

School of Economics and Finance

Econometric Studies of Business Cycles in the History of Econometrics

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Working Paper No. 669

July 2010

ISSN 1473-0278



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Abstract

This study examines the evolution of econometric research in business cycle analysis during the 1960-90 period. It shows how the research was dominated by an assimilation of the tradition of NBER business cycle analysis by the Haavelmo-Cowles Commission approach, catalysed by time-series statistical methods. Methodological consequences of the assimilation are critically evaluated in light of the meagre achievement of the research in predicting the current global recession.

JEL classification: B23

Key words: business cycles, NBER, forecasting

^{*} This paper is based on a draft chapter of a book project: *The Reformation of Econometrics: A Historical Perspective*.

Business cycle studies occupy a prominent position in the history of econometrics. To a large extent, modern macroeconomics and econometrics arose from business cycle studies of the 1930s in the wake of the Great Depression, see Morgan (1990; Part I). Econometric business cycle research has evolved a great deal during the past seven decades. Nevertheless, macro-econometric models still fall considerably short of predicting the latest global recession since 2008. The failure forms the main impetus of the present study. This paper examines how econometric methods for business cycle analysis evolved over the period 1960-90 approximately, especially in the wake of the 1973 oil crisis induced recession, and what lessons we could draw from the history. There are numerous surveys of business cycle research since the end of WWII, eg see Gordon (1949), Koopmans (1949), Roose (1952), Hickman (1972), Zarnowitz (1985; 1992), Laidler (1992), Jacobs (1998). But none of these are exclusively from the angle of the history of econometrics.

1. Background Introduction

Tinbergen's macrodynamic models, especially his model of the US economy (1939), are widely acknowledged as the first major econometric endeavour to model business cycles. Subsequent methodological debates over Tinbergen's models have played a vital role in catalysing the formalisation of econometrics by Haavelmo and the Cowles Commission (CC) research group (see Qin, 1993). A methodological summary of econometric modelling of business cycles is provided by Koopmans (1949) and the methodology follows basically Frisch's structural approach (1937). The backbone of the methodology was the Slutsky-Frisch impulse-propagation scheme (see Frisch, 1933; Slutsky, 1937; also Bjerkholt, 2007; Chapter 2 of Louçã, 2007), which assumed that business cycles are embedded in the dynamics of certain macro variables, such as GDP, and that the dynamics was driven by a few aggregate variables according to available

economic theories plus random shocks. Under the methodology, the task of econometricians was to obtain statistically best estimates for the coefficients of structural models of the impulse-propagation type. Explanation of business cycles was achieved once the best fit was found.

Notice that the above approach sidestepped certain statistically fundamental issues concerning the identification of business cycles and measurement of the extent of their impact to various economic activities/sectors. These issues were actually the very agenda of business cycle studies at the NBER (National Bureau of Economic Research). Starting from the early 1920s under the leadership of Mitchell, the NBER business cycle programme had, by the mid 1940s, evolved a relatively mature procedure in establishing an empirical chronology of business cycles (see Burns and Mitchell, 1946).¹ Based on the definition of business cycles as cyclical movements in aggregate economic activities with the key feature of being recurrent but non-periodic in terms of timing, duration and amplitude,² the chronology comprised mainly of measures of: (a) aggregate cycles; (b) the turning points, lengths, troughs and peaks of the cycles; (c) the extent of cyclical effect. GDP or GNP was a most commonly used indicator from which an aggregate

¹ In this classical work, specific cyclical analysis was carried out on 1277 individual time series of monthly, quarterly or annual frequencies with various sample lengths for four countries, France, Germany, UK, US. The main method of composing leading indicators for business cycles follows their earlier joint work (Mitchell and Burns, 1938).

² The highly quoted NBER definition is: 'Business cycles are a type of fluctuation found in the aggregate activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycles; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own.' (Burns and Mitchell 1946, p.3)

measure of cycles could be built, but it was also a common practice to use the measure of ‘reference cycles’, ie certain averaging of a group of ‘specific cycles’, each derived from the seasonally-adjusted time series of a particular economic activity (ibid, Chapter 2). Possible erratic movements were also filtered out from the series. The cycles were characterised via dating of their turning points, troughs and peaks. Since a large number of series were analysed, diffusion indices were constructed as an indicator the extensiveness of the cycles. The index was based on the proportions of upturn/expanding or downturn/contracting points at each observation of all the series. The phase difference of specific cycles were also analysed to identify series of ‘leads and lags’ for forecasting purposes (ibid, Chapter 4).

The NBER research method was criticised as ‘measurement without theory’ by Koopmans (1947), which was fought back by Vining, who disapproved of the CC approach as being too narrow to allow for any discovery or hypothesis seeking (1949). Their debate set a methodological divide between the CC approach and the NBER approach. Subsequently, the former became accepted as the paradigm of econometric research (see Qin, 2008a). Mainstream macro-econometric modelling during the 1950s and 1960s also moved away from business cycle studies to quantifying comparative static economic theories within the simultaneous-equation model (SEM) framework.

On the other hand, the NBER line of research was carried on and strengthened with the help of time-series statistical techniques (see the next section). The global economic recession triggered by the 1973 oil crises greatly revitalised econometric business cycle research. The resurgence was accompanied and strongly influenced by the rational expectations movement in macroeconomics (see section 3). Consequently, dynamic features of macroeconomic models and time-series properties of macro data attracted focal attention. The rise of time-series econometrics in the 1980s resulted in a

formalisation movement of the NBER business cycle measures (see section 4). The movement also re-orientated macro-econometric modelling research to business cycle forecasting (see section 5). A brief assessment of the history over the three decades since the late 1950s concludes the chapter (see section 6).

2. Prelude: Business Cycle Research Programme at Princeton

In the late 1950s, a major work on the international propagation of business cycles through financial markets was carried out by O. Morgenstern under the Econometric Research Programme of Princeton University. Following the NBER procedure, Morgenstern (1959) analysed a large number of financial time series of mainly monthly frequency from France, Germany, UK and USA for the periods of the gold standard era (1870-1914) and the interwar period (1925-1938). Particular attention was paid to the co-movement (covariation) of cross-boarder financial series as well as between cyclical movements of the financial series and the reference business cycles of each country. Data evidence was also used to verify theories such as interest rate parity. The findings revealed a considerable gap between data and available theories. Morgenstern thus concluded that methodological advance was in need for both theoretical and econometric research. In particular, theories should shift away from notions of ‘equilibrium’ and ‘stability’ to games and strategies between market players while ‘more penetrating mathematico-statistical analysis of data may produce surprises’ (ibid, Chapter 11).

The more penetrating approach that was possibly on Morgenstern’s mind was spectral analysis.³ Based on his business cycle research experience, Morgenstern (1961) saw the future of research lying with Wald’s (1936) decomposition of economic time series into trend, cycles, seasonal and irregular fluctuations rather than the Frisch-Slutsky

³ It is recorded in a number of historical studies that von Neumann suggested the spectral method to Morgenstern (see Cargill, 1974; Phillips, 1997).

scheme. A key figure he brought into his research team was CWJ Granger. Their initial study on weekly New York stock price series by means of cross-spectral analysis revealed that the ‘business cycle’ component was insignificant in the price series and that their role of indicating/leading macro business cycles was weak. The result cast doubt on the existence of stock market ‘specific cycles’ derived by the NBER method (Granger and Morgenstern, 1963). However, when cross-spectral analysis was applied to a number of NBER business-cycle indicators, the identified cyclical components were found to confirm broadly those derived by the NBER method, although the duration of the average lead or lag was significantly longer than that by the NBER method (see Granger and Hatanaka, 1964; Chapter 12).

Interestingly, the exploratory time-series work of the Princeton Programme was criticised by Wold (1967) as ‘empiricism without theory’ for the main reason that the nonparametric approach of spectral techniques was ill-suited to the parametric tradition of structural econometric modelling. In the case of business cycles, it was obviously difficult to equate cycles identified by spectral techniques with what economists reckoned as business cycles. But the criticism was soon shown to be unwarranted by Granger’s introduction of a causality test (1969), via cross-spectral methods, on the basis of the feedback mechanism of a bivariate VAR model. Ironically, Granger’s approach was noted to be essentially identical to Wold’s causal chain modelling approach (see Sims, 1972 and also Qin, 2008b). The test has generated enormous interest in the econometric circle (eg see Qin, 2010) and marked a new era in business cycle research – a rapid fusion of time-series methods into the structural econometric modelling approach (eg see Granger and Newbold, 1977).

8.3 Theory led time-series reforms

As mentioned in Section 8.1, ‘reference cycles’ were assumed to be embedded in the dynamics of a few macro variables. Therefore, examination of the applicability of macroeconomic models to business cycle analysis was mainly conducted via dynamic simulations, led by the seminal work of Adelman and Adelman (1959). A large scale examination was organised by a conference held at Harvard University sponsored partly by the NBER in 1969. Dynamic properties of several macroeconomic models were tested including the Wharton model and the Brookings model, see Hickman (1972).⁴ Most of the models were built on the Slutsky-Frisch scheme. Interestingly, the source of cycles emerged as a contending issue through various simulation results. Purely random/erratic shocks were found unable to produce cycles; they would only arise from either autocorrelated error-term shocks or perturbation of exogenous variables. But the inevitability of model mis-specification, especially with models having autocorrelated error terms, made it difficult to rule out the possibility that the source should have been structurally internal, ie correct theoretical models should be dynamically cyclical.

Indeed, more theoretical models containing the property of self-sustaining cycles were postulated since the mid 1960s. One type of models, which gained rapid prominence, postulated that cycles arose from the expectation-augmented disequilibrium in the short-run wage-price dynamics. The research was led by M. Friedman and E.S. Phelps and extended by R.E. Lucas. The subsequent rise of the rational expectations movement in the early 1970s effectively moved the focal point of macroeconomic modelling from comparative static equilibrium to dynamics, especially short-run dynamics and its transitory properties as compared to long-run equilibrium solutions. From that respect, the lack of dynamically adequate structural models was blamed for poor econometric model performance in forecasting the oil shock induced business cycles

⁴ For more detailed description of the history of these models, see Bodkin, *et al* (1991; Part II).

of the early 1970s (eg see Lucas and Sargent, 1978). In response, econometric business cycle research evolved along two diverging methodological strands – one with reduced reliance on *a priori* structural model formulation and the other on econometric estimation but with greater reliance on computer simulated theoretical modelling.

The first strand is the VAR (Vector AutoRegression) modelling approach initiated by Sargent and Sims (see Qin, 2008b). Under the proposition to do ‘business cycle modelling without pretending to have too much *a priori* theory’, Sargent and Sims (1977) sought to reform the mainstream econometric approach by adapting the ‘NBER style quantitative business cycle analysis’. They first examined the NBER method of identifying the ‘reference cycle’ by reformulating the method into what they referred to as ‘unobservable-index models’. They chose 14 time-series variables, all detrended quarterly aggregates over the 1949-1971 period,⁵ and extracted, using factor analysis, one common factor from the set as well as from different subsets of the variables. The factor was regarded as the ‘reference cycle’ indicator of the chosen variable set. They then pointed out that one factor was generally inadequate in representing the co-movement of a chosen variable set, a point indicating the general inadequacy of the NBER ‘reference cycle’ measure for business cycles. That led them to the ‘observable-index model’ approach, ie the mainstream econometric approach in modelling key macro variables. There, their innovation was to start from a general dynamic model, known as a VAR, instead of an *a priori* formulated structural model. In particular, they built a five-variable VAR to capture the US business cycles.⁶ To locate the sources of cyclical movements, they resorted to Granger causality test for identifying cross-variable sequential (lead and lag) dependence. To evaluate the magnitude of random shock impact, they performed

⁵ They also examined some monthly series when such observations were available.

⁶ The variables are money, unemployment rate, price and wage indices, and a demand-pressure proxy by unfilled orders for durable goods/total shipments.

impulse analysis to simulate short-run dynamics caused by ‘structural’ shocks (see Qin and Gilbert, 2001). The two techniques were soon to become the pillar of the VAR approach.⁷

However, the VAR approach was greeted by various scepticism and criticism. One popular line of attack was on its lack of theory (see Qin, 2008b). A relatively theory-rich strand, known as the real business cycle (RBC) approach, was initiated by Kydland and Prescott (1982). Departing from the monetary school in attributing monetary disturbances as the source of business cycles, Kydland and Prescott built a model in which the source came from technological shocks (ie a ‘real’ factor rather than a nominal factor). In their study, business cycle features were assumed to be embodied in the autocorrelation of real output (GDP) and its covariance with other aggregates such as total consumption and fixed investment. Simulation of cyclical features formed the primary goal of their modelling activities. Methodologically, they chose to build their model within the general equilibrium system and calibrate the structural parameters following the ‘computable general equilibrium’ (CGE) modelling approach.⁸ Different from extant CGE models, their model was focused on postulating a feasible dynamic and stochastic propagation channel of business cycles, thus extending the CGE approach to a new branch – the dynamic stochastic general equilibrium (DSGE) models. Econometrics was minimised to simple time-series statistics of the aggregates concerned, eg in the sample standard deviation of the real output in the Kydland-Prescott model.⁹ These statistics served largely as references for adjusting and evaluating model simulation results.

⁷ Further examples include Sims’ exploratory work on monetary business cycle (1980; 1983).

⁸ The general argument for calibration was the unidentifiability of structural parameters, especially when structural models become more disaggregated. See Mitra-Kahn (2008) for more on the history of CGE models.

⁹ Kydland and Prescott use this estimate to anchor the magnitude of their simulated real output.

Indeed for DSGE modellers, econometrics became designated to producing time-series properties of aggregate variables, properties which set the targets of mimicking for simulations of their conjectured RBC models. For example, Long and Plosser (1983) postulated a multi-sector RBC model which enabled the economic norm plus stochastic behaviour of producers and consumers to generate business cycles by sector specific shocks. The time-series features of significantly autocorrelated output and strong comovement between outputs of various sectors formed their target of model simulation – to mimic simple time-series properties of outputs of six sectors including agriculture, manufacturing and service. Their model was extended to include money and banking by King and Plosser (1984) to account for the phenomena of significant co-movement between money, inflation and real economic activities. The phenomena were presented by both static and dynamic regressions between the aggregate output growth and growth rates of monetary and nominal variables.

The DSGE approach has carried forward and formalised the NBER tradition of emphasising the role of sector-specific shocks in business cycle research at the expense of replacing econometric estimation by calibration and nullifying consequently the associated econometric criteria for model testing. However, the approach has not repudiated econometrics in spite of the contentious position of Kydland and Prescott (1991) to denounce the CC structural approach as ill-suited for DSGE modelling of business cycles. Econometrics has proved useful at least in two respects. One involves using parameter estimates from extant econometric studies, especially micro and sector studies, as the basic reference for calibration; hence calibration could be seen as a kind of estimation (see Gregory and Smith, 1990). The other is to utilise econometric studies of the time-series features of aggregate economic variables to assess how well DSGE models could match these features. The assessment could also be formalised into a

statistical test procedure (eg see Watson, 1993). The latter aspect has exerted positive feed back to the rising popularity of time-series econometric research.

8.4 Time-series Formalisation of Business cycle Measurements

The 1980s saw rapid formalisation of the NBER business cycle measures by time-series econometrics. One of the leading topics of attention was the nonstationary feature in economic variables, especially those exhibiting significant trends. It was an old and well-established view that trend and cycle were two separable components in economic time series. Although a trend component was not filtered out in the original Burns-Mitchell procedure of dating specific cycles, they were not unaware of the desirability to filter out secular trends before identifying the cyclical component and attributed the reason for not doing so to resource constraints (1946). Moreover, Mitchell had actually used already detrended business activity indices in dating US business cycles for the pre-1927 era in his earlier works, as shown by Romer (1994).

An explicit trend filter was introduced at the NBER by Mintz (1969). Mintz ran into difficulty in dating, by the Burns-Mitchell procedure, German business cycles from highly trended time-series indices and therefore went for ‘deviation cycles’, ie defining the cycles as swings around the long-run trend curves, which were taken as 75-month (6-7 years) centred moving averages of the indices. Mintz also examined another way of detrending, ie the use of (monthly) growth-rate indices as the base of extracting cyclic measures and defined such cycles as ‘step cycles’. She demonstrated that it was harder and required more complicated criteria to extract step cycles because of ‘highly jagged’ growth-rate data and the unfeasibility to ‘delimit cycle phases’ directly by the peaks and troughs in the data. The German business cycle index that Mintz chose eventually was based on deviation cycles alone. Subsequently, cyclical measures built on undetrended

level data series became called ‘classical cycles’ while measures derived from detrended data series were often referred to as ‘growth cycles’.¹⁰

Mintz’s work demonstrated the intimate dependence of business-cycle dating methods on trend decomposition methods. But the latter remained *ad hoc* until the notion of nonstationarity was brought in as the statistical base for trend filter by Beveridge and Nelson (1981). Essentially, the Beveridge-Nelson trend filter assumed nonstationarity for all of the economic variables to be used for business-cycle dating. Since nonstationary (or technically known as ‘integrated’) processes could be decomposed into a stochastic nonstationary trend and a stationary component, Beveridge and Nelson proposed to use the former as the trend filter and to date business cycles from the latter part alone. To justify themselves, they related their decomposition to Friedman’s (1957) classic work in dissecting income into permanent and transitory parts, albeit their decomposition did not involve any economic principles. Technically, the Beveridge-Nelson filter was defined upon a particular univariate $I(1)$ (integrated of order one) time-series model known as ARIMA (autoregressive integrated moving average) model. For instance, a simple random walk with drift $I(1)$ series, y_t , has an ARIMA representation of its first difference, $\Delta y_t = y_t - y_{t-1}$:

$$(1) \quad \begin{aligned} y_t &= \mu + y_{t-1} + \varepsilon_t \\ \Delta y_t &= \mu + \varepsilon_t \end{aligned}$$

Different model assumptions would result in different filters.¹¹ For instance, Hodrick and Prescott (1981) chose to filter the trend by Whittaker-Henderson method used in actuarial

¹⁰ Mintz (1969) quoted a remark by R.A. Gordon at a London conference in 1967 which argued for examining business cycles around the growth rate of output and employment and called such cycles ‘growth cycles’.

science, which effectively allowed y_t being an $I(2)$ series. Even under the same assumed degree of integration, filters could vary with different assumptions on the source of the random drift in the trend. For example, starting from the conventional decomposition of y_t into a trend, a cycle and an irregular component:

$$(2) \quad y_t = \tilde{y}_t + \psi_t + \varepsilon_t$$

Harvey (1985) assumed $I(1)$ of the trend component, \tilde{y}_t :

$$(3) \quad \tilde{y}_t = \mu + \tilde{y}_{t-1} + \eta_t.$$

Substituting (3) into (2) and taking the first difference would result in:

$$(4) \quad \Delta y_t = \Delta \psi_t + \mu + \eta_t + \Delta \varepsilon_t.$$

This model differs clearly from the lower equation in (1) unless $\Delta \psi_t + \eta_t = \varepsilon_{t-1}$, ie when there is only one single stochastic factor as the source of shocks for both the trend and cyclical components. Harvey referred to (2) as the structural model and the ARIMA specification as its reduced form, although (2) bore little resemblance to the kind of structural models referred to in mainstream econometrics. Nevertheless, Harvey's discussion highlighted the need for additional information concerning the random source of the trend component once it was agreed to be stochastic rather than deterministic (see eg Stock and Watson, 1988). Within the univariate context, the information had to be assumed, as none of the components were directly observable. Various assumptions led to various filters. The lack of consensus laid bare the information inadequacy of identifying a unique stochastic trend from univariate series. The impasse was brought to light by the fast rise to fashion of 'cointegration' analysis in the late 1980s. The analysis

¹¹ More general ARIMA models result from more complicated formulations of the upper equation of (1). For example, model $y_t = \mu + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \lambda_0 \varepsilon_t + \lambda_1 \varepsilon_{t-1}$ becomes an ARIMA(1,1,1) when the characteristic function of the autoregressive part of y_t contains a unit root.

showed that nonstationarity of a variable could be explained by its co-trending with other nonstationary variables. If the stochastic trend component of a variable were the result of cointegration, the time-series approach to detrending single variables would be meaningless.

Although the issue of how best to detrend nonstationary variables remained unsettled, the discussion turned many modellers to work with growth-rate data as a convenient way to avert nonstationarity. The practice could be seen from forecasting VAR models and was adopted in those formalised techniques of identifying turning points of business cycles (see below). Mintz's differentiation of 'deviation cycle' versus 'step cycle' was buried under 'growth cycle', somehow with a conviction that 'step cycle' was a shortcut for 'deviation cycle'.¹²

In the NBER dating method, location of specific cycles was the prerequisite of identifying turning points as these were selected from the peaks and troughs of specific cycles. The selection involved certain 'censoring rules', such as mid-run duration, large enough amplitudes, factors which were essentially underpinned by economic judgment.¹³ The aggregate turning points could be derived from the mode of the specific turning points (eg see Mintz, 1969) or from the aggregate reference cycle (eg see Bry and Boschan, 1971). Comparison between disaggregate turning points and the aggregate ones formed an important step in the NBER method. It not only enabled classification of specific series into leading, coincident and lagging indicators, so as to utilise the lead/lag information for ex-ante forecasting, but also facilitated verification of the aggregate turning points via the ex-post forecasting performance of the indicators. Failure of the

¹² Klein and Moore (1985; Introduction) credit Mintz's 1969 work as the major methodological turning point from classical cycles to growth cycles.

¹³ See also Harding and Pagan (2002) for a summary of the NBER's method.

latter could evoke revisions of the aggregate turning points, which actually made the dating procedure an iterative one (eg see Klein and Moore, 1985, pp 7-8).

Formalisation of the NBER method of turning point identification was, however, narrowly focused on automating the selection process from binary series of peaks and troughs. The NBER selection process was regarded as lacking statistical rigour in terms of probability specification, making it impossible to choose appropriate statistical models for forecasting turning points (eg see Wecker, 1979). Neftci (1982) proposed to use the specification of discrete-state Markov processes in single time-series models for forecasting turning points in macro economic variables, such as unemployment.¹⁴ Neftci's route was expanded by Hamilton (1989). Taking the Beveridge-Nelson finding of the widespread nonstationary feature in level variables, Hamilton chose to apply the Markov-process specification to first difference of an $I(1)$ series, such as y_t in (1), ie treating its growth rate as a nonlinear stationary process. A simple two-state extension of the lower equation in (1) would be:

$$(5) \quad \Delta y_t = \mu_{S_t} + \varepsilon_t \quad S_t = \begin{cases} 1 & t = 1, \dots, t_0 \\ 2 & t = t_{0+1}, \dots \end{cases} \quad \Pr(S_t = j | S_{t-1} = i) = p_{ij}$$

The model effectively identified business cycles within the short-run growth movement of y_t by defining the cyclical turning points as distinct shifts associated with very small probability in the time-varying parameter, μ_{S_t} . Hamilton applied a version of (5), in which an autoregressive ε_t was assumed, to modelling the quarterly series of postwar US real GNP growth rate and found recurrent shifts, which were shown to conform largely to the NBER dating of recessions. Hamilton's devise gained great popularity as its

¹⁴ Neftci also tried the same specification for identifying asymmetry in single macro series (1984), since asymmetry was believed to be a key feature of business cycles.

application to single macro variables yielded numerous shifts, which were handily interpreted as evidence of regime shifts or structural breaks (see Qin, 2009).

The interpretation, however, has strengthened the gap between the time-series notion of 'structure', such as the time-series decomposition in equation (3), and the traditional econometric concept of a structural model, which is crucially dependent on multivariate interdependence. Moreover, it has forsaken the NBER tradition to derive turning points from filtered cyclical series, since growth rate data, especially those of higher than annual frequency data, could filter out much of the mid-range information upon which business cycle measures were originally defined.

To a large extent, the departure of these newly invented time-series models from the econometric tradition or the NBER approach can be attributed to a lack of adequate empirical objectives. Rough conformation with the NBER business cycle chronology was used widely as their empirical sanction, since there were no unique or officially established business cycle measures anyway. A tougher sanction would entail proof of these models being capable to outperform the NBER chronology in forecasting the dynamic movements of key macro variables.

8.5 Forecasting business cycle with time-series modelling

One common criterion in using macro variables to define an oncoming recession is a decline in real GNP/GDP for two consecutive quarters. The Neftci-Hamilton approach provides an obvious means for forecasting such events. Empirical evidence was however inconclusive if the approach could significantly outperform simple autoregressive time-series models in forecasting GNP (eg see Goodwin, 1995). Other routes to elaborate simple time-series models were explored, for example, augmenting the autoregressive scheme by leading indicators and explicitly specified Bayesian loss functions for

forecasting values (eg see Zellner *et al.* 1990). But forecasts of recessionary downturns remained disappointing.

To many, single time-series models were clearly incapable of capturing the interdependent information of economic variables. Once it came to forecasting on the basis of multivariate time-series modelling, the VAR approach presented an obvious route for experiments. The pioneer work was mainly carried out at the Federal Reserve Bank in Minneapolis, where a 46-equation monthly forecasting model of the US was built and maintained using the time-varying parameter and Bayesian VAR (BVAR) technique developed by Doan *et al* (1984) (see also Qin, 2008b). Meanwhile, Litterman, the key modeller, experimented with a six-variable quarterly BVAR mainly for research purposes (see Litterman, 1986). He later expanded the model to nine variables in an attempt to improve its inflation forecasts.¹⁵ The model was subsequently taken over by Sims. In order to rectify its forecasting deterioration, Sims chose to append the BVAR technique with more probabilistic assumptions. In particular, he introduced nonstationary mean priors to trended time series and drastically relaxed the classical assumptions on the residuals – allowing them to be conditionally heteroscedastic and non-normally distributed (1993).¹⁶ In spite of all this, his strategy failed to payoff when it came to forecasting the onset of the 1990-91 recessionary downturn in GNP growth rates. The forecasts tracked closely behind the data series.¹⁷

Meanwhile, a more exploratory route of multivariate forecasting was explored by Stock and Watson. They resumed the experiment, abandoned by Sargent and Sims (1977),

¹⁵ The original six variables are: real GNP, the GNP price deflator, real business fixed investment, the 3-month Treasury bill rate, the unemployment rate, and the money supply; the added three variables: exchange rate, SP 500 stock price index and commodity price index.

¹⁶ The paper was presented at a NBER conference in May 1991.

¹⁷ Note that the lack of predictive power of this kind could not be identified by those forecasting tests based on the averaging of modelling errors, eg see Fair (1984), which were commonly used at the time.

of using factor analysis to reformulate the NBER ‘reference cycle’ measure for the key purpose of attaining probability-model based forecasts of recessions. Stock and Watson started from filtering, by a dynamic factor model (DFM), a single coincident index from the variable lists used by the NBER for its coincident indicator (1989).¹⁸ To circumvent possible nonstationary trends, they took the first difference of those trended series just as Hamilton did. For example, a simple DFM would be:

$$(6) \quad \begin{aligned} \Delta X_t &= \beta_0 + \beta_1 \xi_t + U_t \\ \xi_t &= \alpha_0 + \alpha_1 \xi_{t-1} + e_t \end{aligned}$$

where ΔX_t denoted a set of detrended or stationary series and U_t the idiosyncratic component. The common factor, ξ_t , estimated by means of Kalman filter, was regarded as representing the co-movement of ΔX_t and hence called ‘the coincident index’. Next, a small set of leading indicators/variables were selected to form a VAR with ξ_t in order to predict its future values as well as the associated probabilities. The predicted ξ_{t+j} was referred to as ‘the leading index’ and used to forecast GNP cycles. Stock and Watson (1989) tried their approach on US monthly data. A six-month ahead VAR forecast of ξ_{t+j} was shown to track well the real GNP at its business cycle frequencies. However, it missed the downturn when used in forecasting the US 1990-91 recession. A thorough re-examination of the model led Stock and Watson to the conclusion that it was mainly the inadequate choice of specific leading indicators, rather than the modelling approach, which caused the mis-prediction (1993). The finding highlighted the importance of identifying timely particular shocks which would generate non-periodic business cycles.

In fact, Watson was already aware of the importance. The statistical nature of shocks formed the subject of one of his earlier empirical studies, which was jointly done

¹⁸ Four variables are used in this case: the growth rates of industrial production, personal income, employment, manufacturing and trade sales.

with Blanchard (1986). That study traced the source of business cycles to a mixture of large and small shocks, rather than purely small shocks as portrayed by the Slutsky-Frisch impulse-propagation scheme. Moreover, the shocks were found to have stemmed equally likely from fiscal or monetary factors as from real-sector demand and supply factors. The finding probably played a key role in motivating Watson into exploring the DFM route in his subsequent collaboration with Stock. But the short of expected forecasting success of their 1989 experiment kept many modellers in doubt of the adequacy of the DFM approach in providing better forecasts without using any economic theory. While time-series modellers continued to elaborate various statistical devices, eg merging DFM with switching-regime models and experimenting with probit models to focus on probability forecasts of turning points, more conventional modellers endeavoured to build dynamically robust structural models which would survive regime shifts. The most prominent models there were the error-correction type, often with embedded long-run cointegrating relations (see Qin, 2009), to accommodate the postulate that recessionary turning points indicated shifts in the long-run trend of co-trending variables rather than just transitory swings. Still, more theoretical minded modellers pursued the DSGE approach with the belief that more accurate forecasts should result from larger scale DSGE models because it offered a clear causal rationale of how shocks from various sectors would propagate through a well-defined economic system. The 1990s became an era of diverse research pursuits in business cycle modelling. Irrespective of different research strategies, however, prediction of onset of recessions remained tenaciously beyond reach, in spite of visible improvement of models in terms of internal consistency, technical complexity and reduction of *ad hoc* judgments involved.

8.6 Critical Assessment

The over four decades of econometric research on business cycles after WWII exhibit a significant shift away from the Haavelmo-CC paradigm. Modellers' attention has shifted from SEMs to dynamic models, from estimating structural parameters to simulating shock effects via dynamic models and devising statistic measures to characterise cyclic phenomena, from focusing on modelling the mechanism of cyclical movements associated with long-run equilibrium of an idealised economy to forecasting shorter-run fluctuations in macro data series. As research trends swing from confirmative analyses of given theories to data exploratory analyses, the Haavelmo-CC structural modelling tradition has apparently been negated and forsaken.

A closer reflection on the history, however, reveals an opposite side – a methodological assimilation of the tradition of NBER business cycle analysis by the Haavelmo-CC approach, catalysed by time-series statistical methods. To a great extent, the past decades have been dominated by statistical formalisation of NBER's ad hoc measures and procedures, as shown from the previous sections. The formalisation was essentially aimed at scientisation of those measures and procedures in that they should be built on the probability foundation with maximum internal rigour and minimum use of outside-model human judgments. Such a methodological conviction has guided econometric studies in business cycles to more detailed, segmented and narrowed-down issues, such as whether cyclic measures should be based on trended or detrended data, whether cycles should be asymmetric with respect to their upturns and downturns, and whether the shocks supposedly triggering business cycles should be small or large, purely erratic or autocorrelated, or be originated from the real sector of the monetary sector. The extensive and synthetic style of the Burns-Mitchell tradition has been long neglected.

So what is the achievement of amalgamating the Haavelmo-CC methodology with the NBER approach? The scientific advance in econometric business cycle studies is

undeniably substantial since the Burns-Mitchell era. The rift between the CC and the NBER camps has been long buried and econometric modelling has extended its field from adding empirical content to business cycle theories to exploring data features and devising new representative measures. But the advance lessens significantly when it comes to practical results, especially judging by the success rate in forecasting onsets of recessions. The latest financial crisis and the subsequent economic contraction went virtually undetected by the radar of regular forecasters aided by econometric models. In fact, there remains a considerable gap between what the academic has embraced and endeavoured to achieve in research and the ways that econometrics has been used by practitioners in producing business forecasts. None-model based human judgment plays an indispensable role in the making of those forecasts, eg see Turner (1990) and Clement (1995). Furthermore, it is often the case that a simple pool of forecasts would outperform individual forecasts based on particular modelling methods, eg see Stock and Watson (1999). These observations remind us of the impossibility of ever building a correct model to match the economic reality perfectly and, in particular, of the empirical limit of econometric methods in utilising all the information relevant to business cycles.

Ironically, the limit has been assessed critically periodically but somehow ignored by the core research community. One early major critique by Morgenstern (1928) even precedes the Slutsky-Frisch scheme.¹⁹ For the postwar period, severe doubt on both the CC approach and the NBER approach was expressed by Wright in a sweeping statement, ‘I simply do not believe that any set of econometric models, or any set of mathematical formulae, will ever suffice for reliable economic forecasting over any great length of time. The element of novel social conception is always breaking in’ (1951; p147). Shortly prior to that, Gordon (1949) grouped the two approaches under the name of ‘statistical

¹⁹ For a critical summary of the book, see Marget (1929).

approach’, as opposed to the ‘historical approach’ which placed its focus on explaining particular cycles using all kinds of relevant information, and argued for a blend of the two, a ‘quantitative-historical’ approach, as the promising direction of future research, see also Roose (1952). After years of statistical research in business cycles, Burns acknowledged ‘that it is vital, both theoretically and practically, to recognize the changes in economic organization and the episodic and random factors that make each business cycle a unique configuration of events. Subtle understanding of economic change comes from a knowledge of history and large affairs, not from statistics or their processing alone’ (1969, p85). These messages were reiterated by Zarnowitz twenty years after, ‘because business cycles are not all alike and are subject to historical changes along with the structure and institutions of the economy, it is not surprising that the numerous efforts to model them as a uniform by-product of one type of random shock or another have failed’ (1992, p17).

The above quotations ascribe the limit to neglect of unique social-historical conditions of different business cycles in econometric research. Amalgamation of the Haavelmo-CC methodology with the NBER methods has certainly led the ‘statistical approach’ further away the ‘historical approach’. Wide conviction of superiority of the science method has converted the econometric community largely to a group of fundamentalist guards of mathematical rigour and internal consistency. It is often the case that mathematical rigour is held as the dominant goal and the criterion for research topic choice as well as research evaluation, so much so that relevance of the research to business cycles is reduced to empirical illustrations. To that extent, probabilistic formalisation has entrapped the econometric business cycle research in pursuit of means at the expense of ends.²⁰ It is thus not unforeseeable that those studies have failed to

²⁰ See the recent book by Swann (2006) for a more general and thorough critique of the attitude of taking econometrics as a ‘universal solvent’ at the expense of ‘vernacular knowledge’ in applied economics.

generate any significant breakthrough in predicting and explaining business cycles in the real world.

On the other hand, the history of science tells us that major paradigm shifts would not occur until all possible routes within the existing paradigm have been trodden. Once the depth and precision of the formalisation has gone far outpaced what is needed for analysing the extensive and multi-facet attributes of business cycles, the research community would hopefully readjust its considerable underestimation of the importance of the historical approach, or the 'art' side in business cycle research.

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**This working paper has been produced by
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