Measurement Error in General Equilibrium: The Aggregate Effects of Noisy Economic Indicators

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Abstract

I analyze the business cycle implications of noisy economic indicators in the context of a dynamic general equilibrium model. Two main results emerge. First, measurement error in preliminary data releases can have a quantitatively important effect on economic fluctuations. For instance, under efficient signal-extraction, the introduction of accurate economic indicators would make aggregate output 10 to 30 percent *more* volatile than suggested by the post-war experience of the U.S. economy. Second, the sign—but not the magnitude—of the measurement error effect depends crucially on the signal processing capabilities of agents. In particular, if agents take the noisy data at face value, significant improvements in the quality of key economic indicators would lead to considerably *less* cyclical volatility.

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1 Introduction

From the GDP to M2, to productivity growth to the index of leading economic indicators, preliminary releases of economic data are routinely subject to sizable revisions as more information becomes available in subsequent periods. The existence of pure noise in these and other economic indicators has been the subject of several studies, but the associated literature is primarily statistical and of a partial equilibrium nature.[1] In this paper I take a novel and complementary approach, examining the effects of indicator noise in a fully articulated dynamic macroeconomic model. The model explicitly features individual decision-making under incomplete information and is rich enough to allow for a quantitative assessment of its aggregate implications.

This paper can be thought of as a well defined sequence of computational experiments (Kydland and Prescott, 1996). Motivated by the findings of the empirical literature on indicator noise—which are summarized in section 2—I pose a very simple question: if economic data are as noisy as suggested by the statistical literature, what are the likely consequences for individual and macroeconomic behavior?[2] The theoretical framework used to answer this question is a version of the well known real-business-cycle model of Baxter and King (1991), which I augment to include a noisy productivity indicator. In sections 3 and 4, I describe the model and lay out the solution to the representative agent's dynamic optimization problem. The solution to this problem, which assumes that agents use fully efficient signal extraction techniques, characterizes the business cycles of the artificial economy. Using the conventional tools of the quantitative approach to macroeconomics

[1] The work of Oh and Waldman (1990, 1995), which I discuss below, is an important exception to this rule.

[2] This paper attempts to extend and quantify the main results derived by Bomfim (1998), who used a very simple model to discuss the macroeconomic implications of indicator noise under alternative characterizations of agents' expectations.

(King, 1995), I calibrate the model to the U.S. postwar data and run, in section 5, a series of experiments designed to quantify the aggregate effects of noisy information. I find that that the presence of measurement error in preliminary data can have a non-trivial effect on economic fluctuations. In particular, the introduction of more accurate economic indicators would make aggregate output 10 to 30 percent more volatile than suggested by the postwar experience of the U.S. economy. The results are supported by a battery of sensitivity tests on key model parameters. The paper also highlights the quantitative role played by agents' information processing capabilities in business cycle fluctuations. For instance, as discussed in section 6, if agents are boundedly-rational and take the preliminary data at face value, though the aggregate effect of indicator noise remains sizable, its sign is reversed: better economic indicators would lead to considerably less cyclical volatility. Finally, the model is compared to a prototypical real-business-cycle framework, which has thus far suggested only a limited scope for the types of informational problems discussed here. This comparison and other concluding remarks are included in section 7.

2 How reliable are preliminary economic data?

Several studies in the statistics and empirical economics literature document the existence of low signal-to-noise ratios in preliminary releases of key economic data. For instance, Diebold and Rudebusch (1991) examined revisions in the composite index of leading economic indicators and reported a signal-to-noise ratio of 1.3. Likewise, Mankiw, Runkle and Shapiro (1984) found significant measurement error in preliminary announcements of the money stock, with estimated signal-to-noise ratios as low as 0.56.[3]

While most professional studies have tended to discuss the statistical properties of particular economic indicators, little has been done in terms of assessing the economic significance of the associated degree of informational imperfection. Indeed, this assessment has been limited, for the most part, to press accounts, which often attempt to provide a link between some potentially problematic data series and a particular economic issue.[4] Nevertheless, if the economist could be blamed for focusing too much on the numbers, the opposite could be said of the typical reporter or news analyst, whose analyses tend to be anecdotal and of a qualitative nature.

Exceptions to the above characterization of the economists' and journalists' approaches to the measurement error problem do exist both in the economics literature and in press accounts. For example, a 1994 cover story in *BusinessWeek* attempted to provide both a macroeconomic perspective and a rough quantitative assessment of the effects of inaccurate economic data (BusinessWeek, 1994). In the professional economics literature, the work of Oh and Waldman (1990, 1995) is especially noteworthy, as they were probably the first to explicitly discuss and try to measure the aggregate effects of indicator noise. Oh and Waldman examined the macroeconomic implications of the "errors" contained in the initial announcements of the index of lead-

[3]Other contributions to the indicator noise literature include Diebold and Rudebusch's (1988) early work on the leading indicators, Kennedy's (1993) study of the industrial production index, and Mankiw and Shapiro's (1986) analysis of GNP revisions. Of these, Mankiw and Shapiro were the only ones not to find support for the measurement error hypothesis, though their estimated variance of GNP revisions was quite large relative to the variance of the final numbers.

[4]For instance, noisy U.S. productivity numbers are often the subject of newspaper editorials on whether or not the Federal Reserve should let the economy exceed its presumed trend growth rate. Moreover, the growing importance of the service sector—where output is harder to measure than in the manufacturing and agriculture sectors—has only heightened concerns about measurement error and data reliability.

ing economic indicators. Based on a series of reduced-form regressions, they reported that these errors account for as much as 20 percent of the variance of U.S. industrial production in the postwar period.

This paper follows the Oh-Waldman tradition in that my primary focus is to measure the aggregate consequences of noisy economic indicators. However, my approach differs a great deal from Oh and Waldman's. Rather than focusing on reduced-form regressions based on any one indicator, my analysis is carried out in the context of a fully specified dynamic general equilibrium model. The main advantage of this approach is that, in addition to pursuing the same quantitative questions raised by Oh and Waldman, I am also able to give an explicitly structural interpretation to the results. Moreover, because the theoretical framework I use is a simple variant of a conventional real-business-cycle model, my results can be directly and quantitatively compared to other common specifications in the modern macroeconomics literature.

3 The Model

The theoretical framework is an extension of the well-known dynamic general equilibrium model of King, Plosser and Rebelo (1988). To the KPR specification I add two main features. First, as in Baxter and King (1991), my model allows for the possibility of strategic complementarity in the production function.[5] Second, instead of the perfectly observable technological shocks that buffet the KPR and Baxter-King economies, I assume that agents have to infer the current state of the world based on a noisy productivity indicator.[6]

[5] However, because of conflicting evidence on the importance of complementarity in the U.S. economy, I will also analyze a version of the model without production externalities.

[6] I assume an information structure similar to Kydland and Prescott's (1982).

3.1 The Production Function

As in Baxter and King (1991), individual output (y_t) is a function not only of labor and capital inputs (n_t and k_{t-1}) and a composite productivity index (A_t), but also of per capita aggregate output (Y_t).

$$y_t = \exp(A_t) k_{t-1}^{\theta_k} n_t^{1-\theta_k} Y_t^{\phi} \tag{1}$$

The ϕ parameter in equation (1) embodies the complementarity assumption; it determines the extent to which individual output depends on aggregate output.[7]

The state of technology is subject to both persistent and white-noise shocks, denoted as $A_{1,t}$ and $A_{2,t}$, respectively:

$$A_t = A_{1,t} + A_{2,t} \tag{2}$$

The persistent component of the technology shifter follows a first-order autoregression:

$$A_{1,t} = \rho A_{1,t-1} + a_{1,t} \tag{3}$$

where $|\rho| \leq 1$, and $\{a_{1,t}\}$ is a zero-mean, normally distributed white noise process with variance σ_{a1}^2. The variance of $A_{2,t}$ is similarly denoted as σ_{a2}^2.

3.2 Evolution of the Capital Stock

Output not consumed constitutes gross investment, i_t. With k_t representing the capital stock at the end of period t, and assuming that this stock

[7] Cooper and John (1988) provide a useful description of the role of complementarities in macroeconomics.

depreciates at the rate δ, $0 \leq \delta < 1$,

$$k_t = (1 - \delta)k_{t-1} + i_t \tag{4}$$

3.3 Preferences

The momentary utility function of a representative agent is:

$$u(c_t, l_t) = \log(c_t) + \theta_l \log(l_t) \tag{5}$$

where c_t denotes consumption, and l_t is leisure—expressed as a proportion of the unit time endowment.

3.4 Information Structure

At the beginning of each period, agents observe a preliminary announcement of the current state of technology. This preliminary announcement (π_t) is subject to measurement error (e_t):

$$\pi_t = A_t + e_t \tag{6}$$

where e_t is white noise with variance σ_e^2.

As in Kydland and Prescott (1982), agents follow a two-stage decision process. In the first stage, they make their factor allocation decisions, which are based on the preliminary announcement. Once production takes place, the second stage begins. The representative agent can use its knowledge of output and inputs to deduce the value of the productivity shock (A_t), but not its persistent and transitory components ($A_{1,t}$ and $A_{2,t}$). Given this larger information set, agents update their forecasts of future economic conditions and consumption takes place.

The assumption that $A_{1,t}$ and $A_{2,t}$ cannot be observed separately is designed to capture the "informational confounding" effect described by Kasa (1996). I include it here not only because it can potentially strengthen the internal propagation mechanism of the model, but also to allow for a more interesting, and perhaps more realistic, role for signal extraction in the decision-making process.[8]

3.5 Individual Behavior

All agents are infinitely lived, forward looking, and discount the future at the rate β. Subject to time and goods constraints,

$$l_t + n_t \leq 1 \tag{7}$$

$$c_t + i_t \leq y_t, \tag{8}$$

as well as to conventional initial and transversality conditions, agents maximize expected utility over an infinite horizon. Abstracting from uncertainty, the objective function can be written as:

$$\sum_{t=0}^{\infty} \beta^t \left\{ u(c_t, 1-n_t) + \lambda_t [z_t k_{t-1}^{\theta_k} n_t^{1-\theta_k} Y_t^{\phi} - c_t - k_t + (1-\delta) k_{t-1}] \right\} \tag{9}$$

where λ_t is the discounted Lagrange multiplier and $z_t \equiv \exp(A_t)$.

Given the stochastic sequence $\{\pi_t\}_{t=0}^{\infty}$, as well as a particular expectation-formation mechanism for the agents in this economy, the values of $\{n_t, c_t, i_t, \lambda_t\}_{t=0}^{\infty}$ that maximize the expected value of (9) characterize the business cycles of this artificial economy.

[8] Without the information confounding effect, signal extraction would be reduced to the first stage of the decision-making process. Once production takes place, all fundamental shocks would become immediately observed. For completeness, however, I do present some results based on a version of the model without information confounding.

4 Equilibrium Determination

Setting expectational issues aside for the moment, the derivation of the system of Euler equations that corresponds to the maximization of (9) is straightforward. This system can be written as follows:[9]

$$u_C(C_t, 1 - N_t) - \Lambda_t = 0 \tag{10}$$

$$u_L(C_t, 1 - N_t) - (1 - \theta_k)\Lambda_t Y_t / N_t = 0 \tag{11}$$

$$\beta \Lambda_{t+1}[\theta_k Y_{t+1}/K_t + (1 - \delta)] - \Lambda_t = 0 \tag{12}$$

$$Y_t - C_t - K_t + (1 - \delta)K_{t-1} = 0 \tag{13}$$

where all variables are expressed in per capita terms (denoted in upper-case letters) to reflect the notion that, given that all agents are identical, the resulting equilibrium is symmetric.

4.1 Perfect-Foresight Equilibrium Laws of Motion

The perfect-foresight equilibrium paths of consumption, investment, and labor effort are given by the solution to the system formed by equations (10) through (13). It is well known, however, that in general there is no closed-form solution to this system. I will focus instead on an approximate solution, obtainable by log-linearizing the system around its steady state.[10] The re-

[9] $u_i(.)$ $[F_i(.)]$ corresponds to the first derivative of the utility [production] function with respect to i. Note, e.g., that the private marginal product of labor can be written as:

$$\exp(A_t) F_N(k_{t-1}, n_t) Y_t^{\phi} = (1 - \theta_k) y_t / n_t$$

[10] The log-linear approximation method used here is described in detail in King et al. (1990).

sulting (approximate) equilibrium laws of motion take the form

$$\begin{aligned} x_{t+1} &= \ ,_{x} x_t + \ ,_{\lambda} \tilde{\Lambda}_t + R A_{t+1} + Q A_t && (14) \\ \Psi_t &= G_x x_t + G_\lambda \tilde{\Lambda}_t && (15) \\ \tilde{\Lambda}_t &\equiv \sum_{j=0}^{\infty} \mu^j (H_a A_{t+j+1} + H_b A_{t+j}) && (16) \end{aligned}$$

where $x_t \equiv [\hat{K}_{t-1}, \hat{N}_{t-1}, \hat{\Lambda}_{t-1}, \hat{K}_t]'$ is the vector of predetermined variables at time t, and $\Psi_t \equiv [\hat{N}_t, \hat{\Lambda}_t]'$.

A "caret" over a symbol denotes that the variable is expressed in percentage deviations from the steady state (e.g., $\hat{Y}_t \equiv \log(Y_t/\bar{Y})$). The matrices $,_{i}$, G_i, R, and Q, as well as the μ parameter, are all functions of various steady-state properties of the model, such as the economy's capital-output ratio and the steady-state labor's share of total income.[11]

4.2 Decision Rules under Uncertainty

Equations (14) through (16) correspond to the solution to the agents' decision making problem in the absence of uncertainty. To turn these equilibrium conditions into the optimal decision rules that characterize individual behavior in a stochastic environment, we need to substitute all variables that are unobserved as of the beginning of time t by their respective prediction formulae. Essentially, what this step requires is deriving the j-step-ahead prediction formula for A_t.

Assuming that the representative agent uses an efficient signal-extraction method to deal with the noise component of the productivity indicator, the prediction formula for A_t during the first stage of the decision-making process

[11] The derivation of (14) through (16) follows King et al. (1990) and Blanchard and Kahn(1980) very closely.

is based on the following state-space form:

$$\alpha_t = D\alpha_{t-1} + a_t \tag{17}$$

$$\pi_t = B\alpha_t + e_t \tag{18}$$

where $\alpha_t \equiv [A_{1,t}, A_{2,t}]'$, $D \equiv \begin{bmatrix} \rho & 0 \\ 0 & 0 \end{bmatrix}$, $a_t \equiv [a_{1,t}, a_{2,t}]'$, and $B \equiv [1,1]$. Generating an optimal forecast for A_t in this case is a straightforward application of the Kalman filter. Thus, letting Ω_{t-1} denote the information set just before the time-t preliminary announcement is made, the j-step-ahead forecast of A_t conditional on the announcement is

$$E[A_{t+j}|\Omega_{t-1}, \pi_t] = BD^j E[\alpha_t|\Omega_{t-1}, \pi_t] \tag{19}$$

where

$$E[\alpha_t|\Omega_{t-1}, \pi_t] = (I - \xi_1 B)DE[\alpha_{t-1}|\Omega_{t-1}] + \xi_1 \pi_t, \tag{20}$$

I is the identity matrix, and the projection coefficient ξ_1 is a function of the signal-to-noise ratio $((\sigma_{a1}^2 + \sigma_{a2}^2)/\sigma_e^2)$.

Given equations (17) through (20), a general representation of the factor allocation decision rules is

$$\hat{K}_t = G_{kk}\hat{K}_{t-1} + G_{kx}E[\alpha_{t-1}|\Omega_{t-1}] + G_{kp}\pi_t \tag{21}$$

$$\hat{N}_t = G_{nk}\hat{K}_{t-1} + G_{nx}E[\alpha_{t-1}|\Omega_{t-1}] + G_{np}\pi_t \tag{22}$$

where it can be shown that the G_{ij} parameters depend not only on the long-run properties of the economy, but also on the signal-noise ratio of the productivity indicator. The expression for $E[\alpha_{t-1}|\Omega_{t-1}]$, which denotes the expected value of $[A_{1,t-1}, A_{2,t-1}]'$ conditional on all information available at the end of t-1, is derived below.

Once the labor and capital decision rules are made, production takes place. This allows the agents to deduce the current value of the composite productivity shock (A_t). However, agents still face a signal extraction problem when trying to predict future movements in A_t because they cannot break down the composite shock into its persistent ($A_{1,t}$) and white noise ($A_{2,t}$) components. Thus, the second-stage decision making process is based on the following state-space form,

$$\alpha_t = D\alpha_{t-1} + a_t \tag{23}$$

$$A_t = B\alpha_t \tag{24}$$

from which we can derive the prediction formula for α_t conditional on all information available at time t:

$$E[\alpha_t|\Omega_t] = (I - \xi_2 B)E[\alpha_t|\Omega_{t-1}, \pi_t] + \xi_2 A_t \tag{25}$$

where ξ_2 is a function of the ratio of the variances of $a_{1,t}$ and $a_{2,t}$. With this updating rule for the expectation of α_t, the general form of the consumption decision rule, which is based on a larger information set, can be written as:

$$\hat{C}_t = G_{ck}\hat{K}_{t-1} + G_{cx}E[\alpha_{t-1}|\Omega_{t-1}] + G_{cp}\pi_t + G_{ca}A_t \tag{26}$$

where it can be seen that knowledge of A_t is incorporated into the optimal decision rule for consumption. Equations (21), (22), and (26), along with an analogous expression for $\hat{\Lambda}_t$, correspond to to the solution to the model.

5 Computational Experiments

The main question asked in this paper is whether measurement error in preliminary economic data can have a quantitatively significant effect on macroeconomic fluctuations. To address this question I run a series of computational experiments.[12] Using available data for the U.S. economy, I calibrate all key parameters of the model and measure the implied time series properties of the artificial economy. Subsequently, I vary the degree of signal-to-noise ratio in the productivity indicator and assess the quantitative implications for the stochastic properties of the model. Throughout this section, my emphasis will be on cyclical volatility, though I will also address some issues related to persistence generation.

5.1 Model Calibration

With the exception of strategic complementarity parameter, ϕ, and the variances of the productivity innovations and indicator noise—σ_{a1}^2, σ_{a2}^2, σ_e^2—all model parameters are calibrated as in King, Plosser and Rebelo (1988). The first panel of table 1 shows this basic parameterization. The parameters shown in the second panel are discussed below.

Strategic complementarity parameter. The calibration of the strategic complementarity parameter (ϕ) is partly guided by the empirical work of Baxter and King (1991), Caballero and Lyons (1989, 1992), and Cooper and Haltiwanger (1993). However, even a casual look at these papers reveal a very wide range of estimates for ϕ. For instance, Baxter and King and Caballero and Lyons report estimates that range from from 0.1 to 0.49, and Cooper and

[12]See Kydland and Prescott (1996) and King (1995) for a discussion of the use of computational experiments in macroeconomics.

Haltiwanger find even larger numbers. For the purposes of this paper, rather than making a case for any particular estimate of ϕ, I run my experiments with ϕ set at 0.24, about midpoint between the standard RBC model—which sets ϕ at zero—and the upper bound of the range of estimates of Baxter and King (1991) and Caballero and Lyons (1992).[13] This parameterization happens to be very close the the "preferred" estimates reported by Baxter and King (1991) and Caballero and Lyons (1989); however, to address the concerns raised more recently by Basu and Fernald (1995, 1996), I also report some results based on lower values of ϕ.

Volatility of shocks. The variance of the productivity indicator, π_t, is a function of three potentially free parameters: σ_{a1}^2, σ_{a2}^2, and σ_e^2. To reduce the number of free parameters to 2, I calibrate the variance of π_t so that the model-based measure of output volatility exactly matches the variance of output in the U.S. economy.

Next, I restrict the magnitude of the signal-to-noise ratio of π_t to be comparable to estimated signal-to-noise ratios of typical economic indicators of the real world. Based on the work of Diebold and Rudebusch (1991) and Mankiw *et al.* (1984), I run my baseline experiments with $(\sigma_{a1}^2 + \sigma_{a2}^2)/\sigma_e^2$ set at 1, again about the midpoint of the range of estimates reported by these authors. One might correctly argue that Diebold and Rudebusch and Mankiw and his co-authors studied series that are not quite the empirical counterpart of the theoretical productivity indicator examined in this paper—their analyses involved the composite leading indicator (CLI) index and the money stock, respectively. However, from a functional standpoint, these two series are very much related to π_t. Like the composite productivity indicator specified in this paper, the CLI and money supply announcements

[13] In general, values of ϕ that exceed 0.5 lead to indeterminacy and are thus not examined here.

were two prominent leading economic indicators widely used for forecasting future economic activity over the time period covered by the Diebold and Rudebusch and Mankiw *et al.* studies. Thus, in the absence of direct estimates of $(\sigma_{a1}^2 + \sigma_{a2}^2)/\sigma_e^2$, I attempt to restrict my baseline parameterization to be in line with the signal-to-noise ratios actually facing individuals in the U.S. economy.

After the restrictions related to matching the variance of output and estimated signal-to-noise ratios are in place, we are still left with one free parameter. As discussed below, this remaining free parameter will be set indirectly by experimenting with a grid of values for the variance ratio involving the persistent and white-noise components of the productivity shock.

Persistence parameters. The most obvious persistence parameter is ρ, the autocorrelation coefficient of $A_{1,t}$. However, I will also include in this category the ratio of the variances of the innovations in the persistent and white-noise components of the productivity shock $(\sigma_{a1}^2/\sigma_{a2}^2)$. For given ρ, the higher this ratio, the greater the relative importance of $A_{1,t}$ in output fluctuations, and thus the more persistent these fluctuations will be. The calibration of the persistence parameters touches upon a number of outstanding questions in the empirical and theoretical literatures. First, there is the question of how to measure A_t empirically so that its stochastic properties can be adequately estimated. Two main approaches have been followed here. Prescott (1986) was one of the first to propose measuring the productivity shocks of RBC models as the series of Solow residuals that falls out of standard decompositions of output growth into growth in inputs.[14] On this basis, the data would suggest near-unit root processes for A_t. On the other hand, the work of Hall (1987) and others has questioned the Solow residual approach, suggesting

[14]The issue of persistent versus white-noise components of A_t is not addressed by the conventional Solow residual approach.

that the measured residuals capture more than just the technological shocks implied by theory. Needless to say, this second approach makes calibrating ρ and $\sigma_{a1}^2/\sigma_{a2}^2$ a bit harder.

I this paper I will parameterize ρ and $\sigma_{a1}^2/\sigma_{a2}^2$ so that the model roughly matches the degree of serial correlation in output that is observed in the U.S. data. This of course implies that one of the parameters is free so below I will report the results of sensitivity analysis exercises. To retain the information-confounding effect, I set $\sigma_{a1}^2/\sigma_{a2}^2$ to 2, which means that the innovation to the persistent component of the productivity shock is twice as volatile as the white-noise component. Compared to other works in the literature that feature the information-confounding effect, this parameterization is relatively conservative. For instance, the seminal work of Kydland and Prescott (1982) set this ratio to 1. Given my parameterization of this variance ratio, setting ρ to 0.9 is sufficient to make the model consistent with the degree of output persistence in the data.[15]

5.2 Baseline Experiment and Results

Using the parameter values listed in table 1, the basic experiment I run is a simple one. First, I solve the model with the noisy productivity indicator and compute the same moments that are listed in the first panel of table 2 for the U.S. data. The resulting model moments are shown in the middle panel of the table. As shown, the model is roughly consistent with the data, except that investment is more volatile in the model. This "excess" volatility of investment, however, is not a peculiarity of the indicator noise feature of the model. As shown in the bottom panel of table 2, a version of the model

[15] As discussed by Cogley and Nason (1995), this reliance of highly persistent technological shocks highlights the weak propagation mechanism of this class of models. I will return to this issue below in the discussion of the sensitivity analysis.

that allows for full information, which is essentially the model developed by Baxter and King (1991), also has investment more volatile than in the data.

The similarities between the middle and bottom panels of table 2 are so striking that one is tempted to wonder why bother to consider the incomplete information version of the model. The answer is that the two panels are not really perfectly comparable. In solving the model for each case, the variances of the stochastic shocks are recalibrated so that the model can exactly match the output volatility in the data. Suppose, however, that we take the view that the real world is characterized by noisy economic indicators and imperfect information, a picture that corresponds to the middle panel. This takes us to the second part of the computational experiment. Consider now a new scenario where the data-collection agency effectively manages to eliminate the measurement error in its productivity indicator. Of course, this should have no effect on the total variance of the "fundamental" shock (A_t). Therefore, without recalibrating the model, what happens to cyclical volatility after the introduction of the more accurate indicator? The results are reported in table 3. For convenience, the moments of the noisy-indicator economy are reproduced in the upper panel of the table. The bottom panel shows how these same moments would look like in the absence of measurement error in the composite productivity indicator, i.e., after a dramatic improvement in the quality of the available indicator. The most striking result is a sizable increase in the volatility of the business cycle of this artificial economy. After the perfect indicator is introduced, the variance of output increases almost 14 percent, and the variances of all macro variables also increase significantly.[16]

The increase in cyclical volatility after the elimination of the noise com-

[16]As shown in the table, the version of the model with the noisy indicator has a stronger internal propagation mechanism for output fluctuations. The relationship between signal extraction and persistence is discussed in Kasa (1996).

ponent of the indicator might, at first, appear surprising to some readers. One might be tempted to reason that a reduction in uncertainty (elimination of indicator noise) would likely decrease cyclical volatility. As shown in table 3, this is decidedly not the case. As discussed by Bomfim (1998), there is a very intuitive explanation to this finding. When the indicator is noisy, agents effectively discount all preliminary announcements by always attributing some fraction of each new reading to measurement error.

Perhaps the magnitude of the aggregate effect of measurement error is more surprising than its sign. Especially given that the signal-to-noise error ratio in this experiment is not really that low, either relative to previous work—e.g., Kydland and Prescott (1982)—or in relation to estimated signal-to-noise ratios in typical economic indicators. Furthermore, as discussed in the next subsection, the 14 percent increase in output volatility reported here might actually be a conservative estimate of the macroeconomic implications of noisy economic indicators.

5.3 Sensitivity Analysis

Several factors contribute to the magnitude of the noisy-indicator effect reported above. Because some of these factors are not well measured in the data, I run below additional computational experiments designed to assess the robustness of the results to variations in selected parameters.

Production Externalities. As discussed above, the baseline experiment is based on an intermediate value of ϕ, the strategic complementarity parameter. Given the degree of imprecision with which this parameter is estimated, I also ran the same experiment reported in table 3 for two polar values of ϕ. For $\phi = 0$—a number closer to the views of Basu and Fernald (1995, 1996)—I find that the percentage increase in the variance of output is smaller, but still a sizable 10 percent. Thus, though the multiplier effects associated with strategic complementarity do play a role in my model, the baseline value of the complementarity parameter is not what drives my main result. In fact, one could argue that the baseline parameterization is perhaps too low. For instance, with ϕ at 0.49—the upper end of the range of estimates reported by Baxter and King (1991) and Caballero and Lyons (1992), but still below the Cooper-Haltiwanger (1993) estimates—output volatility would have surged nearly 20 percent after the improvement in the productivity indicator.

Persistence Parameters. The composite productivity shock that buffets the model is very persistent, both in terms of the autocorrelation coefficient of the persistent component and the variance-ratio of the persistent and white-noise components. As discussed above, the assumption of strong serial correlation in the underlying shocks is needed to make up for the weak internal propagation mechanism of most RBC models.

The fact that the composite shock is so persistent attenuates the informational problems associated with its noisy indicator by effectively making it more forecastable. To illustrate this, I ran two additional experiments. In the first I introduced even more persistence in A_t by setting the variance-ratio involving the persistent and white-noise components of the shock to 25, the same parameterization adopted by Kydland and Prescott (1982). As expected, the noisy indicator effect is smaller than in the baseline case, but still quantitatively significant: output becomes 9 percent more volatile after the introduction of the better indicator. More important, if this variance ratio is reduced to 0.25, so that the variance of the persistent component is only one fourth of the variance of its transitory counterpart, a better indicator would increase output volatility by almost one third![17]

[17] Similar results are obtained by varying the autocorrelation coefficient (ρ).

Here again I find that though the results are sensitive to variations in the persistence parameters, they remain, nevertheless, quantitatively important. Moreover, if one believes that transitory shocks such as $A_{2,t}$, and not just the highly persistent ones depicted by $A_{1,t}$, play an important role in macroeconomic fluctuations, then, again, the case for the aggregate effects of noisy indicators becomes even stronger.

Signal-to-Noise Ratio. Have I under- or overstated the degree of noisiness in the productivity indicator? How sensitive are my results to variations in the signal-to-noise ratio? A definitive answer to the first question is hard to come by. The signal-to-noise ratio assumed in the baseline experiment is higher than the estimates obtained by Mankiw *et al.* (1984) for money stock announcements, but smaller than the number reported by Diebold and Rudebusch (1991) for the composite leading indicators. Moreover, the fact that agents in the real world make decisions based on not just one, but presumably a gamut of economic indicators, makes it even harder to assess what would be an appropriate value for the signal-to-noise ratio. Clearly, the higher this ratio, the closer we get to the case of no measurement error, and the smaller would be the effect of adopting a better indicator. For instance, if we had started with a signal-to-noise ratio of 5, the aggregate effect of eliminating the indicator's noise would be to increase output volatility by only 3.8 percent; whereas if we had started with the much lower signal-to-noise ratio estimated by Mankiw and his co-authors (0.56), the indicator noise effect would be near 20 percent.

To conclude this sensitivity analysis, I find that the 14 percent increase in output volatility after the elimination of measurement error in the baseline experiment does not seem to be an exaggeration. As we would expect, the only factor that would have significantly reduced this effect to well below 10 percent is the assumed initial signal-to-noise ratio of the indicator.

6 Expectations: A Testable Implication

It has been argued elsewhere that the potential aggregate effects of indicator noise crucially depend on the signal extraction capabilities of agents (Bomfim, 1998). In particular, the sign of the aggregate effect of measurement error is reversed if we assume that, instead of relying on efficient signal extraction methods, the agents follow a bounded rationality strategy by simply taking the noisy indicator at face value. Under this alternative characterization of agents' expectations, I then repeat the same computational experiment described in section 5.2. Using the baseline parameterization from table 1, the presence of measurement error in the preliminary announcements of A_t *increases* the variance of output in the artificial economy by about 13 percent. Thus, better economic indicators have the potential to reduce cyclical volatility in a quantitatively important way if agents signal extraction capabilities are less than fully efficient.

Taken together, the quantitative significance of indicator noise under both full and bounded rationality offers a potentially valuable opportunity to test empirically these two views of the world. Simply stated, if we can identify two time periods—one with superior data, the other more prone to measurement error problems—the one with better economic indicators should have higher cyclical volatility, other things being equal, if agents fully satisfy the rational expectations assumption. I plan to examine this issue in future research.

7 Concluding Remarks

Traditional decompositions of sources of macroeconomic fluctuations tend to emphasize the importance of supply versus demand shocks, permanent versus transitory, monetary versus real, etc. The computational experiments run in this paper uncovered an additional factor underlying these fluctuations: the very nature of the economic indicators on which agents based their decisions. Under efficient signal-processing, the presence of noise in key economic data has a dampening effect on business cycle volatility. Accordingly, an appreciable improvement in the accuracy of economic indicators would likely contribute to significantly larger gyrations in the economy.

Following Bomfim (1998), this paper also highlighted the importance of agents' information processing capabilities in understanding the aggregate effects of noisy economic indicators. In particular, given the strikingly different conclusions that can be drawn from the fully rational and boundedly rational characterizations of the model, I outlined a future research plan aimed at exploring this novel way to empirically distinguish between these two views of the world.

Moreover, regardless of the way real-world agents form their expectations, a well-known characteristic of the U.S. economy in the postwar period makes the quantitative findings of this paper especially relevant. I am referring here to the declining relative importance of sectors such as agriculture, mining, and manufacturing—for which we currently have more reliable data—and the growing importance of the harder to measure service sector. What this trend suggests is that the problem of noisy economic data is unlikely to disappear soon, making the need to understand its implications for business cycle fluctuations that much more important.

Finally, I should caution those who might feel tempted to interpret the rational-expectations based results to mean that better economic indicators are bad because they lead to higher macroeconomic volatility. In the model presented in this paper, all fluctuations are optimal responses to shifting opportunities in the leisure-consumption tradeoff. Therefore, there is an important sense in which noisy data are always bad because they make it harder for agents to fully identify and respond to these shifts.

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Table 1 — Parameter Definitions and Baseline Calibration

Parameter	Definition
	A. Standard RBC Parameters[a]
$\theta_n = 0.58$	long-run share of labor income
$\delta = 0.025$	quarterly rate of depreciation
$\bar{N} = 0.20$	steady-state hours (proportion of time spent working)
$\beta = 0.988$	utility discount rate
	B. Productivity Shock and other Selected Parameters[b]
$\rho = 0.90$	AR(1) coefficient of persistent technology shock
$\sigma_{a1}^2 = 0.5809$	variance of innovation to persistent technology shock
$\sigma_{a2}^2 = 0.2904$	variance of innovation to white-noise technology shock
$\sigma_e^2 = 0.8713$	variance of indicator noise
$\phi = 0.24$	strategic complementarity parameter

[a]Source: King, Plosser, and Rebelo (1988).

[b]See discussion of baseline parameterization in text.

Table 2 — Comparing Selected Moments[a]

Series	Std Dev	Rat. SD	auto(1)	auto(2)	auto(3)
A. U.S. Postwar Quarterly Data[b]					
Output	5.62	1.00	.96	.91	.85
Consumption	3.86	0.69	.98	.95	.93
Investment	7.61	1.35	.93	.78	.62
Hours	2.97	0.52	.94	.85	.74
B. Model with Noisy Indicator (Baseline Case)[c]					
Output	5.62	1.00	.91	.86	.81
Consumption	3.79	0.67	.99	.98	.97
Investment	12.45	2.22	.83	.74	.66
Hours	2.51	0.45	.77	.67	.57
C. RBC Model with Perfect Indicator[d]					
Output	5.62	1.00	.94	.89	.83
Consumption	3.90	0.69	.99	.99	.97
Investment	12.10	2.15	.89	.79	.70
Hours	2.45	0.44	.87	.75	.64

[a]The first column of numbers shows the standard deviation of each series; the second column shows ratios of standard deviations of each series with output. Columns 3 through 4 show first, second, and third autocorrelation coefficients.

[b]Source: King, Plosser, and Rebelo (1988).

[c]All other parameters calibrated as shown in Table 1.

[d]This is the production externalities model of Baxter and King (1990) with all parameters set as in table 1, except for the variances of the indicator noise and white-noise component of A_t, which are set to zero. In addition, the variance of the (now perfect) indicator is recalibrated to match the variance of output in the data.

Table 3 — Measuring the Effects of Indicator Noise[a]

Series	Std Dev	Rat. SD	auto(1)	auto(2)	auto(3)
A. **Before** *improvement in indicator quality...*					
Output	5.62	1.00	.91	.86	.81
Consumption	3.79	0.67	.99	.98	.97
Investment	12.45	2.22	.83	.74	.66
Hours	2.51	0.45	.77	.67	.57
B. **After** *improvement in indicator quality...*					
Output	5.98	1.00	.88	.83	.78
Consumption	4.03	0.67	.99	.98	.97
Investment	13.37	2.23	.77	.69	.61
Hours	2.76	0.46	.73	.63	.54

[a]Table entries are explained in the first footnote of table 2. All parameter values are set according to table 1, except for σ_e^2, which is set to zero in the panel describing the situation "**after** the improvement in indicator quality."