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LARGE SHOCKS, SMALL SHOCKS, AND ECONOMIC FLUCTUATIONS: OUTLIERS IN MACROECONOMIC TIME SERIES

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SUMMARY

We analyse fifteen post-World War II US macroeconomic time series using a modified outlier identification procedure based on Tsay (1988a). 'Large shocks' appear to be present in all the series we examined. Furthermore, there are three basic outlier patterns: (1) outliers seem to be associated with business cycles, (2) outliers are clustered together—both over time and across series, (3) there appears to be a dichotomy between outlier behaviour of real versus nominal series. Also, after controlling for outliers, much of the evidence of non-linearity in many of the time series is eliminated.

1. INTRODUCTION

Relatively infrequent but important events such as oil shocks, wars, natural disasters, and changes in policy regimes can have important effects on macroeconomic performance. Yet most analyses of macroeconomic time series typically employ linear models that assume (either implicitly or explicitly) Gaussian innovations.[1] For example, traditional Box–Jenkins analysis of time series focuses on the analysis of the first and second moments of the data and, therefore, is unable to examine the relative importance of infrequent, large shocks. Furthermore, presentations of 'stylized facts' for macroeconomic time series typically consider only the first two moments of the data.[2] As we show below, however, most macroeconomic time series exhibit non-Gaussian behaviour indicating the possibility of infrequent large shocks.

In a previous paper (Balke and Fomby, 1991) we used the Tsay (1988a) outlier identification

[1] There is a growing literature on non-linear models for macroeconomic time series. The following studies found evidence of non-linearity: Hinich and Patterson (1985) and Scheinkman and LeBaron (1989a) for stock price data, Hsieh (1989) for exchange rate data, and Brock and Sayers (1988) for industrial production and employment series. Examinations of asymmetry include Neftci (1984) (see, however, Sichel, 1989), DeLong and Summers (1986), and Falk (1986). The Markov regime switching model of Hamilton (1989) is another example of a non-linear time-series model. There is also the large literature on autoregressive conditional heteroscedasticity (ARCH) and numerous extensions of ARCH. Prominent papers in this literature include Engle (1982), Weiss (1984), Bollerslev (1986), and, more recently, Nelson (1991).

[2] See, for example, the stylized fact discussion at the beginning of Blanchard and Fischer (1988).

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procedure to consider whether the unit root behaviour of real GNP and its deflator are the result of infrequent permanent shocks. In this paper we are interested in determining the importance of large shocks, in general. That is, we attempt to establish the frequency, timing, and persistence of large shocks and whether they are important contributors to the variation in macroeconomic time series. Furthermore, we attempt to match these shocks with identifiable economic events.

Using a modified outlier identification procedure based on Tsay (1988a) we investigate 15 major post-World War II macroeconomic time series. We find significant evidence to favour the view that 'large shocks' are likely to be typical of macroeconomic time series. We identify three basic outlier patterns. First, many of the identified outliers seem to be associated with business cycles, particularly turning points and recessions. Second, there appears to be a clustering of outliers within series and across series—outliers tend to be bunched over time and several different series tend to have outliers on the same date. Third, outlier dates in output and employment series do not overlap substantially with outlier dates in nominal price series such as the GNP deflator. That is, there appears to be a dichotomy between outlier behaviour of real versus nominal macroeconomic time series.

In addition, controlling for outliers eliminates much of the evidence of non-linearity in many of the time series examined. This points to a link between identified outliers and possible non-linearity in the time series. While generalized autoregressive conditionally heteroscedastic (GARCH) variance models are also capable of capturing the non-linearity in many of the time series, GARCH models do not always offer as rich an explanation of non-Gaussian behaviour in many macroeconomic time series as the outlier model does. Apparently, important anomalies may go unexplained by GARCH specifications, leaving standardized residuals that are frequently non-Gaussian and that appear to contain outliers.

Our results support and extend the evidence found by Blanchard and Watson (1986), who examined this large shock/small shock hypothesis within the context of a structural vector autoregression (VAR) that included aggregate prices, output, money, and a fiscal policy variable. They found excess kurtosis in the residuals of their VAR and, hence, argued that this is consistent with large infrequent shocks. Our analysis differs from Blanchard and Watson in that the Tsay (1988a) outlier procedure used to identify the large shocks is a univariate procedure that is quite flexible in modelling the dynamic effects of outliers. Also, outlier searches based on univariate time series models are likely to be more conservative in its identification of large shocks than a multivariate model because shocks in univariate representations of macroeconomic time series are likely to be complicated aggregates of different structural shocks. This aggregation would have a tendency to obscure the effect of large shocks. While univariate analysis by its nature limits the kinds of interesting economic interactions that can be uncovered, it does allow us to examine many more series more flexibly than is possible in a multivariate framework.

The remainder of the paper is organized as follows. In Section 2 we provide a formal description of the large shock hypothesis. We discuss the outlier search procedure in Section 3. In Section 4 we present empirical results for the 15 quarterly macroeconomic time series. We also attempt to link the outlier dates with identifiable economic events. We examine monthly versions of three of the time series in Section 5 to determine the effect of temporal aggregation on the outlier identification. In Section 6 we examine the linkage between outliers and evidence of non-linearity. We conclude in Section 7.

2. OUTLIER MODEL

We begin by positing a univariate time-series model in which there are two components: a regular and an outlier component. The idea is that there are extraordinary, infrequently occurring events or shocks that have large, significant effects on time series. Again, economic examples of these types of shocks might include the effects of an oil shock, a change in policy regime, the effects of a war or natural disaster, etc. These extraordinary shocks are orthogonal to shocks in the regular component and need not have the same dynamic effect on the time series as a regular shock.

To formalize this notion, consider the following outlier model described in Tsay (1988a). Let

$$Y_t = B_\omega(L)\omega I_t + B_a(L)a_t \tag{1}$$

where a_t is a Gaussian variate with zero mean and variance σ_a^2. Let $B_a(L)a_t$ be the moving average representation of an ARMA(p, q) where $B_a(L) = \theta(L)/\phi(L)$. $\theta(L)$ is a lag polynomial of order q, and $\phi(L)$ is a lag polynomial of order p. One can think of $B_a(L)a_t$ as the regular component of the time series Y_t; that is, in the absence of extraordinary large shocks or outliers, $B_a(L)a_t$ is the moving average representation of Y_t.

The variable ωI_t in equation (1) is the outlier variable. I_t is an indicator variable that takes the value of zero when no outlier is present and is one in the presence of a large shock. ω is the size of the outlier. $B_\omega(L)$ represents the dynamic effect that the outlier has on Y_t. If $B_\omega(L) = 1$, then ω is an additive outlier (AO); this outlier has only a one-period effect on the series. If $B_\omega(L) = B_a(L)$, then ω is an innovative outlier (IO); this outlier has the same dynamics as the regular component. If $B_\omega(L) = 1/(1 - L)$, then ω is a level shift (LS). Level shifts have a permanent effect on the time series; in effect, they permanently shift the mean of the series.[3] Thus, these outlier types are distinguished by the persistence they have on the time series with the additive outlier having the least persistence and the level shift with the most persistence. Note that this model can capture even richer large shock dynamics by combining the various outlier types at the same or adjacent dates.[4]

3. SEARCHING FOR OUTLIERS

If the date and type of the outlier is known, one can model the irregular component in the form of an intervention model (Box and Tiao, 1975) in which estimates of ω can be obtained from the coefficients on the intervention dummies. In our empirical work below, once possible outliers/level shifts have been identified, we use an intervention model to estimate ω. However, before we can estimate this intervention model, we must determine the timing of outliers.

To determine the existence of outliers, we use the outlier detection method described by Tsay (1988a). Define $y_t = (\phi(L)/\theta(L))Y_t$, which is equivalent to the ARMA residuals under the null hypothesis of no outliers. Define $\pi(L) = 1 - \pi_1 L - \pi_2 L^2 - \cdots = \phi(L)/\theta(L)$ and $\eta(L) = 1 - \eta_1 L - \eta_2 L^2 - \cdots = \pi(L)/(1 - L)$. For the case where $\theta(L)/\phi(L)$ and σ_a are known,

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[3] Rappoport and Reichlin (1989) and Balke and Fomby (1991) discuss shifting trends in terms of infrequent permanent shocks.

[4] For example, consider the case where there is an additive outlier in the level of the variable and the regular component contains a unit root or $B_a(L) = C_a(L)/(1 - L)$. If the analysis is conducted in first differences, then

$$(1 - L)Y_t = \omega I_t - \omega I_{t-1} + C_a(L)a_t$$

In this case, the additive outlier in the level series becomes a sequence of additive outliers of equal size but opposite signs in the differenced data. In the analysis below which employs first differences of the data, we find evidence of this type of behaviour for consumption during the Korean War.

Tsay suggests the following test statistics for the various types of outliers:

$$\lambda_{\mathrm{IO},t} = y_t/\sigma_{\mathrm{a}}$$

$$\lambda_{\mathrm{AO},t} = \rho^2_{\mathrm{A},t}\Big(y_t - \sum_{i=1}^{T-t} \pi_i y_{t+i}\Big)\Big/(\rho_{\mathrm{A},t}\sigma_{\mathrm{a}}) \text{ and}$$

$$\lambda_{\mathrm{LS},t} = \rho^2_{\mathrm{L},t}\Big(y_t - \sum_{i=1}^{T-t} \eta_i y_{t+i}\Big)\Big/(\rho_{\mathrm{L},t}\sigma_{\mathrm{a}})$$

where $\rho^2_{\mathrm{A},t} = (1 + \Sigma_{i=1}^{T-t} \pi_i^2)^{-1}$, $\rho^2_{\mathrm{L},t} = (1 + \Sigma_{i=1}^{T-t} \eta_i^2)^{-1}$, σ^2_{a} is the variance of a_t, and T is the sample size.

The numerator of the λ statistics is the estimate of the size of the outlier or level shift while the denominator is its standard error. This is most easily seen for $\lambda_{\mathrm{IO},t}$; $\lambda_{\mathrm{IO},t}$ is just the standardized residual from the ARMA. Under the null of Gaussian errors (no outliers) 'large' standardized residuals are rare; hence a large $\lambda_{\mathrm{IO},t}$ is evidence that an innovative outlier is present. If an innovative outlier is indeed present, then y_t is an unbiased estimate of the outlier. Because additive outliers and level shifts have different dynamics from regular shocks (a_t), the $\lambda_{\mathrm{AO},t}$ and $\lambda_{\mathrm{LS},t}$ statistics must strip out the effect of these interventions from the residuals (y_t). These adjustments are reflected in both the numerators and denominators of the $\lambda_{\mathrm{AO},t}$ and $\lambda_{\mathrm{LS},t}$ statistics.

Let $\lambda_{\max} = \max\{\lambda_{\mathrm{IO},\max}, \lambda_{\mathrm{AO},\max}, \lambda_{\mathrm{LS},\max}\}$, where $\lambda_{j,\max} = \max_{1 \leqslant t \leqslant T}\{|\lambda_{j,t}|\}$, $j = \mathrm{IO}$, AO, LS. If the $\lambda_{\max}$ statistic exceeds a given critical value, then an outlier has occurred. In this application, we choose a critical value of three; roughly, only shocks greater than three standard deviations are considered as outliers. In practice, $\theta(L)/\phi(L)$ and σ_{a} are unknown; however, under the null of no outliers Tsay suggests that these can be replaced by consistent estimates.

Tsay suggests a sequential algorithm for identifying outliers. First, estimate an ARMA model and extract the residuals and the residual variance. Second, search for outliers in the residuals using the statistics described above. If an outlier is found, remove the effect of the outlier and recalculate the residuals and residual variance. Continue searching and adjusting until no more outliers are indicated. Re-estimates the ARMA model using the adjusted series and extract the residuals. Once again, search for outliers. Stop the algorithm when no additional outliers are found.

Note that the initially estimated ARMA model is the correct specification of the regular dynamics ($B_{\mathrm{a}}(L)$) and can be consistently estimated under the null hypothesis of no outliers. If, however, outliers are present, then the initial ARMA model for the regular component can be poorly estimated; furthermore, if a level shift is present the ARMA estimates will be inconsistent.[5] Unfortunately, estimation of the initial ARMA model can lead to misidentification of outliers. In particular, series in which a level shift outlier is present will exhibit a high degree of serial correlation regardless of the regular dynamics. In this case, the initial ARMA model for the regular dynamics implies greater serial correlation than is in fact the case and, therefore, the residuals from this model will not reflect the true nature of the outlier. Balke (1993) has shown that an outlier search where the initial ARMA model is estimated can misidentify level shifts as innovative outliers or misses the level shifts altogether.

[5] See Perron (1989), Chen and Tiao (1990), and Balke and Fomby (1991) for discussions of the effect of level shifts on Dickey–Fuller tests, ARIMA models, and measures of persistence.

Therefore, in order to control for this type of misspecification, we use a modification to the Tsay procedure suggested by Balke (1993). Here, in addition to conducting an outlier search as in Tsay, we also conduct an outlier search in which the initial ARMA model is specified as an ARMA(0, 0).[6] Initializing the level shift/outlier search with the ARMA(0, 0) improves the power of level shift detection and, unlike the case when an initial ARMA model is estimated, will not misidentify level shifts as innovative outliers. The problem with beginning the outlier search with an ARMA(0, 0) is that there is a tendency to identify spurious level shifts when there is substantial serial correlation in the regular component.[7]

If a level shift is indicated in the course of the ARMA(0, 0) search, then we combine the results from both outlier searches into a single intervention model using dummy variables to model the outlier effects. To lessen the possibility of spurious outliers or level shifts, we stepwise eliminate intervention dummies with a t-statistic whose absolute value is less than a prespecified critical value—dropping the intervention dummy with the lowest t-statistic at each step. As in the outlier searches, we use a critical value of three for our stepwise elimination.[8] The ARMA model is also re-evaluated at this stage with unnecessary ARMA parameters dropped.

The dynamic structure of the various outlier types imposes restrictions on the intervention model. For example, for the case where the model is given by

$$y_t = c_0 + (1 - L)^{-1}\omega_{\mathrm{LS}} I_{\mathrm{LS},t} + \omega_{\mathrm{AO}} I_{\mathrm{AO},t} + (1 - \phi L)^{-1}\omega_{\mathrm{IO}} I_{\mathrm{IO},t} + (1 - \phi L)^{-1} a_t$$

where c_0 is a constant term, $I_{j,t} = 1$ (j = IO, AO, LS) if an outlier is identified to have occurred at time t and 0 otherwise. Rewriting this equation yields

$$y_t = c_0' + (1 - \phi L)(1 - L)^{-1}\omega_{\mathrm{LS}} I_{\mathrm{LS},t} + (1 - \phi L)\omega_{\mathrm{AO}} I_{\mathrm{AO},t} + \omega_{\mathrm{IO}} I_{IO,t} + \phi y_{t-1} + a_t$$

Non-linear least squares is used to estimate the above equation so that the restrictions implied by the different outlier types can be imposed during estimation.

4. EMPIRICAL ANALYSIS

In this section we examine 15 quarterly macroeconomic time series spanning 1947Q1–1992Q4 to determine whether outliers are present in these series. The output series include real GNP, real consumption, real fixed investment (which includes residential as well as business investment), and industrial production. We also examine civilian non-institutional employment and the unemployment rate as well as labour productivity in manufacturing. The price series we examine are the GNP deflator, the consumer price index (CPI), nominal compensation per hour in manufacturing, the Standard and Poors 500 stock price index, as well as yields on AAA bonds. We also examine the monetary base, M1, and M2.[9] We use growth rates (log first

[6] The white-noise (ARMA(0, 0)) specification is used only in the initial iteration. In subsequent iterations, an ARMA model is specified and estimated as in Tsay (1988a).

[7] Of course one could calculate robust standardization factor (i.e. the Newey–West, 1987, correction) for the level shift statistic based on the ARMA(0, 0) model. However, recall that the residuals of this ARMA model will overstate the true serial correlation when level shift is present. This reduces the power of the level shift detection statistic (see Balke, 1993). Therefore, we prefer to eliminate spurious level shifts at the intervention model stage described below.

[8] In a previous version of this paper we used a critical value of two. For most of the series, the final intervention model was very similar to those presented below.

[9] The unemployment and employment data span 1948Q1 to 1992Q4 while real GNP, the GNP deflator, compensation, and labour productivity data span 1947Q1 to 1992Q3. We also examined real GDP and the GDP deflator for the period 1947Q1 to 1992Q4 and found essentially the same results as for GNP and the GNP deflator. As is common in the literature, seasonally adjusted data were used for industrial production, productivity, employment, unemployment, CPI, compensation, and money aggregates. The use of seasonally adjusted data probably makes it even more difficult to uncover outliers.

differences) for all the series except for the unemployment rate, which is analysed in first differences. After differencing, an autoregressive model was estimated for each series. Autoregressive lags were added until there was no evidence of linear serial correlation in the residuals. Because some analysts have suggested that the growth rate of money contains a time trend (Stock and Watson, 1989), we included a time trend for the monetary base and M1 series.[10]

Table I displays the ARI specifications of all the variables.[11] The residuals from autoregressive models indicate that all but one of the series—the money base—show significant (at the 5% level) evidence of excess kurtosis. Many of the series also indicate significant skewness. Clearly, the assumption of Gaussian errors is not appropriate.

Consistent with the evidence of excess kurtosis, we detect evidence of outliers in all the series. These outliers can explain a substantial proportion of the volatility in some of the time series. For many of the series, outliers explain over 20% of the volatility in the series.[12] Indeed, large shocks explain more than 50% of the volatility in the GNP deflator, the CPI, nominal

Table I

	Basic ARI model				Outlier model				
Variable	ARI model	SEE	Kurt.[a]	Skew.[b]	ARI model	SEE	Kurt.[c]	Skew.[d]	Variance explained (%)[e]
Real GNP	(2, 1)	0·0095	4·2[h]	0·02	(2, 1)	0·0083	3·0	−0·10	27
Consumption	(2, 1)	0·0075	5·4[h]	−0·52[h]	(2, 1)	0·0060	2·7	−0·03	35
Fixed investment	(1, 1)	0·0250	4·5[h]	−0·19	(1, 1)	0·0224	3·0	−0·03	11
Indust. prod.	(4, 1)	0·0186	4·9[h]	−0·41[g]	(4, 1)	0·0155	3·7[g]	0·01	17
Productivity (Man)	(4, 1)	0·0109	3·9[g]	−0·52[h]	(4, 1)	0·0101	3·2	−0·17	15
Unemployment rate	(4, 1)	0·3186	4·0[g]	0·52[h]	(4, 1)	0·3000	3·8[g]	0·40[g]	13
Employment	(1, 1)	0·0050	5·1[h]	−0·39[g]	(1, 1)	0·0043	3·2	−0·19	18
GNP deflator	(2, 1)	0·0056	8·7[h]	−0·56[h]	(2, 1)	0·0034	3·1	−0·08	80
CPI	(5, 1)	0·0051	8·9[h]	−0·80[h]	(4, 1)	0·0036	3·2	0·04	70
Compensation per hour (manuf.)	(3, 1)	0·0069	5·7[h]	0·90[h]	(3, 1)	0·0055	3·4	0·27	55
AAA bond yields	(2, 1)	0·0387	4·3[h]	−0·09	(2, 1)	0·0332	3·0	0·05	28
Stock prices	(2, 1)	0·0556	5·8[h]	−0·50[h]	(2, 1)	0·0485	3·2	0·13	23
Money Base[f]	(3, 1)	0·0048	3·3	−0·44[g]	(3, 1)	0·0043	2·9	−0·21	13
M1[f]	(4, 1)	0·0074	6·7[g]	0·52[h]	(4, 1)	0·0062	3·5	0·00	28
M2	(5, 1)	0·0056	7·3[g]	1·81[h]	(5, 1)	0·0045	3·2	0·04	57

[a] Kurtosis in the ARI model residuals.
[b] Skewness in the ARI model residuals.
[c] Kurtosis in the residuals after adjusting for outliers.
[d] Skewness in the residuals after adjusting for outliers.
[e] Proportion of variance (in percent) attributable to outliers.
[f] Includes a linear time trend.
[g] Significant at the 5% level.
[h] Significant at the 1% level.

[10] No linear time trend was indicated for M2 for the sample period considered here.

[11] Tables that detail the basic ARI model and outlier/intervention model results are available upon request.

[12] The proportion of the total variance explained by outliers is calculated by comparing the variance of the raw series (the growth rate of the series) and variance of the outlier component. In terms of the model described by equation (1), this proportion is:

$$(1 - \mathrm{Var}[B_a(L)a_t])/\mathrm{Var}[Y_t]$$

Table II. Outlier dates and magnitudes by variable

Variable	Type	Date	Size	S.E.	Events
GNP Growth	IO	1950Q1	0·035	0·008	1st quarter of recovery
	AO	1958Q1	−0·026	0·008	Trough
	AO	1975Q1	−0·028	0·008	Trough
	AO	1980Q2	−0·032	0·008	Trough
Consumption	IO	1950Q3	0·027	0·006	Korean War
	IO	1950Q4	−0·033	0·006	Korean War
	AO	1951Q2	−0·020	0·006	Korean War
	AO	1958Q1	−0·019	0·006	Trough
	AO	1974Q4	−0·021	0·006	Recession
	AO	1980Q2	−0·028	0·006	Trough
Fixed Investment	AO	1952Q3	−0·091	0·020	Steel strike
	AO	1980Q2	−0·097	0·020	Trough
Industrial Production	AO	1950Q3	0·038	0·012	Korean War
	IO	1958Q3	0·054	0·016	2nd quarter of recovery
	IO	1959Q3	−0·059	0·016	Steel strike
	AO	1960Q1	0·044	0·012	Peak
	IO	1975Q1	−0·077	0·017	Trough
	AO	1978Q2	0·037	0·012	
Labour Productivity (manufacturing)	IO	1959Q3	−0·042	0·010	Steel strike
	AO	1974Q1	−0·033	0·009	1st quarter of recession
Unemployment	AO	1954Q1	0·813	0·246	Recession, Korean War disarmament
Rate	IO	1975Q1	1·138	0·308	Trough
Employment Growth	IO	1950Q2	0·016	0·004	2nd quarter of recovery
	AO	1953Q1	0·019	0·004	Korean War, quarter before peak
	IO	1958Q1	−0·014	0·004	Trough
	AO	1975Q1	−0·012	0·004	Trough
Inflation (GNP Deflator)	AO	1947Q4	0·015	0·004	Post-World War II inflation
	LS	1948Q4	−0·017	0·003	End of post-WWII inflation, peak
	IO	1948Q4	−0·076	0·022	End of post-WWII inflation, peak
	AO	1948Q4	0·067	0·022	End of post-WWII inflation, peak
	AO	1950Q3	0·018	0·003	Korean War
	AO	1951Q1	0·028	0·003	Korean War
	IO	1951Q2	−0·013	0·004	Korean War, price controls
	LS	1967Q3	0·007	0·001	Vietnam War build-up
	LS	1973Q2	0·007	0·001	Nixon expansion/food price shocks
	IO	1974Q3	0·015	0·004	end of wage and price controls, recession
	LS	1982Q1	−0·010	0·001	Volcker disinflation, recession
Inflation (CPI)	IO	1948Q4	−0·020	0·004	End of post-WWII inflation, peak
	AO	1950Q1	−0·010	0·003	1st quarter of recovery
	AO	1951Q1	0·025	0·003	Korean War
	AO	1951Q3	−0·013	0·003	Korean War, price controls
	LS	1967Q3	0·007	0·002	Vietnam War
	LS	1973Q1	0·009	0·002	Nixon expansion/food price shocks
	LS	1981Q4	−0·012	0·002	Volcker disinflation, recession
	AO	1986Q2	−0·010	0·003	Reduction in energy prices

continued

Table II. *Continued*

Variable	Type	Date	Size	S.E.	Events
Compensation per hour (Manufacturing)	AO	1948Q1	0·024	0·005	Post-WWII inflation
	AO	1949Q4	−0·020	0·005	Trough
	IO	1950Q4	0·033	0·005	Korean War
	AO	1952Q4	0·016	0·005	Korean War
	LS	1973Q1	0·011	0·002	Nixon expansion/food price shocks
	LS	1982Q4	−0·014	0·002	Volcker disinflation, trough
AAA Yields Growth	IO	1979Q4	0·122	0·034	Oil shock, peak
	AO	1980Q1	0·165	0·033	Oil shock, recession
	AO	1982Q4	−0·142	0·031	Volcker disinflation, trough
	LS	1984Q3	−0·028	0·007	
	AO	1987Q2	0·092	0·031	
SP500 Index	IO	1974Q3	−0·184	0·049	End of wage and price controls, recession
	IO	1982Q4	0·169	0·049	Volcker disinflation, trough
	AO	1987Q4	−0·261	0·045	October 1987 stock market crash
Money Base Growth	AO	1958Q2	0·012	0·004	1st quarter of recovery
	AO	1981Q1	−0·014	0·004	Quarter before peak
	LS	1987Q3	−0·008	0·003	
	AO	1991Q1	0·015	0·004	Trough
M1 Growth	AO	1980Q2	−0·033	0·006	Trough
	IO	1982Q4	0·022	0·006	Volcker disinflation, trough
	LS	1987Q3	−0·022	0·003	
	LS	1991Q4	0·019	0·005	
M2 Growth	LS	1960Q3	0·011	0·002	Recession
	IO	1975Q2	0·017	0·005	1st quarter of recovery
	IO	1980Q3	0·022	0·005	1st quarter of recovery
	AO	1983Q1	0·024	0·003	1st quarter of recovery
	LS	1987Q2	−0·009	0·003	

Table III. Outlier dates in chronological order

Date	Variable	Events
1947Q4	GNP deflator	Post-WWII expansion
1948Q1	Compensation	Post-WWII expansion
1948Q4	GNP deflator (−), CPI (−)	Recession, 1st quarter
1949Q4	Compensation (−)	Recession, trough
1950Q1	Real GNP	Expansion, 1st quarter
1950Q2	Employment	Expansion, 2nd quarter
1950Q3	Consumption, GNP deflator, industrial production	Korean War

continued

Table III. *Continued*

Date	Variable	Events
1950Q4	Consumption (–), compensation	Korean War
1951Q1	GNP deflator, CPI	Korean War
1951Q2	Consumption (–), GNP Deflator (–)	Korean War
1951Q3	CPI (–)	Korean War, price controls
1952Q3	Fixed investment (–)	Korean War, steel strike
1952Q4	Compensation	Korean War
1953Q1	Employment	Korean War, quarter before peak
1954Q1	Unemployment	Korean War disarmament, recession
1958Q1	Real GNP (–), consumption (–), employment (–)	Recession, trough
1958Q2	Monetary Base	Expansion, 1st quarter
1958Q3	Industrial production	Expansion, 2nd quarter
1959Q3	Industrial production (–), productivity (–)	Steel strike
1960Q1	Industrial production	Peak
1960Q3	Monetary Base	Recession
1967Q3	CPI, GNP deflator	Vietnam War expansion
1973Q1	CPI, compensation	Nixon expansion
1973Q2	GNP deflator	Nixon expansion
1974Q1	Productivity (–)	Recession, 1st quarter
1974Q3	GNP deflator, stock prices (–)	Recession, end of price controls
1974Q4	Consumption (–)	Recession
1975Q1	Employment (–), unemployment (–), real GNP (–), industrial prod. (–)	Recession, trough
1975Q2	M2	1st quarter of recovery
1978Q2	Industrial production	
1979Q4	AAA bond yields	Peak, oil shock
1980Q1	AAA bond yields	Recession, oil shock
1980Q2	Real GNP (–), consumption (–), fixed investment (–), M1 (–)	Trough
1980Q3	M2	Expansion, 1st quarter
1981Q1	Monetary Base (–)	Volcker disinflation (?)
1981Q4	CPI (–)	Volcker disinflation, recession
1982Q1	GDP deflator (–)	Volcker disinflation, recession
1982Q4	Compensation (–), stock prices, M1, AAA bond yields (–)	Volcker disinflation, recession, trough
1983Q1	M2	Expansion, 1st quarter
1984Q3	AAA bond yields (–)	
1986Q2	CPI (–)	Reduction in energy prices
1987Q2	AAA bond yields, M2 (–)	
1987Q3	Money base (–), M1 (–)	
1987Q4	Stock prices (–)	October stock market crash
1991Q1	Monetary Base	Recession, trough
1991Q4	M1	Expansion

Note: (–) indicates that the outlier or level shift was negative.

compensation, and M2. Furthermore, once the outliers have been removed, we find no evidence of significant excess kurtosis or skewness in the series with the exception of unemployment and industrial production.

In order to discern patterns in the identified outliers, we present the outlier results in two ways. Table II describes the outliers found for each series, the type and size of the outlier as well as the date at which it occurred. In addition, we also try to link the date of each outlier to an economic event that occurred at or near that date. For example, real GNP experienced an innovative outlier in 1950Q1 and additive outliers in 1958Q1, 1975Q1, and 1980Q2. The first quarter of 1950 corresponds to the first full quarter of a recovery while the other dates correspond to the troughs of recessions. Table III organizes the same information in a different way, presenting the outlier dates in chronological order and listing the series that have outliers on that date. By listing the outlier dates in chronological order, it is easier to show the patterns of outliers across time as well as determine which series experience outliers at or near the same date.

An examination of Tables II and III suggest a few rough patterns that appear to exist among the outliers and that are linked with identifiable economic events. First, many of the identified outliers seem to be associated with business cycles, particularly recessions or early in the recovery. Second, there appears to be a clustering of outliers within series and across series. Third, the number and type of outliers for the real output and employment series are substantially different from those of the nominal price series.

In many respects, the pattern of outliers we found are similar to the 'large shocks' identified by Blanchard and Watson. Based on an examination of a four-variable VAR that included real GNP, the GNP deflator, M1 and a fiscal policy variable, they also found that 'large shocks' were common during turning points and recessions and tended to be clustered across time and series. Because our criterion for identifying a large shock was more restrictive than that of Blachard and Watson and, as we suggested above, the univariate approach tends to aggregate multivariate shocks making detection more difficult, we found fewer large shocks per series. However, when aggregating across series so that we compare the dates listed in Table III to those found in Blanchard and Watson, many of the same dates show up in both analyses.

In the following three subsections we examine further the three basic patterns of outliers previously mentioned.

4.1. Business Cycles and Outliers

Well over half of the outliers in the output and employment series are associated with business cycles, particularly recessions. All the outliers in the real GNP series are associated with turning points in the business cycle. Apart from the Korean War outliers, all the outliers in consumption are associated with recessions. Real fixed investment, industrial production, labour productivity, employment, unemployment rates all have outliers associated with recessions or turning points. In addition, several nominal series experience outliers or level shifts during recessions. Interestingly, three of the five outliers or level shifts associated with M2 occur during the first quarter of business cycle expansions.

However, not every business cycle or recession is represented (no outliers are present from the 1970 recession) nor do all the series experience outliers at the same date or even during the same recession. In fact, the 1980Q2 recession is the only common outlier date for real GNP, fixed investment, and consumption. Perhaps the relatively short but steep recession in 1980 makes it easier for the outlier identification procedure to classify this recession as an outlier.

Overall, the fact that turning points in the business cycle and recessions feature prominently in the identified outlier dates suggests that post-war US business cycle behavior is inconsistent with linear Gaussian models. Even a linear, Gaussian, multivariate framework is unlikely to explain this outlier behaviour since linear aggregation of different Gaussian random variables is still Gaussian. We must look elsewhere to model business cycles. Furthermore, the fact that each business cycle is reflected in different ways by the outliers suggests a multi-causal approach to business cycles—as Blanchard and Watson (1986) suggest, not all business cycles are alike.

4.2. Clustering of Outliers

Several series show a clustering of outliers across time. For example, the GNP deflator and the CPI show numerous outliers in the late 1940s and early 1950s and relatively few outliers in the rest of the sample. Similarly, more than half the outliers for AAA bond yields occur in the three-year period between 1979Q3 and 1982Q4. This reflects the well-documented increase in the volatility of interest rates during this period. This period coincides with a change in monetary policy operating procedures as well as being a period of financial innovation and deregulation. This clustering of outliers across time would be symptomatic of series with ARCH variance processes.

There is also a clustering of outliers across series. This suggests that there may be common sources for these groups of outliers. Table III brings out this clustering across series quite emphatically. There are numerous instances in which different series have outlier or level shifts at or near the same date. For example, the dates 1980Q2, 1975Q1, and 1982Q4 each have four outliers in them (note that they happen to correspond to troughs in a recession). Two additional dates have three outliers associated with them: 1950Q3 and 1958Q1. The recessions of 1957–8, 1974–5, 1980, and 1981–2 contain multiple outliers. Similarly, numerous outliers, both real and nominal, are present during the Korean War. The period preceding the stock market crash in 1987Q4 contains outliers in AAA bond yields, monetary base, M1, and M2, possibly indicating turmoil in the financial markets that culminated in the stock market crash.

The GNP deflator, the CPI, and compensation show evidence of level shifts at or near the same time: late 1967/early 1968, early 1973, and late 1981/1982.[13] These level shifts are associated with expansion of the Vietnam War, the acceleration of inflation of the early-to-mid-1970s, and the Volcker disinflation. The first two level shifts are more likely picking up the general acceleration in inflation rather than the direct effect of a particular shock or event. All three level shifts are reflecting changes in inflationary regimes that occurred during these time periods.

4.3. Real versus Nominal Outliers

The pattern of outliers in the real output and employment series is substantially different from that of the nominal price series. The real output series (GNP, consumption, fixed investment, industrial production, etc.) and the employment series tend to have fewer outliers and the importance of these outliers is substantially less than the nominal price series (the GNP deflator, the CPI, and nominal compensation). Furthermore, the timing and type of the real series outliers is different from that of the nominal series outliers. Outliers in real series tend to be associated with business cycles and are all temporary; there are no large permanent shifts

[13] While the final specification of compensation did not contain a level shift in 1967/8, there was some evidence of a level shift at this time—its t-statistic was 2·30, which failed to meet the prespecified critical value.

in the growth rates of these series. The nominal price series, except for the Korean War outliers, exhibit almost no overlap with the dates of the outliers for the real series.

Furthermore, the growth rates of the price series do exhibit level shift outliers, or permanent large shocks. These level shifts reflect changes in the average inflation rate that occurred at or around these dates. Yet these level shifts do not coincide with outliers (temporary or permanent) in any of the real series. These results suggest a dichotomy between the real output series and the aggregate price series and that fluctuations in these series may have different sources.[14]

4.4. Miscellaneous Outliers

In addition to the general patterns discussed above, there are some interesting outliers among the individual series. The GNP deflator experiences an innovative outlier in 1974Q3 which reflects the lifting of the Nixon era wage and price controls. The 1986Q2 outlier in the CPI reflects the decline in energy prices that occurred during 1986. Steel strikes in 1952 and 1959 show up as outliers in fixed investment in 1952Q3 and in industrial production and labour productivity in 1959Q3.

The growth rate of stock prices shows outliers in 1974Q3, 1982Q4, and 1987Q4. Two of these outliers (1974Q3 and 1982Q4) occur during recessions and also coincide with outliers in the inflation rate (GNP deflator or compensation). The 1987Q4 outlier reflects the stock market crash of October 1987. Friedman and Laibson (1989), using different techniques, decompose stock market returns into ordinary and extraordinary components. They also find four 'large shocks' occurring in 1962Q2, 1970Q2, 1974Q3 and 1987Q4. While the standardized residuals from the 'large shock' intervention model are relatively large in 1962Q2 and 1970Q2 ($-2\cdot51$ and $-2\cdot18$, respectively), they are not large enough to be classified as outliers.

Finally, the preponderance of negative outliers for consumption is consistent with the finding of Dynarski and Sheffrin (1986), who found substantial negative skewness in consumption. Because controlling for these outliers appears to eliminate the skewness in the consumption residuals, our analysis suggests that the source of the consumption asymmetry is primarily due to large negative responses of consumption during recessions and during the Korean War.[15] The 1950Q3 outlier in consumption coincides with the outbreak of the Korean War, which began in June 1950. The boom in consumption in 1950Q3 was followed by a negative outlier in 1950Q4. The consumption boom during 1950Q3 may have been caused by consumer purchases in anticipation of wartime shortages that were present during World War II. Consumers, having made large purchases initially (especially durable), may have cut back on additional purchases, hence the negative outliers in 1950Q4 and 1951Q2.

5. EFFECT OF TIME AGGREGATION: OUTLIERS IN MONTHLY DATA

In the analysis above we used quarterly data in order to better compare outlier behaviour across series. However, several of the series examined above are available at a higher frequency than quarterly. Because time aggregation would tend to obscure the presence of large shocks,

[13] While the final specification of compensation did not contain a level shift in 1967/8, there was some evidence of a level shift at this time—its t-statistic was $2\cdot30$, which failed to meet the prespecified critical value.

[14] King *et al.* (1991) suggest a similar dichotomy in the long-run trend components. Here the dichotomy shows up with respect to large shocks, in particular, the level shift shocks.

[15] If consumption is disaggregated into consumption of durables and consumption of non-durables and services, most of this excess asymmetry and most of the outliers are coming from consumer durables.

Table IV. Outlier dates in selected monthly series

Variable	Type	Date	Size	S.E.	Events
Industrial Production	AO	1949:10	−0·051	0·006	Recession, trough
	IO	1950:3	0·022	0·007	Recovery, 5th month
	IO	1950:9	−0·026	0·007	Korean War
	IO	1952:8	0·068	0·007	Korean War, steel strike ended in previous month
	IO	1956:7	−0·028	0·007	Steel strike
	IO	1956:8	0·054	0·007	Steel strike ended previous month
	AO	1956:11	−0·025	0·006	
	IO	1958:6	0·023	0·007	Recovery, 2nd month
	AO	1958:11	0·021	0·006	Recovery, 7th month
	IO	1959:7	−0·027	0·007	Steel strike
	AO	1959:8	−0·027	0·006	Steel strike
	IO	1959:12	0·054	0·007	Steel strike ended previous month
	IO	1960:2	−0·026	0·007	2 months before peak
	IO	1964:11	0·035	0·007	
	AO	1970:12	0·027	0·006	Recovery, 1st month
	IO	1974:11	−0·027	0·007	Recession
	IO	1974:12	−0·034	0·007	Recession
	IO	1978:4	0·021	0·007	
	IO	1980:4	−0·025	0·007	Recession
	AO	1982:2	0·028	0·006	Recession, double dip
	AO	1984:1	0·021	0·006	
Stock Prices	AO	1950:7	−0·097	0·028	Korean War
	AO	1962:6	−0·116	0·028	
	AO	1970:5	−0·118	0·028	Recession
	IO	1973:11	−0·089	0·028	Peak, oil shock
	IO	1974:7	−0·089	0·028	Recession
	IO	1974:8	−0·099	0·028	Recession
	AO	1974:12	−0·097	0·028	Recession
	IO	1976:1	0·086	0·028	
	IO	1980:3	−0·113	0·028	Recession
	AO	1981:9	−0·100	0·028	Recession
	IO	1982:9	0·104	0·028	Recession, 2 months before trough
	IO	1987:10	−0·127	0·028	October crash
	IO	1987:11	−0·108	0·029	
	IO	1990:8	−0·091	0·028	Recession, Iraqi invasion of Kuwait
	IO	1991:2	0·103	0·028	End of Gulf War, 1 month before trough
Inflation (CPI)	IO	1948:2	−0·012	0·002	End of post-WWII inflation
	IO	1948:3	−0·012	0·002	End of post-WWII inflation
	AO	1948:4	0·010	0·002	
	LS	1948:8	−0·011	0·002	End of post-WWII inflation
	AO	1949:7	−0·009	0·002	Recession
	IO	1950:12	0·012	0·002	Korean War
	AO	1951:1	0·008	0·002	Korean War
	AO	1951:2	0·013	0·002	Korean War

continued

Table IV. *Continued*

Variable	Type	Date	Size	S.E.	Events
	LS	1967:6	0·003	0·001	Vietnam War expansion
	LS	1973:2	0·003	0·001	Nixon expansion
	AO	1973:7	−0·007	0·002	Price freeze (13 June to 12 August)
	AO	1973:8	0·012	0·002	Price controls—start of Phase IV
	LS	1978:4	0·003	0·001	
	IO	1980:7	−0·008	0·002	Expansion
	LS	1981:10	−0·006	0·001	Volcker disinflation
	AO	1986:3	−0·007	0·002	Reduction in energy prices
	AO	1986:4	−0·006	0·002	Reduction in energy prices
	AO	1990:1	0·007	0·002	

we examine three monthly series—stock prices, industrial production, and consumer prices—to determine whether the characterization of the outlier behaviour changes at higher frequencies. The sample period for all three series runs from January 1947 to December 1992.

Table IV presents outlier/level shift dates and sizes for the three series.[16] As expected, more outliers are found in the monthly data than in the quarterly data. However, relative to the number of observations in the sample (184 quarterly observations versus 552 monthly observations), the number of outliers is not too different in the monthly time series than in the quarterly series. Furthermore, the pattern of outliers displayed in the quarterly series also shows up in the monthly series. Most of the outliers in both industrial production and stock prices are associated with business cycles. Episodes such as the steel strike in 1958 for industrial production and the stock market crash in 1987 for stock prices show up significantly in the monthly data. Like the quarterly CPI inflation series, the monthly CPI series contains level shifts in 1967, 1973, and 1981 as well as the outliers in 1948, the Korean War, and 1986.

The outlier search in the monthly series does pick up episodes missed in the quarterly series. The effects of two short steel strikes in July 1952 and 1956 appear in the monthly industrial production data. The double-dip recession of 1981–2 may be responsible for the positive outlier in February 1982 for industrial production. For monthly stock prices, several outliers are indicated to have occurred during recessions (1970, 1980, and 1990–91) that are not represented in the quarterly data. For the CPI, the price freeze implemented from to 13 June to 12 August 1973 shows up as a negative outlier in July 1973 and a positive outlier in August 1973 in the monthly series but was not detected in the quarterly series. Also, two additional level shifts are found in the monthly CPI series (1948:8 and 1978:4) that were not present in the quarterly data. While time aggregation should not obscure the presence of level shifts, the fact that both of these were followed by outliers or level shifts of the opposite sign almost three years later may make these episodes more difficult to detect as permanent level shifts with quarterly data. Finally, the timing for certain episodes is changed slightly when the analysis is conducted with monthly data. For quarterly industrial production, outliers are indicated to have occurred in 1960Q1 and 1975Q1 while in the monthly data outliers are indicated to have occurred in 1959:12 and in 1974:11 and 1974:12.

[16]The ARI specifications for the seres were: ARI(12, 1) for industrial production, ARI(1, 1) for stock prices, and AR(12, 1) for CPI. For all three series there was significant evidence of excess kurtosis in the residuals of the basic ARI model but insignificant evidence once the outliers were controlled for.

6. OUTLIERS AND NON-LINEARITY

It is clear that linear, univariate models with Gaussian innovations do not adequately characterize many commonly used macroeconomic time series. On the other hand, the large shock/outlier models adequately characterizes the data; the residuals of the large shock models exhibit very little excess kurtosis and skewness and, furthermore, the outliers often correspond to identifiable economic events. However, it may be possible that evidence of outliers may reflect the presence of deeper non-linearities. Indeed, as we have suggested above, a clustering of outliers across time would be consistent with ARCH variance processes. Furthermore, the preponderance of outliers during recessions might be consistent with non-linear cyclical behaviour. Indeed, non-linear models such as Hamilton's (1989) Markov switching model and threshold autoregressions (Teräsvirta and Anderson, 1992) have been used to model capture univariate business cycle behaviour in output (see also Brock and Sayers, 1988). Chaotic or other non-linear behaviour in time series may cause outlier type behaviour in simple linear models. To examine these possibilities, we test for GARCH and general non-linearity in the various series before and after controlling for outliers.

Table V summarizes the tests for GARCH and general non-linearity. A GARCH(p, q) model for the variance was specified based on the autocorrelations and partial autocorrelations of the squared residuals. The ARI-GARCH models were then estimated via maximum likelihood and tested by a Likelihood Ratio test.[17] If GARCH is indicated, we calculate the standardized residuals from the GARCH model and examine whether there remains excess kurtosis and skewness. To determine whether GARCH type processes were present in the residuals of the outlier/intervention model, we examined the Ljung–Box Q-statistic for general autocorrelation in the squared residuals and conducted Lagrange Multiplier test as in Engle (1982) for particular GARCH$(0, q)$ models.[18]

To test for general non-linearity, we apply the Brock, Dechert, and Scheinkman (1987) (BDS) test statistic to the residuals from the basic ARI model and to the residuals from the outlier model.[19] Because the BDS tests were not always conclusive, in our summary of the tests we categorize the test for non-linearity as either rejecting linearity (Y), failing to reject linearity (N), or providing mixed results (M). We also consider two tests for non-linearity proposed by Tsay (1986, 1991). The Tsay1 test in Table V is the test for non-linearity proposed by Tsay (1986). For this test, the number of lagged terms equals the number of lags in the linear specification. The second test (the Tsay2 test below) proposed by Tsay (1991) is based on an arranged autoregression where the ordering of the sample is based on the value of a threshold variable, here Y_{t-d}, where d is the delay parameter; we considered possible delay parameters $d = 1$ to 4 for quarterly data and $d = 1$ to 12 for monthly data.[20] Table V reports test statistics for a delay parameter with the lowest p-value (i.e. the test with the strongest evidence against linearity).

Most of the raw series show some evidence of either GARCH or non-linearity. After fitting the outlier model and controlling for the effects of the outliers, the evidence of GARCH and non-linearity in many of these series is substantially weaker. The primary exceptions are the

[17] Detailed results of the tests for GARCH and the maximum likelihood estimates of the ARI-GARCH model are available from the authors.

[18] Since we were only interested in establishing the presence of GARCH type behaviour in the residuals of the outlier/intervention model, we did not estimate the full intervention-GARCH model by maximum likelihood.

[19] We examine the BDS statistic for embedding dimensions $m = 2$, 3, and 4 and $e = 0{\cdot}5$ and 1.

[20] The arranged autoregressions for the tests reported in Table V are arranged from low to high values of Y_{t-d}. We also considered arranged autoregressions arranged from high to low values of Y_{t-d}. For most of the series, the alternative ordering does not result in substantially different results.

Table V. Summary of tests for ARCH and non-linearity

		Basic ARI model			Outlier model				GARCH model	
Variable	GARCH (p, q)[a]	BDS[b]	Tsay1[c]	Tsay2[d]	GARCH[e]	BDS[b]	Tsay1[c]	Tsay2[d]	Kurt.	Skew.
Real GNP	None	M	0·04	0·28	N	N	0·83	0·25	—	—
Consumption	(1, 1)	N	0·34	0·00	N	N	0·63	0·38	4·2[g]	−0·37[f]
Fixed Investment	(0, 1)	N	0·80	0·00	N	N	0·67	0·01	4·5[g]	−0·38[g]
Indust. Prod.	(1, 1)	Y	0·00	0·00	N	N	0·17	0·01	4·2[g]	−0·34
Productivity	(1, 1)	N	0·22	0·20	Y	N	0·56	0·17	3·6	−0·50[g]
Unemployment rate	(1,3)	Y	0·00	0·00	Y	N	0·00	0·00	3·8[f]	0·64[f]
Employment	(1, 1)	Y	0·04	0·00	N	N	0·24	0·02	3·5	−0·13
GNP deflator	(0, 1)	Y	0·00	0·00	Y	N	0·79	0·03	7·2[g]	0·31
CPI	(0, 1)	Y	0·00	0·00	N	Y	0·00	0·02	5·8[g]	−0·51[g]
Compensation	(0,3)	M	0·18	0·01	N	N	0·75	0·15	3·6	0·28
AAA bond yields	(1, 1)	Y	0·00	0·01	Y	Y	0·63	0·01	5·2[g]	0·45[f]
Stock prices	None	N	0·42	0·01	N	N	0·92	0·22	—	—
Money Base	None	Y	0·23	0·40	N	N	0·09	0·46	—	—
M1	(1, 1)	M	0·28	0·02	N	N	0·50	0·06	4·2[g]	0·06
M2	(0, 1)	N	0·47	0·12	N	N	0·28	0·17	7·7[g]	1·30[g]
Monthly series										
Indust. Prod.	(1, 1)	Y	0·10	0·00	N	N	0·84	0·20	5·8[g]	−0·11
CPI	(1, 1)	Y	0·00	0·00	Y	Y	0·01	0·02	4·7[g]	0·07
Stock Prices	(0, 1)	M	0·80	0·05	N	N	0·11	0·02	4·1[g]	−0·37[g]

[a] Evidence of GARCH at the 5% level in the ARI model residuals.
[b] Evidence of non-linearity in the model residuals using BDS statistics: Y—strong evidence, M—mixed evidence, and N—weak evidence.
[c] p-values for the Tsay (1986) test for non-linearity with lags equal to AR terms in the linear ARI model. For outlier model, the test is conducted after removing the effect of the outliers.
[d] The minimum p-value for the Tsay (1991) test for nonlinearity for delay lags 1 to 4 for quarterly data and lags 1 to 12 for monthly data. The autoregression is arranged from low to high values of lagged dependent variable with delay d. The number of with lags equal to AR terms in the linear ARI model. For outlier model, the test is conducted after removing the effect of the outliers.
[e] Evidence of GARCH at the 5% level in the outlier model residuals.
[f] Significant at the 5% level.
[g] Significant at the 1% level.

unemployment rate, the CPI, and AAA bond yields. These series retain strong evidence of non-linearity even after the effect of the outliers is removed. For industrial production, fixed investment, and employment the Tsay2 test still rejects linearity after removing the outliers but at higher p-values than is the case before removing the outliers. An examination of the monthly series for CPI, industrial production, and stock prices yields similar results as their quarterly counterparts: with the exception of CPI, controlling for outliers eliminates most of the evidence of non-linearity.

Of course, as we suggested above, clusters of outliers may reflect GARCH behaviour and vice versa. For example, the fact that most of the temporary outliers for inflation occurred in the late 1940s and early 1950s or that AAA bond yield outliers occurred during 1979Q3–1982Q4 may be evidence of GARCH. However, even after estimating GARCH models, almost all the series still showed significant excess kurtosis and/or skewness. GARCH models are in some sense a parsimonious characterization of the large shock hypothesis, but the presence of significant excess kurtosis and skewness suggests that the random outlier model for most of these series may still be a better characterization of the data than GARCH. While we do not conduct a formal search for outliers in the ARI/GARCH model, inspection of the standardized residuals from the GARCH model suggests that significant outliers remain.

The fact that controlling for outliers lessens the evidence of non-linearities raises several issues. It could be possible that the world is indeed linear but subject to infrequent, large shocks. This causes possible misspecifications in linear, Gaussian models, and, consequently, these series show evidence of nonlinearity.[21] On the other hand, it is possible that there are indeed non-linearities that the linear outlier model captures as outliers. There are numerous other non-linear models which we did not examine, such as Markov regime switching and threshold autoregression models, that may capture the excess skewness and kurtosis as well as the non-linearities in the data.[22] The fact that the timing of many of the outliers coincided with identifiable economic events such as recessions suggests a possible link between business cycles and non-linear processes.

One possible link between large shocks and non-linear (or asymmetric) behaviour in economic time series is through the effect that large shocks have on degree of synchronization of agents in the economy. Because of non-convex (and asymmetric) adjustment costs, economic agents may follow infrequent or non-linear adjustment rules.[23] However, as pointed out by Caballero (1992), these microeconomic non-linearities tend to get washed out in the aggregate if there is sufficient heterogeneity among economic agents. Large shocks are more likely to bring out the non-linear nature of the microeconomic adjustment at the aggregate level by causing economic agents to synchronize their adjustment decisions.

7. CONCLUSIONS

We have shown that within the context of linear autoregressive models there is significant evidence that large, infrequent shocks are an important source of variability in many macroeconomic time series. In addition, the estimated outliers account for nearly all of the

[21] Both Tsay (1988b) and Petruccelli (1990) discuss the effect of outliers on non-linear time series modelling and suggest the presence of outliers in a linear time series can cause the false detection of non-linearity. Scheinkman and LeBaron (1989b) also found that controlling for unusual periods reduced the evidence of non-linearity in real GNP.

[22] As an anonymous referee pointed out, if one takes Hamilton's regime switching model and conditions an information set that includes the previous period's state, then one would treat the resulting model as linear but non-Gaussian.

[23] The (S, s) adjustment rule is an example of a non-linear adjustment rule.

excess kurtosis and skewness present in the data and are capable of explaining much of the non-linearity present in the data. Furthermore, several patterns emerge from the outlier analysis: many of the identified outliers seem to be associated with turning points in the business cycle; outliers tend to be clustered both within and across series; and there appears to be a dichotomy between real and nominal series with respect to large shocks. Because so many of the outliers are associated with recessions, our analysis implies that linear, Gaussian models of the business cycle are not appropriate.

Our analysis also suggests several extensions. The fact that many series have outliers at the same date suggests that a multivariate outlier analysis may prove useful in shedding additional light on the source of these outliers. Additionally, the link present between outliers in linear models and evidence of non-linearity found in this paper warrants further investigation.

DATA APPENDIX

Quarterly Series

Real GNP (1987 dollars): CITIBASE series GNPQ, 1947Q1 to 1992Q3.
Consumption (1987 dollars): CITIBASE series GCQ, 1947Q1 to 1992Q4.
Fixed Investment (1987 dollars): CITIBASE series GIFQ, 1947Q1 to 1992Q4.
Industrial Production, Total: CITIBASE series IP, 1947Q1 to 1992Q4.
Labour Productivity, Manufacturing: CITIBASE series LOUTM, 1947Q1 to 1992Q3.
Unemployment Rate: CITIBASE series LHUR, 1948Q1 to 1992Q4.
Employment, Civilian Non-institutional: CITIBASE series LHEM, 1948Q1 to 1992Q4.
Implicit GNP Deflator: CITIBASE series GD, 1947Q1 to 1992Q3.
Consumer Price Index, Urban Consumers All Items: CITIBASE series PUNEW, 1947Q1 to 1992Q4.
Compensation per hour, Manufacturing: CITIBASE series LCPM, 1947Q1 to 1992Q4.
AAA Bond Yields: CITIBASE series FYAAAC, 1947Q1 to 1992Q4.
Stock Prices, S&P 500 Index: CITIBASE series FSPCOM, 1947Q1 to 1992Q4.
Monetary Base, St Louis: CITIBASE series FMBASE, 1947Q1 to 1992Q4.
M1: CITIBASE series FM1, 1959Q1 to 1992Q4. Linked to 'Old' M1 from various issues of the Federal Reserve Bulletin, 1947Q1 to 1958Q4.
M2: CITIBASE series FM2, 1959Q1 to 1992Q4. Linked to 'Old' M2 from various issues for the Federal Reserve Bulletin, 1947Q1 to 1958Q4.

Monthly series

Monthly series are from same sources as quarterly series.

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