



## Commentary

Mark W. Watson

**H**amilton's paper (2005) asks two provocative questions. First, are business cycles "real" in the sense that recession/expansion phases represent fundamental shifts in the dynamic model characterizing the macroeconomy? Second, are business cycles "real" in the sense of being caused by real shocks such as productivity or labor supply? Hamilton's careful empirical analysis of the postwar unemployment rate and of interest rates in nineteenth century and postwar periods leads him to answer yes to the first question; on the basis of this analysis he conjectures that the answer to the second question is no.

My comments will address the first of Hamilton's questions. I first ask whether the nonlinear switching models of the sort estimated by Hamilton for the unemployment rate are necessary to explain business cycles of the sort experienced by the United States in the postwar period. My answer, like the answer given by Slutsky (1937), is no. I next ask whether nonlinear models provide a better fit and produce more-accurate forecasts than linear models for postwar U.S. macroeconomic data. My answer is a cautious maybe.

### DO WE NEED "REAL" BUSINESS CYCLES TO EXPLAIN THE CYCLE?

The first panel of Figure 1 plots quarterly values of the logarithm of real gross domestic product (GDP) for the United States relative to its

value in 1948. Evident in the figure is sustained growth that is occasionally interrupted by one of the ten recessions in the postwar period. These alternating periods of expansion and recession are the "business cycle," and in his paper, Hamilton uses a Markov-switching model for the unemployment rate to delineate these expansions and recessions. As Hamilton shows, the dynamics of the unemployment rate are quite different in the expansion and recession states. In this sense, the business cycle is real; that is, unemployment dynamics are significantly different during expansions and recessions.

The remaining panels of the figure show results for three other economies, and I often begin my time-series course by asking students to identify the economies that I have plotted. All three countries show periods of expansions and recession like the United States. Country 1 experienced a sharp and severe recession in 1975 along with several other less severe recessions. Country 2 suffered a minor recession in 1953, but then grew more or less steadily until its 1970 recession; it weathered 1975 without a recession, but has suffered four recessions since the late 1970s. Country 3 grew rapidly from 1948 until 1963, when it experienced its first postwar recession, then suffered a prolonged recession from 1967 to 1970, a mild recession in 1980, but has been performing well since then. Foreign students typically have a better idea of international business cycles than domestic students and often recognize these business cycle patterns.

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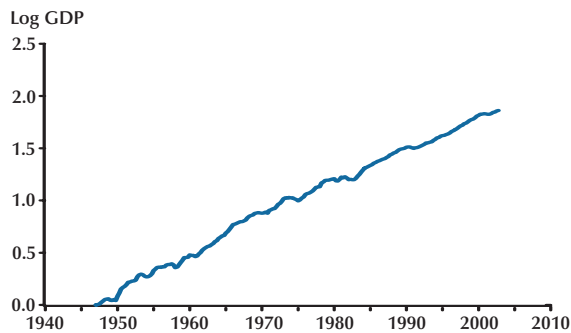
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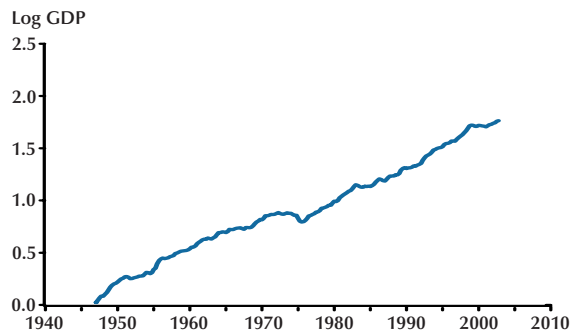
## Figure 1

### Logarithm of GDP for the United States and Three Other “Countries”

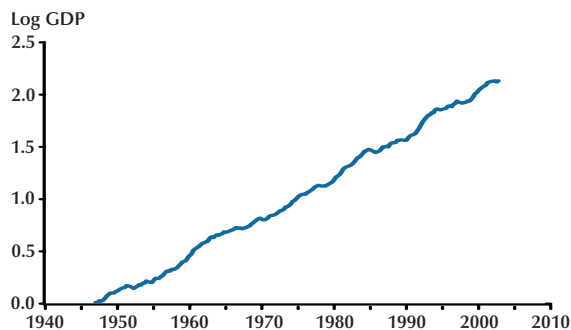
A. Quarterly U.S. Data



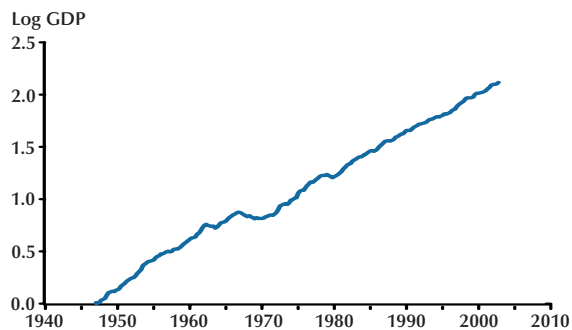
B. Country 1



C. Country 2



D. Country 3



Most students seem surprised when I announce that I produced the plots for countries 1, 2, and 3 using a random number generator. More precisely, these plots were produced using three realizations from a linear AR(2) model with i.i.d. Gaussian innovations that was calibrated to the U.S. data. Of course, this is just an updated version of the remarkable simulations shown in the classic paper by Slutsky (1937).

Slutsky’s simulations have important implications for business cycle analysis. They show that simple time-invariant linear time-series models are capable of generating realizations that have the important cyclical properties that we have come to call the business cycle. Evidently, nonlinear switching models are not required to generate business cycles.

This discussion highlights an important differ-

ence in empirical characterizations of the business cycle. One characterization—Hamilton’s—is that recessions and expansions represent fundamental shifts in the *stochastic process* characterizing the macroeconomy. Another characterization—Slutsky’s—is that recessions and expansions are features of the *realization* of the stochastic process; the process doesn’t shift, but sometimes it produces data that decline (recessions) and sometimes it produces data that grow (expansions).

## EVIDENCE ON “REAL” BUSINESS CYCLES

While nonlinear models are not required to generate time series with business cycle characteristics, nonlinear models may provide better

**Table 1****Performance of Linear and Nonlinear Univariate Forecasting Models for 215 Series**

Series category (No. of series)	Percentage best	
	Linear	Nonlinear
Production (24)	21	79
Employment (29)	21	79
Wages (7)	29	71
Construction (21)	5	95
Trade (10)	50	50
Inventories (10)	30	70
Orders (14)	7	93
Money and credit (21)	57	43
Interest rates (11)	45	55
Producer prices (16)	50	50
Consumer prices (15)	63	37
Consumption (5)	80	20
Other (31)	52	48

NOTE: This table summarizes the forecasting experiment in Stock and Watson (1999) involving linear and nonlinear methods for forecasting 215 series in the 13 categories, shown in the first column. The second and third columns show the percentage of series for which the linear model outperformed the nonlinear model (column 2) or the reverse (column 3).

descriptions of the stochastic processes characterizing typical macroeconomic series than simple linear models. A series of papers building on Hamilton's (1989) original contribution have shown that Markov-switching models provide an improvement on the fit of linear models for several important macroeconomic time series. (Examples include Chauvet, 1998, Diebold and Rudebusch, 1996, and Filardo, 1994.) Stock and Watson (1999) compared the forecast performance of various linear and nonlinear univariate forecasting models for 215 monthly macroeconomic time series using a pseudo out-of-sample forecasting experiment. Table 1 contains a summary of their findings. For several categories of series (production, employment, construction, inventories, orders, interest rates, and wages), the nonlinear models outperformed linear models.

Does the three-state Markov-switching model that Hamilton proposes in this paper produce more precise forecasts of the state of the business cycle than linear models? To investigate this, I computed the one-sided ("filtered") estimates of

the state probabilities from Hamilton's model. These filtered probabilities are plotted in Figure 2 and are the one-sided versions of the probabilities plotted in Hamilton's Figure 4. I considered six different monthly series that serve as coincident indicators of the business cycle: the unemployment rate, the index of industrial production (logarithm), real personal income (logarithm), manufacturing and trade sales (logarithm), employment (logarithm), and an index of coincident indicators constructed as a weighted average of the last four series. Using data from 1959-2003, I estimated regression models of the form

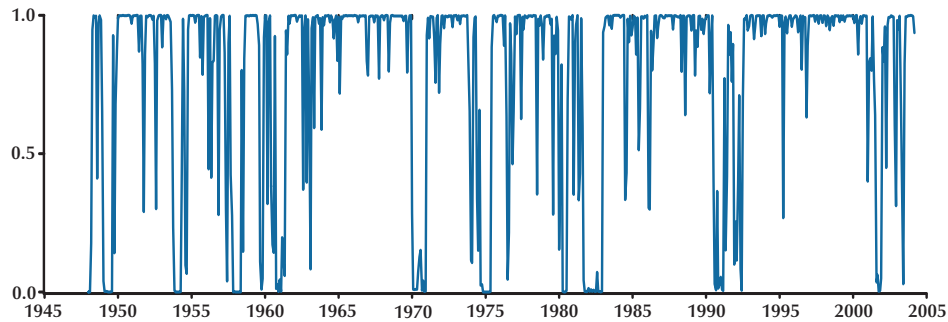
$$(1) \quad y_{t+h} - y_t = \beta_0 + \phi(L)\Delta y_t + \gamma(L)u_t + \beta_2 p_{2t/t} + \beta_3 p_{3t/t} + \varepsilon_{t+h}$$

where  $y_t$  denotes the indicator being forecast,  $u_t$  denotes the unemployment rate, and  $p_{2t/t}$  and  $p_{3t/t}$  denote the filtered state probabilities (that is, the nonlinear functions of the unemployment rate plotted in Figure 2). Results for this regression are shown in Table 2 for 1-month-ahead ( $h = 1$ )

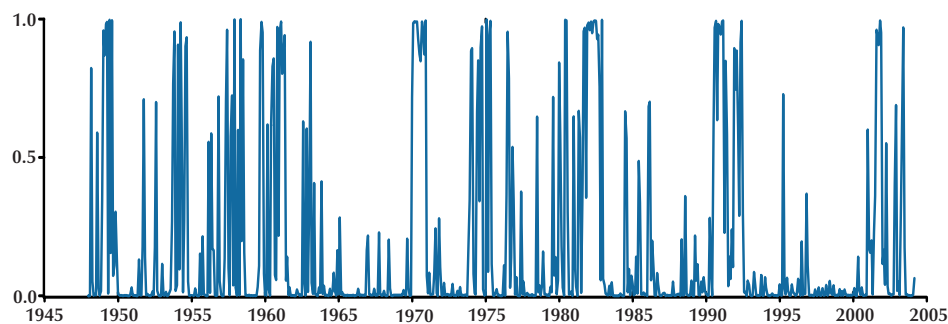
## Figure 2

### Filtered Probabilities of Unemployment Rate States

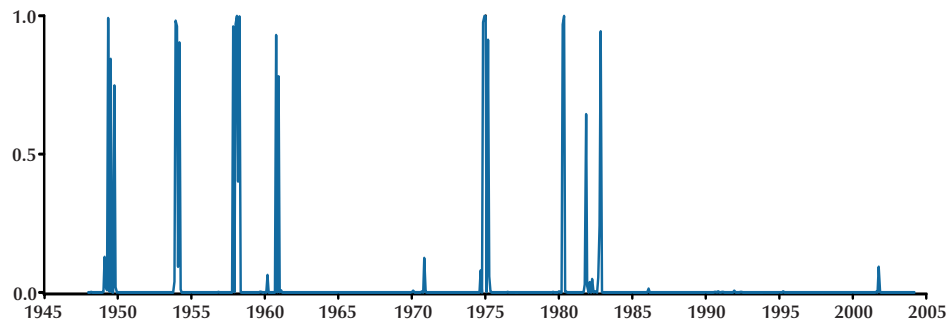
#### A. Probability of State 1



#### B. Probability of State 2



#### C. Probability of State 3



and 3-month-ahead ( $h=3$ ) forecasts. There does seem to be evidence that  $p_{2t/t}$  and  $p_{3t/t}$  help predict the indicators, particularly at the 1-month horizon.

An alternative, and arguably more compelling test of the predictive power of  $p_{2t/t}$  and  $p_{3t/t}$  comes from using recursive estimates of the parameters of (1) to compute pseudo out-of-sample forecasts.

Table 3 summarizes results from these calculations over the 1970-2003 out-of-sample forecast period. The results presented in the table are the mean-squared forecast errors for various versions of (1) relative to a simple AR model. The results shown in the column labeled “P” are for the model that includes  $p_{2t/t}$  and  $p_{3t/t}$  in addition to lags of  $\Delta y_t$  (so that  $\gamma(L) = 0$ ); the results in the column labeled

**Table 2****Granger-Casualty Tests for the Model**

$$y_{t+h} - y_t = \beta_0 + \phi(L)\Delta y_t + \gamma(L)u_t + \beta_2 p_{2t/t} + \beta_3 p_{3t/t} + \varepsilon_{t+h}$$

Series forecast	Forecast horizon $h = 1$			Forecast horizon $h = 3$		
	$\beta_2$	$\beta_3$	F-statistic, p-value	$\beta_2$	$\beta_3$	F-statistic, p-value
Unemployment rate	0.09 (0.04)	0.34 (0.12)	0.01	0.15 (0.10)	0.35 (0.27)	0.33
Industrial production	-1.08 (2.20)	-11.56 (4.89)	0.05	-1.33 (2.47)	-6.71 (4.00)	0.18
Personal income	-1.39 (1.14)	-2.43 (2.83)	0.47	-1.09 (1.06)	-1.11 (1.85)	0.58
Manufacturing and trade sales	1.15 (2.69)	-11.98 (6.30)	0.05	-1.53 (2.06)	-5.33 (4.60)	0.50
Employment	-0.55 (0.54)	-3.17 (1.38)	0.07	-0.58 (0.56)	-1.47 (1.06)	0.38
Coincident index	-0.94 (1.41)	-6.47 (3.25)	0.13	-1.19 (1.51)	-3.87 (2.74)	0.37

NOTE: The table shows OLS estimates of  $\beta_2$  and  $\beta_3$ , HAC standard errors, and p-values for the F-test that  $\beta_2 = \beta_3 = 0$ .

**Table 3****Out-of-Sample Mean-Squared Error Relative to Univariate Autoregressive Model**

$$y_{t+h} - y_t = \beta_0 + \phi(L)\Delta y_t + \gamma(L)u_t + \beta_2 p_{2t/t} + \beta_3 p_{3t/t} + \varepsilon_{t+h}$$

Series	All			Recessions			Expansions		
	P	U	U-and-P	P	U	U-and-P	P	U	U-and-P
<b>A. Forecast horizon <math>h = 1</math></b>									
Unemployment	0.98			0.97			0.98		
Industrial production	0.95	0.97	0.97	0.87	0.88	0.88	1.00	1.03	1.02
Personal income	0.95	0.93	0.93	0.92	0.92	0.92	0.95	0.93	0.94
Manufacturing and trade sales	0.99	0.99	1.01	1.01	0.95	1.07	0.99	1.00	0.99
Employment	0.96	0.96	0.97	0.89	0.87	0.86	1.00	1.02	1.02
Coincident index	0.97	0.97	0.97	0.94	0.94	0.95	1.02	1.01	1.02
<b>B. Forecast horizon <math>h = 3</math></b>									
Unemployment	1.01			1.00			1.01		
Industrial production	0.98	0.97	0.98	0.94	0.94	0.95	1.02	1.01	1.02
Personal income	0.92	0.89	0.90	0.90	0.90	0.90	0.93	0.89	0.90
Manufacturing and trade sales	0.99	0.97	0.99	1.00	0.96	1.00	0.99	0.97	0.99
Employment	0.96	0.94	0.96	0.89	0.91	0.90	1.04	0.98	1.02
Coincident index	0.96	0.94	0.95	0.93	0.92	0.93	0.99	0.96	0.98

NOTE: The table shows the mean-squared forecast error for each model relative to that for the univariate AR model. The model labeled "P" imposes the constraint that  $\gamma(L) = 0$ ; the model labeled "U" imposes the constraint that  $\beta_2 = \beta_3 = 0$ , and the model labeled "U-and-P" imposes no constraints. Results are shown for the full 1970-2003 out-of-sample and for the recession and expansion subsamples.

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“U” are for the model that includes lags of  $u_t$  and  $\Delta y_t$  (so that  $\beta_2 = \beta_3 = 0$ ), and the results in the column labeled “U and P” include all of the terms in (1). Relative mean-squared errors are shown for the entire out-of-sample period and for recessions and expansions separately.

Most of the table entries are less than 1.0, indicating an improvement on the univariate AR model. However, it is less clear whether the model with nonlinear functions of the unemployment rate ( $p_{2t/t}$  and  $p_{3t/t}$ ) outperform the linear model that includes the unemployment rate. There are few entries in which the P or U-and-P models outperform the U model.

My interpretation of the evidence in Tables 2 and 3 is that they provide some additional (albeit weak) evidence supporting the “real” switching model proposed by Hamilton.

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