{t-1} + \underset{(.32)}{0.063} \Delta \log Q_{t-2} + \underset{(0.62)}{0.121} \Delta \log Q_{t-3} + \underset{(1.9)}{0.385} \Delta \log Q_{t-4}$$

$$- \underset{(-0.25)}{3.43} \varepsilon^2_{t-1} + \underset{(1.7)}{60.2} \varepsilon^2_{t-2} + \underset{(0.79)}{9.79} \varepsilon^2_{t-3} - \underset{(-.49)}{13.6} \varepsilon^2_{t-4}$$

$$+ \underset{(.35)}{16.3} n\varepsilon^2_{t-1} - \underset{(-1.0)}{45.8} n\varepsilon^2_{t-2} + \underset{(0.71)}{31.4} n\varepsilon^2_{t-3} + \underset{(1.96)}{79.7} n\varepsilon^2_{t-4}.$$

The ε^2 terms include both positive and negative forecast errors, while the $n\varepsilon^2$ terms denote the squares of only the negative errors. From the estimates of the cointegrating vector it can be seen that the sum of the squared negative errors enter insignificantly, so that the negative forecast errors have no long-term independent effect. Second, the only lagged negative squared error that is significant is the fourth lag, and it has a *positive* rather than a negative effect on GNP growth. Thus there is no evidence that the negative squared forecast errors are leading to the negative relationship between volatility and output.

A second asymmetry argument, based on Hamilton's (1989) findings, concerns forecast volatility. Hamilton has argued, using his Markov scheme, that the forecast from a linear model will have higher variance during a recession than during a boom. We have shown, however, that the negative relationship between volatility and growth holds for both the ASA-NBER point forecasts and conditional variances, which do not necessarily derive from linear forecasting models. Further, the results from the VECM show that output growth does not Granger-cause the squared forecast errors, in contrast to Hamilton's finding that the state of the economy should predict the squared forecast errors.

How, then, do we reconcile the VECM results with Hamilton's findings? We propose that the forecasts produced from the ASA-NBER survey already incorporate the nonlinearities that Hamilton has found, so that the corresponding squared forecast errors are not predictable. To support this claim we present two regressions. The first equation, which corresponds to Hamilton's results, regresses the squared residuals from an AR(4) (estimated for the period 1953:1 to 1990:1) on the lag of a dummy variable for recessionary periods, where the recessionary periods are those defined by Hamilton's smoother, presented in Table II of his paper. The second equation regresses the squared forecast errors from the ASA-NBER data on the same lagged dummy variable. Both regressions are for the period 1969:1 to 1990:1. The results are presented below:

$$\text{Squared AR(4) errors}_t = \text{constant} + \underset{(3.5)}{.000132}\ \text{Dummy}_{t-1}, \quad T\,R^2 = 10.87.$$

$$\text{Squared ASA-NBER errors}_t = \text{constant} + \underset{(0.88)}{.0000139}\ \text{Dummy}_{t-1}, \quad T\,R^2 = 0.778.$$

(t-statistics in parentheses)

The results show clearly that although the recession dummy variable has predictive power for the squared AR(4) errors, it does not predict the squared ASA-NBER errors. Thus the argument that our results presented earlier are due to omitted nonlinearities is not supported by the data.

F. Relationship to Increasing Returns Literature

At first glance, the model and results of this paper may seem to contradict some of the theory and results of the recent literature on temporal agglomeration (c.f. Hall (1988)). For example, Murphy, Schleifer and Vishny (1989) present a model in which declining marginal cost up to a capacity constraint leads firms to vary production, even when there is no underlying volatility in the economy. V. Ramey's (1991) study of inventories presents empirical evidence that firms in seven industries behave as if they face declining marginal production costs. This type of cost function leads production to be more volatile than sales. Thus, this literature suggests that volatility may actually enhance efficiency.

The apparent contradiction disappears when one makes the distinction between *endogenous*, or planned, volatility and *exogenous*, or unplanned, volatility. Consider the following modified labor requirement function:

$$L(Q,K) = \alpha Q + \gamma Q^2 + \beta(Q-K)^2.$$

Suppose there exists an interior solution to the firm's cost minimization problem (this would follow from the presence of sufficiently high inventory holding costs, for example). If γ is negative and β is positive, then marginal costs are declining in the level of *planned* production, where Q equals K, but will be increasing in deviations of actual production from planned production. Although firms will optimally introduce volatility into planned production, unexpected changes in their environment will lead to higher average costs and resource dissipation.

Further, the addition of the β term does not invalidate the estimates of γ from inventory models that do not include the β term. If K is interpreted as the expected value of output based on earlier information, then the β term appears in the stochastic Euler equation as an expectational error. As long as the instruments have the appropriate lags, they will not be correlated with this expectational error.

For the seven industries studied in V. Ramey (1991), all of the correlations between mean and unconditional variance of output lie between 0 and -0.3, with the exception of the chemical industry which has a correlation of -0.6.[17] Thus, while there are significant nonconvexities in planned output, there seem to be costs of deviations from planned output.

3. Conclusion

Are economic fluctuations costly? Looking solely at the effect of variance on the representative consumer's expected utility, Lucas answers negatively. When we study the problem in a general equilibrium context in which firms must make technology commitments, we come to a different conclusion: for empirically reasonable values of the parameters, we find that business cycles are costly indeed. Our empirical results suggest that the volatility in the U.S. during the last 35 years has led output growth to be just under two percentage points lower than it would have been in the absence of volatility. We consider this a significant cost.

While our results are suggestive of significant first moment effects in the U.S. economy, more work is needed before the results can be linked to policy analysis. To this end, we plan to extend this line of research in several ways. First, we propose to extend the theory by analyzing the effect of other sources of volatility. One natural source would be government spending. Further, we intend to extend the dynamic analysis to incorporate physical capital into the production technology; this would permit analysis of the effects of volatility on saving and investment behavior.

On the empirical side, we are developing a test of our technology commitment theory, and of the relationship between planned output volatility and unplanned volatility, that can be implemented using plant-level data. On the aggregate level, we propose to quantify the dependence of forecast errors on exogeneous determinants of volatility and thereby to uncover the main sources of volatility in the economy.

---

[17]All industries save autos use monthly data from 1960 to 1983, split into three year periods; autos use monthly data from 1967 to 1978, split into two year periods. We study mean and variance of output levels in autos and tobacco, and of growth rates in the other industries.

APPENDIX 1

Proofs of Lemmata and Proposition 1

Proof of Lemma 1: Profit maximization generates the following supply function:

$$Q_S = \frac{P - \alpha}{2\beta} + K \tag{A1}$$

and maximized profits are:

$$\Pi = (P - \alpha)K + \frac{(P - \alpha)^2}{4\beta} \tag{A2}$$

Demand for the consumption good as a function of P, $\bar{L}$ and nonlabor income Π is:

$$Q_D = \frac{\bar{L} + \Pi}{2P}$$

Setting $Q_S = Q_D$ and plugging in Π gives (2). The equilibrium exists as long as the discriminant in (2) is nonnegative and $P \geq 0$. To show the nonnegativity, consider the following quadratic function:

$$\beta^2 x^2 + \beta(\alpha - 2\beta K)x + (\alpha - 2\beta K)^2 + 3\beta(\bar{L} - \beta K^2) \tag{A3}$$

for arbitrary real x. The discriminant of this function is:

$$\beta^2(\alpha - 2\beta K)^2 - 4\beta^2[(\alpha - 2\beta K)^2 + 3\beta(\bar{L} - \beta K^2)]$$

$$= -3\beta^2[\alpha^2 + 4\beta(L - \beta K^2)] < 0$$

under part (a) of the feasibility condition. Thus (A3) has no real roots, making it positive for all x; in particular, at x = 0 (A3) gives the discriminant of (2). It is easy to show directly that part (a) of the feasibility condition implies P > 0. Q.E.D.

Proof of Lemma 2: In a rational expectations equilibrium the firm chooses K to maximize, using (A2):

(A4) $$E[\tilde{\Pi}] = E[\tilde{P} - 1/\tilde{\theta}]K + \frac{E[(\tilde{P} - 1/\tilde{\theta})^2]}{2\beta}$$

From (A1) it follows that $E[\tilde{Q}] = K$ if and only if $E[\tilde{P} - 1/\tilde{\theta}] = 0$; thus $E[\tilde{Q}] = K$ is sufficient for equilibrium. If $E[\tilde{Q}] > K$, we have $E[\tilde{P} - 1/\tilde{\theta}] > 0$ and a profit-maximizing choice of K does not exist. Suppose that $E[\tilde{Q}] < K$, so that $E[\tilde{P} - 1/\tilde{\theta}] < 0$ and the profit-maximizing technology choice is K = 0. For K = 0 the PPF has slope $-1/(1/\tilde{\theta} + 2\beta Q)$ in the leisure-output plane, and thus for every $\tilde{\theta}$ the equilibrium price satisfies:

$$\frac{-1}{\tilde{P}} = \frac{-1}{1/\tilde{\theta} + 2\beta\tilde{Q}} > -\tilde{\theta}$$

whence $\tilde{P} - 1/\tilde{\theta} > 0$, in contradiction of our hypothesis. Q.E.D.

Proof of Proposition 1: (a) Using (A1) and (2), equilibrium output may be written:

(A5)
$$\tilde{Q} = \frac{\tilde{H}}{3\beta} + K$$

where:

(A6)
$$\tilde{H} = [(1/\tilde{\theta} - 2\beta K)^2 + 3\beta(\tilde{L} - \beta K^2)]^{1/2} - 1/\tilde{\theta} - \beta K$$

One may easily verify that $\tilde{H}$ is strictly increasing in $\tilde{\theta}$, and consequently $\tilde{Q}$ is strictly increasing in $\tilde{\theta}$. Further, $\tilde{Q} = K$ if and only if $K = \tilde{L}\tilde{\theta}/2$. Put:

$$\underline{K} \equiv \frac{\tilde{L}\underline{\theta}}{2}, \quad \bar{K} \equiv \frac{\tilde{L}\bar{\theta}}{2}$$

For $\tilde{\theta} > \underline{\theta}$ and $K = \underline{K}$ we have $\tilde{Q} > \underline{K}$, so that $E[\tilde{Q} | K = \underline{K}] > \underline{K}$. Similarly, $E[\tilde{Q} | K = \bar{K}] < \bar{K}$. Since $E[\tilde{Q}]$ is a continuous function of K, it follows that $E[\tilde{Q} | K = K'] = K'$ for some $K' \in (\underline{K}, \bar{K})$.

This proof is valid as long as the feasibility condition is satisfied for $\tilde{\theta} = \underline{\theta}$ and all $K \in [\underline{K}, \bar{K}]$; if not, it may be impossible to find K such that $E[\tilde{Q}] = K$ and feasibility is satisfied for $\tilde{\theta}$ near $\underline{\theta}$. We know, however, that feasibility holds at $\tilde{\theta} = \underline{\theta}$, $K = \underline{K}$, and it will continue to hold if $\bar{K}$ lies close enough to $\underline{K}$; to assure this we must take $\bar{\theta}$ sufficiently close to $\underline{\theta}$.

(b) It is easy to show that $\partial\tilde{Q}/\partial K \geq 1$ implies $\beta K \geq 2/\tilde{\theta}$ and $\beta\tilde{L} \leq 1/\tilde{\theta}^2$. These conditions together imply:

$$1/\tilde{\theta}^2 + 4\beta(\tilde{L} - K/\tilde{\theta}) \leq -3/\tilde{\theta}^2 < 0$$

in violation of the feasibility condition. Thus $\partial E[\tilde{Q}]/\partial K < 1$ if feasibility holds over the whole support, and $E[\tilde{Q}] = K$ is possible for at most one value of K. Q.E.D.

<u>Proof of Lemma 3</u>: (a) Using (A6) and $\alpha = 1/\tilde{\theta}$ we have:

(A7)
$$\frac{\partial \tilde{H}}{\partial \alpha} = \frac{\alpha - 2\beta K}{[(\alpha - 2\beta K)^2 + 3\beta(\tilde{L} - \beta K^2)]^{1/2}} - 1$$

(A8)
$$\frac{\partial^2 \tilde{H}}{\partial \alpha^2} = \frac{3\beta(\tilde{L} - \beta K^2)}{[(\alpha - 2\beta K)^2 + 3\beta(\tilde{L} - \beta K^2)]^{3/2}}$$

Further:

(A9)
$$\frac{\partial^2 \tilde{H}}{\partial \tilde{\theta}^2} = \alpha^3(\alpha \frac{\partial^2 \tilde{H}}{\partial \alpha^2} + 2\frac{\partial \tilde{H}}{\partial \alpha})$$

Since $\partial \tilde{H}/\partial \alpha < 0$, we have $\partial^2 \tilde{H}/\partial \tilde{\theta}^2 < 0$ if $\tilde{L} - \beta K^2 \leq 0$. More generally, we have observed that $\tilde{Q} = K$ if and only if $\tilde{\theta} = 2K/\tilde{L}$. Combining (A7), (A8) and (A9), and plugging in $\alpha = \tilde{L}/2K$, gives:

$$\frac{\partial^2 \tilde{H}}{\partial \tilde{\theta}^2} = \frac{-12\alpha^3\beta^2K^4(5\tilde{L} + 4\beta K^2)}{(\tilde{L} + 2\beta K^2)^3} < 0$$

From (A5) it follows that $\tilde{Q}$ will be strictly concave in $\tilde{\theta}$ where $\tilde{Q} = K$, and in a REE we have $K = E[\tilde{Q}]$.

(b) The limit of REE values of K as β approaches infinity is given by:

$$\lim_{\beta\to\infty} K = \frac{L}{2E[1/\tilde{\theta}]}$$

Thus we must have $L - \beta K^2 < 0$ for β sufficiently large, which implies global concavity.

Two further points should be recognised. First, using implicit differentiation it can be established that:

$$\text{sign}(\frac{\partial^2 \tilde{Q}}{\partial\tilde{\theta}^2}) = \text{sign}(-2\tilde{Q}^2/\tilde{\theta} + (K - \tilde{Q})(L - \beta K^2 + 3\beta\tilde{Q}^2))$$

and it follows that in the "small β" case of $L - \beta K^2 > 0$, concavity holds whenever $\tilde{Q} > K$, as depicted in Figure 4. Second, if we instead use the scaling $\alpha = \alpha(\tilde{\theta})$ with $\alpha'' \geq 0$, then we have:

$$\frac{\partial^2 \tilde{\Pi}}{\partial\tilde{\theta}^2} = \frac{\partial^2 \tilde{\Pi}}{\partial\alpha^2}(\alpha')^2 + \frac{\partial\tilde{\Pi}}{\partial\alpha}\alpha''$$

and concavity holds for sufficiently large β. Q.E.D.

Proof of Lemma 4: Differentiation of (3) establishes that $\partial\tilde{Q}/\partial K > 0$ at $\tilde{\theta} = 2K/L$, and $\partial\tilde{Q}/\partial K > 0$ continues to hold for all $K \in [L\underline{\theta}/2, L\bar{\theta}/2]$ if $\underline{\theta}$ is sufficiently close to $\bar{\theta}$. From the proof of Lemma 2 we know that the REE value of K must lie in this interval. Q.E.D.

Proof of Lemma 5: (a) For given $[\underline{\theta},\bar{\theta}]$, it follows as in the proof of Proposition 2 that $\bar{K} \equiv L\bar{\theta}/2$ is the largest K that could arise in a REE; thus part (a) of the feasibility condition is satisfied for all possible REE K if the following holds for all $\tilde{\theta} \in [\underline{\theta},\bar{\theta}]$:

(A10)
$$\frac{1}{\tilde{\theta}^2} + 4\beta(\tilde{L} - \frac{\tilde{K}}{\tilde{\theta}}) = \frac{1}{\tilde{\theta}^2} - \frac{2\beta\tilde{L}\tilde{\theta}}{\tilde{\theta}} + 4\beta\tilde{L} > 0$$

This condition holds necessarily for sufficiently small $\tilde{\theta}$; for large $\tilde{\theta}$, however, $\underline{\theta}$ must be greater than the lower root of the quadratic, or equivalently:

(A11)
$$\frac{1}{\underline{\theta}} < \beta\tilde{L}\tilde{\theta} - ((\beta\tilde{L}\tilde{\theta})^2 - 4\beta\tilde{L})^{1/2}$$

For fixed $D = \tilde{\theta} - \underline{\theta}$, (A11) may be expressed as:

(A12)
$$D < \tilde{\theta} - [\beta\tilde{L}\tilde{\theta} - ((\beta\tilde{L}\tilde{\theta})^2 - 4\beta\tilde{L})^{1/2}]^{-1}$$

It can be shown that the right-hand side of (A12) approaches $+\infty$ as $\tilde{\theta}$ approaches infinity. Thus (A12) is satisfied for sufficiently large $\tilde{\theta}$, or equivalently for sufficiently large $\underline{\theta}$.

Note next that since $\underline{K} \equiv \tilde{L}\underline{\theta}/2$ is the smallest possible REE K, part (b) of the feasibility condition is moot if for all $\tilde{\theta} \in [\underline{\theta}, \tilde{\theta}]$ we have $\tilde{L}\underline{\theta}/2 \geq 1/2\beta\tilde{\theta}$, and a sufficient condition for this is $\underline{\theta} \geq (\beta\tilde{L})^{-1/2}$.

(b) From the proof of Lemma 3 we know that $\partial^2\tilde{Q}/\partial\theta^2 < 0$ if $\tilde{L} - \beta K^2 \leq 0$, and the latter follows immediately from $\underline{\theta} \geq 2(\tilde{L}\beta)^{-1/2}$ and $K \geq \tilde{L}\underline{\theta}/2$. Differentiation of (3) establishes that $\partial\tilde{Q}/\partial K > 0$ if $\theta > 2/\beta K$, which also follows from $\underline{\theta} \geq 2(\tilde{L}\beta)^{-1/2}$ and $K \geq \tilde{L}\underline{\theta}/2$. Q.E.D.

APPENDIX 2

Data Descriptions

ASA-NBER Point Forecast Data

The ASA-NBER survey data on point forecasts were obtained from Citibase and various issues of *Explorations in Economic Research.* We defined the forecast of GNP growth as the difference in the log of forecasted real GNP for the current quarter and the preliminary GNP data for the previous quarter. The forecast error is defined as the deviation of actual GNP growth (based on the revised data) from the forecasted growth rate. A recent article by Keane and Runkle (1990), testing the rationality of price forecasts, argues that the unrevised numbers announced 45 days after the end of the quarter should be used rather than the revised data. However, we found that in the case of GNP growth, the match between the forecast and the revised data was better in the sense that the regression of the actual data on the forecast produced a coefficient closer to one and a Durbin-Watson statistic nearer to two.

Rolling Regression Forecasts

For the rolling regression procedure, we chose the forecasting equation that produced forecast errors with the highest correlation with the ASA-NBER series. Surprisingly, the specification that produced the highest correlation with the ASA-NBER data over the 1969:1 to 1989:4 subsample was a simple second order autoregression on growth rates. Other variables that were tried included the change in the commerical paper rate, the growth of the Solow residual, the risk premium, the inflation rate, and housing starts.

The forecasting equation was estimated for the five year period from 1948:1 to 1952:4, and then used to construct the one-quarter ahead forecast of GNP growth in 1953:1. The equation was subsequently re-estimated for the five year period from 1948:2 to 1953:1, and used to construct the forecast for 1953:2. This rolling regression procedure was continued to construct the entire series of forecasts from 1953:1 to 1989:4. The forecast errors are the difference between actual output growth and this constructed series.

ASA-NBER Probability Data

The data were kindly provided by Wayne Gray at the National Bureau of Economic Research. In the series we constructed, only respondents who had answered at least twelve surveys were included. We eliminated those questionaires for which the probabilities did not add up to one. For nominal GNP the total number of observations left was 1733 and for the implicit price deflator, 1706. The moments of the distribution were calculated exactly as in Zarnowitz and Lambros (1987).

The theory pertains to ex ante uncertainty about *real* GNP growth, but the two uncertainty measures available are for nominal GNP growth and the implicit price deflator. Preliminary investigations showed that the sum of the two measures had a slightly higher correlation with real GNP growth than either of the separate measures, so we used the sum of the variances in our analysis. As long as the conditional covariance between nominal GNP and the implicit price deflator is a constant, the sum of the conditional variances of the two is the best measure of the conditional variance for real GNP.

APPENDIX 3

Calibration

We now reinterpret our empirical evidence to support our calibrations of the conditional variance of output and β that were discussed in Section 1C. For calibration purposes we use the cointegrating relation estimated from the error correction model, which constitutes our best estimate of the relationship between mean and variance of output. We normalize output units by choosing $Q_{t-1} = .9554$, so that in the absence of volatility we would have $E[Q_t | Q_{t-1}] = 1$ under the historical output growth rate augmented by the 1.77 percent increase from elimination of volatility. We take ε_t^2 to be an estimate of the forecast variance $Var(\Delta \log Q_t | Q_{t-1})$, and averaging over the sample gives $Var(\Delta \log Q_t | Q_{t-1}) = .000105$. We obtain the variance estimate $Var(Q_t | Q_{t-1}) = .0015$ by using the approximation $(Q_t - Q_{t-1})/Q_{t-1} \equiv \Delta \log Q_t$, converting to annualized growth rates, and normalizing with $Q_{t-1} = .9554$. Finally, simulation analysis indicates that the point $E[Q_t | Q_{t-1}] = .983$, $Var(Q_t | Q_{t-1}) = .0015$, which is labeled x in Figure 5, is obtained when $\beta = 2.4$.

REFERENCES

Abel, Andrew B., "Optimal Investment Under Uncertainty," *American Economic Review*, 73 (1983): 228-233.

Argote, Linda and Epple, Dennis, "Learning Curves in Manufacturing," *Science* 1990.

Backus, David, Kehoe, Patrick, and Kehoe, Timothy, " In Search of Scale Effects in Trade and Growth," June 1990 manuscript.

Ball, Laurence and Cecchetti, Stephen, "Inflation and Uncertainty at Long and Short Horizons," *Brookings Papers on Economic Activity*, 1990:1, 215-245.

Barro, Robert J., ed., *Modern Business Cycle Theory*, Cambridge, Mass.: Harvard University Press, 1989.

Bernanke, Ben S., "Irreversibility, Uncertainty,, and Cyclical Investment," *Quarterly Journal of Economics*, February 1983, 98, 85-106.

Black, Fischer, *Business Cycles and Equilibrium*, Cambridge, Mass.: Basil Blackwell, Inc., 1987.

Caballero, Ricardo, "On the Sign of the Investment-Uncertainty Relationship," *American Economic Review* 81 (March 1991): 279-288.

Chandler, Alfred D., Jr., *The Visible Hand*, Cambridge, Mass.: Harvard University Press, 1977. Chapter 8.

Delong, Bradford and Summers, Lawrence, "How Does Macroeconomic Policy Affect Output?" *Brookings Papers on Economic Activity* 1988:2, 433-494.

Engle, Robert F., Hendry, David F., and Richard, J.F., "Exogeneity," *Econometrica* 51 (1983): 277-304.

Engle, Robert F. and Granger, Clive W. J., "Co-Integration and Error Correction: Representation, Estimation and Testing," *Econometrica* 55 (March 1987): 251-276.

Engle, Robert F., Lilien, David M. and Robins, Russell P., "Estimating Time Varying Risk Premia in the Term Structure: The Arch-M Model," *Econometrica* 55 (March 1987): 391-408.

Falk, Barry, "Further Evidence on the Asymmetric Behavior of Economic Times Series over the Business Cycle," *Journal of Political Economy* 94 (October 1986): 1096-1109.

Greenwood, Jeremy and Huffman, Gregory, "Tax Analysis in a Real Business Cycle Model: On Measuring Harberger Triangles and Okun Gaps," July 1989 manuscript.

Hall, Robert E., "Temporal Agglomeration," mimeo, September 1988.

Hamilton, James D., "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica* 57 (March 1989):

Hartman, Richard, "The Effects of Price and Cost Uncertainty on Investment," *Journal of Economic Theory*, October 1972, 5, 258-266.

Holt, Charles C., Modigliania, Franco, Muth, John F. and Simon, Herbert A., *Planning Production, Inventories, and Workforce*, Englewood Cliffs: Prentice-Hall, 1960.

Imrohoroglu, Iyse, "The Cost of Business Cycles with Indivisibilities and Liquidity Constraints," *Journal of Political Economy* 97 (December 1989): 1364-1383.

Jalan, Jyotsna, "On Cointegration Between the First Two Moments," UCSD manuscript, May 1991.

Johansen, Soren, "Statistical Analysis of Cointegration Vectors," *Journal of Economic Dynamics and Control* 12 (1988): 231-234.

Johansen, Soren and Juselius, Katarina, "Hypothesis Testing for Cointegration Vectors - with an Application to the Demand for Money in Denmark and Finland, "Preprint, IMS, University of Copenhagen.

Jovanovic, Boyan, and Rob, Rafael, "Long Waves and Short Waves: Growth through Intensive and Extensive Search," *Econometrica* 58 (November 1990): 1391-1409.

Keane, Michael and Runkle, David, "Testing the Rationality of Price Forecasts: New Evidence from Panel Data," *American Economic Review* 80 (September 1990): 714-735.

Kormendi, Roger and Meguire, Philip, "Macroeconomic Determinants of Growth: Cross Country Evidence," *Journal of Monetary Economics* 16 (1985): 141-163.

Kydland, Finn and Prescott, Edward, "Time To Build and Aggregate Fluctuations," *Econometrica*, November 1982, 50, 1345-1370.

Lucas, Robert, "Expectations and the Neutrality of Money," *Journal of Economic Theory*, 1972, 4, 103-24.

-----------, "Some International Evidence on Output-Inflation Tradeoffs," *American Economic Review*, June 1973, 63, 326-334.

-----------, *Models of Business Cycles*, Oxford, UK: Basil Blackwell, 1987.

MacKinnon, James, "Critical Values for Cointegration Tests," January 1990 manuscript.

Mayer, Thomas, "Plant and Equipment Lead Times," *Journal of Business*, 1960, 33, 127-132.

Murphy, Kevin M., Shleifer, Andrei, and Vishny, Robert W., "Building Blocks of Market Clearing Business Cycle Models," *NBER Macroeconomics Annual* 1989, 247-287.

Pindyck, Robert S., "Irreversible Investment, Capacity Choice, and the Value of the Firm," *American Economic Review* 78 (December 1988): 969-985.

Ramey, Valerie, "Nonconvex Costs and the Behavior of Inventories," *Journal of Political Economy* 99 (April 1991): 306-334.

Romer, Christina, "The Prewar Business Cycle Reconsidered: New Estimates of Gross National Product, 1869-1908," *Journal of Political Economy*, February 1989, 97, 1-37.

Rothenberg, Thomas and Smith, Kenneth, "The Effect of Uncertainty on Resource Allocation in a General Equilibrium Model," *Quarterly Journal of Economics* 85 (August 1971): 440-459.

Sichel, Daniel E., "Business Cycle Asymmetry: A Deeper Look," October 1990 manuscript.

Slichter, Sumner, "The Current Labor Policies of American Industries," *Quarterly Journal of Economics*, 1929, 43, 393-435.

Stock, James, "Asymptotic Properties of Least Squares Estimators of Cointegrating Vectors," *Econometrica* 55 (1987): 1035-1056.

Zarnowitz, Victor and Lambros, Louis, "Consensus and Uncertainty in Economic Prediction," *Journal of Political Economy* 95 (June 1987): 591-621.

Zarnowitz, Victor and Moore, Geoffrey, "Major Changes in Cyclical Behavior," in Robert J. Gordon, ed. *The American Business Cycle: Continuity and Change*, Chicago: University of Chicago Press, 1986.