The Great Depression and Output Persistence

by

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ABSTRACT

The persistence of shocks to aggregate output has been the subject of extensive and continuing investigation since Nelson and Plosser (1982) presented empirical evidence suggesting that such shocks are largely permanent and account for most of the variation in real output. More recent literature has produced mixed conclusions, largely due to disagreement about how to treat the period around the Great Depression. Here we present estimates of output persistence based on a parametric bootstrap of a Markov switching model for annual GDP 1870-1994. In that model, the economy can switch into a volatile state such as the Great Depression and out of it. Results suggest that the data are consistent with the hypothesis that real shocks persist indefinitely if we drop the maintained assumption of homoskedasticity in favor of a Markov switching representation of the Great Depression.

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The persistence of shocks to aggregate output has been the subject of extensive and continuing investigation since Nelson and Plosser (1982) presented empirical evidence suggesting that such shocks are largely permanent and account for most of the variation in real output. Methodological innovations such as Rudebusch (1992, 1993), and the advent of longer time series due to the work of Balke and Gordon (1989) and Romer (1989), have stimulated renewed interest in measuring the persistence of real shocks. This recent literature, including contributions by Diebold and Senhadji (1996), Cheung and Chinn (1997), Kilian and Ohanian (1999), Murray and Nelson (2000), and Newbold, Leybourne, and Wohar (2000), has produced mixed conclusions, largely due to an implicit disagreement about how to treat the period around the Great Depression. However, none of these papers produce estimates of persistence that reflect that lack of homogeneity in the historical record.

In this paper, we present a formal statistical model which captures the idea that the events surrounding the Great Depression had large, but transitory, effects on output. We construct estimates of output persistence from a parametric bootstrap of a state space model with Markov switching for the annual time series assembled by Maddison (1995), for the period 1870-1994. Contrary to some previous research on long term annual data, our results suggest a predominant role for permanent shocks.

This paper is organized as follows. Section 1 recaps estimates of persistence under the assumption of homoskedasticity and discusses evidence against that assumption. Section 2 introduces a Markov switching model to model heteroskedasticity in the historical data, and discusses its estimation. In that model, the economy can switch into a volatile state, such as the Great Depression, and out of it. A parametric bootstrap of that model suggests that historical measures of persistence are consistent with an economy in which shocks persist, but which has experienced at least two regimes of volatility. Section 3 summarizes and offers concluding remarks.

1. ESTIMATION OF PERSISTENCE IN OUTPUT AND HETEROSKEDASTICITY

We begin by reviewing very briefly the evidence for the persistence of real shocks under the assumption of homoskedasticity. Maddison (1995) has assembled historical data for a large number of countries including an index of U.S. real GDP for 1870-1994. We take the log of that index as our measure of aggregate output and begin with the standard Augmented Dickey-Fuller (ADF) regression:

$$y_t = a + bt + a y_{t-1} + \sum_{i=1}^{k} y_i \Delta y_{t-i} + u_t \,.$$

In choosing the lag length k, we employ the "general-to-specific" approach advocated by Campbell and Perron (1991), Hall (1994), and Ng and Perron (1995) with a maximum lag of 8, noting that this has become standard procedure in the literature. The criterion chooses k=6, and yields a unit root statistic of –3.75, which we call ADF_6. Judging by the critical values due to Dickey and Fuller (1979), the hypothesis that the largest AR root is unity is rejected at the 5% level. This would imply that shocks to output do not persist indefinitely but rather completely die out over time.

The critical values for the ADF test are based on the maintained hypothesis of homoskedasticity, and a standard diagnostic test is that of White (1980). In this case, White's asymptotic test rejects the null of homoskedastic residuals at the 1% level. A plot of the residuals reveals that their variance was much higher around the period of the Great Depression, and generally was lower after World War II. Given the reliance of the

ADF test on homoskedasticity, we would like to develop an alternative test within which we can allow for heteroskedasticity.

The parametric bootstrap approach suggested by Rudebusch (1993) provides a framework within which this can be done. The strategy is to estimate models under the hypotheses of interest and study the empirical distribution of the test statistic implied by the fitted model. Under the hypothesis that shocks persist indefinitely we have what Nelson and Plosser called the difference stationary (DS) representation of output. Under the assumption of homoskedasticity we estimate the first difference model by least squares and obtain:

$$\Delta y_t = 0.035 + 0.235\Delta y_{t-1} + 0.000\Delta y_{t-2} - 0.062\Delta y_{t-3} - 0.169\Delta y_{t-4} - 0.160\Delta y_{t-5} + 0.109\Delta y_{t-6} + u_t \; ; \; s_u = 0.054.$$

Correspondingly, under the hypothesis that shocks die out and are homoskedastic, we have the trend stationary (TS) parameterization:

$$y_t = 0.706 + 0.007t + 1.130 y_{t-1} - 0.226 y_{t-2} - 0.074 y_{t-3} - 0.124 y_{t-4} - 0.010 y_{t-5} + 0.271 y_{t-6} - 0.195 y_{t-7} + u_t \; ; \; s_u = 0.051.$$

We generate 10,000 series under each of these two parameterizations, using the rndn() command in GAUSS, and compute the ADF test statistic for k=6, denoted ADF_6, for each realization. The fraction of ADF statistics falling below -3.75 constitutes evidence for the DS hypothesis and the fraction above is evidence for TS. These rejection frequencies are in effect empirical p-values. We find:

For DS: Frequency [$ADF_6 < -3.75$] = 0.0181

For TS: Frequency [$ADF_6 > -3.75$] = 0.4041.

Thus, the occurrence of an ADF statistic smaller than what is observed in the historical data is quite infrequent under the DS parameterization, but under the TS alternative we frequently observe an ADF statistic at least as large as what we see in the data. This result is similar, but weaker than that reported in Diebold and Senhadji (1996) who set the maximum lag to 5, and choose k=1.

Alternatively, when we select the lag k within each replication of the bootstrap, denoting the resulting test statistic ADF_{GS}, we obtain:

$$\text{For DS: Freq}[ADF_{GS} < -3.75] = 0.0541$$

$$\text{For TS: Freq}[ADF_{GS} > -3.75] = 0.3173.$$

We note that lag selection plays an important role in the empirical distribution of the ADF statistic and shifts the evidence towards more persistence in output, though under the maintained hypothesis of homoskedasticity the evidence still suggests that real shocks die out.

The next section presents a third parameterization in which homoskedasticity is replaced by the possible existence of a second state in which the volatility and persistence of output can depart temporarily from the normal regime.

2. A STATE-SPACE MODEL OF U.S. REAL GDP WITH MARKOV SWITCHING

Since the maintained hypothesis of homoskedasticity is rejected in the data, we would like to investigate the distribution of the ADF statistic in a model that allows for a plausible form of heteroskedasticity. The most parsimonious model we can think of that allows for the possibility of an anomalous, more volatile sub-period is the following. The observed time series (y_t) consists of a trend component (t_t) and a second component (z_t)

which will be present only if an indicator variable (S_t), governed by a Markov process, is unity. This second component, if present, adds to the volatility of output and may also have a different dynamics, so we allow it to have an AR(2) structure. Thus we have:

$$y_t = t_t + S_t z_t$$

$$t_t = g + t_{t-1} + v_t$$

$$z_t = f_1 z_{t-1} + f_2 z_{t-2} + u_t$$

$$p(S_t = 0 | S_{t-1} = 0) = q$$

$$p(S_t = 1 | S_{t-1} = 1) = p$$

where

$$\begin{pmatrix} v_t \\ u_t \end{pmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} s_v^2 & 0 \\ 0 & s_u^2 \end{bmatrix} \right).$$

The transition probabilities p and q determine the persistence of the normal and volatile states. This model is a variant of Clark's (1987) unobserved components model when $S_t = 1$ in which case the model becomes a standard trend plus cycle representation with homoskedastic innovations. Estimation is by the approximate maximum likelihood method of Kim (1994) and the data are the log of real GDP from Maddison (1995). Parameter estimates are reported in Table 1.

Since inference is asymptotic in this setting, and tests of the existence of a second state are non-standard, we have run a Monte Carlo simulation where we repeatedly generate series using the trend component of the model only, using homoskedastic shocks with variance $\hat{s}_v^2$. We are concerned whether the estimation algorithm will find a second state where none in fact exists. What emerges is that the estimated probability of remaining in the non-existent state has a median of .018, while the probability of remaining in the actual single state has a median of .98. Furthermore, 95% confidence intervals for both f_1 and f_2 contain zero. Thus, a result of the kind we see here, where the turbulent state is estimated to persist, is very unlikely to arise by chance if it is not actually a feature of the data.

Figure 1 presents a plot of the estimated series z_t which switches on in 1892 but is small in magnitude until 1930 when it takes much larger negative and then positive values. The series up to 1930 may reflect measurement errors in the reconstructed historical series (contemporaneous national income accounting begins in 1929), with the remainder corresponding to the turmoil of the Great Depression and World War II. The second component then switches off for good in 1946. Extensions of this model to include a random walk in the growth rate and a non-switching cyclical component were also estimated but were not supported by the data; see Murray (1997) for further results and discussion.

In our bootstrap experiments using this model as a data generating process we generate the Markov-switching state variable three different ways:

1. Set $S_t = 1$ from 1892-1945, as predicted by the smoothed probabilities. Call this MS1.
2. Set $S_t = 1$ from 1930-1945. Call this MS2.
3. Generate S_t randomly, based on the estimated transition probabilities. Call this MS3.

We also need to consider lag selection in the ADF regressions. Our unobserved components model has an ARIMA(2,1,2) representation in reduced form, implying that the true k in the ADF regression is infinite. In selecting k within each bootstrap run we again follow the general-to-specific procedure. We find:

For MS1: Freq[ADF_{GS} < -3.75] = 0.2173

For MS2: Freq[ADF_{GS} < -3.75] = 0.1081

For MS3: Freq[ADF_{GS} < -3.75] = 0.1836.

Evidently, when the data generating process accounts for the heteroskedasticity in the historical time series by generating turbulent episodes modeled on the Great Depression, the observed output persistence is compatible with, if not the same as, what we see in U.S. real GDP.

To check on the robustness of our results, we have redone our simulations using the efficient unit root test of Elliott, Rothenberg, and Stock (1996), with k selected via the "modified information criterion," or MIC, of Ng and Perron (2000). We note that although the MIC chooses k=0 and yields a unit root statistic which is not significant at the 5% level, there are no qualitative differences between the simulation results for the ADF and the "state of the art" unit root tests.

3. CONCLUSIONS

The advent of longer time series, as well as methodological innovations, has lead some researchers to conclude that all shocks to U.S. real output are temporary. The implicit claim is that with the availability of longer time series, there is an accompanying increase in the power of ADF unit root tests, and the data point to no role for permanent shocks. However, our results suggest that these conclusions are quite sensitive to treating the Great Depression as a "regular" occurrence. Once we allow for the possibility that the Great Depression had a large, but transitory effect on output, our results point to a predominant role for permanent shocks.

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Table 1
Parameter Estimates of a Markov Switching Model for Annual U.S. GDP

Parameter	Estimate
f_1	1.2383 (0.1265)
f_2	-0.3834 (0.0783)
g	0.0330 (0.0025)
s_v	0.0275 (0.0025)
s_u	0.0587 (0.0072)
q	0.9878 (0.0134)
p	0.9729 (0.0232)

Standard errors are in parenthesis.

FIGURE 1
Estimated Transitory Component of Real GDP, Maddison (1995) Data