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Sir David Hendry: An Appreciation from Wall Street and What Macroeconomics Got Right

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Sir Davis Hendry is soon celebrating his 80th birthday! Why should Wall Street researchers care about Sir David Hendry? What should be a role for macroeconomic forecasting on portfolio selection? What do the forecasting works and software of Professor Hendry offer Wall Street that its researchers have yet to exploit? This author offers a unique perspective on the outstanding software, Autometrics, of Professor Hendry and his colleagues. The application of saturation variables in a changing world to address structural breaks in financial data. Financial economists since the time of Harry Markowitz, William (Bill) Sharpe, Martin Gruber and Ed Elton, Burton Malkiel, and Haim Levy, have modeled corporate earnings and stock process to create diversified portfolios that may incorporate financial anomalies. Wall Street researchers seek with great effort to beat the stock market. The author believes that the empirical research of Geoffrey Moore, Victor Zarnowitz, and David Hendry should be integrated into portfolio selection. Empirical evidence is reported that the Leading Economic Indicators (LEI), enhanced by Geoffrey Moore and Victor Zarnowitz, have led real US GDP, 1993-2023. A rising US GDP and stock market have been accompanied by outstanding corporate earnings, corporate earnings per share forecasts, and active portfolio returns, 1995 -2023. Professor Hendry's software, Autometrics, could be a great resource of enormous value to portfolio construction and management as a tool for portfolio lambda setting.

The author believes that the macroeconomic empirical research of Geoffrey Moore, Victor Zarnowitz, and David Hendry should be integrated into portfolio selection to enhance the Markowitz and Sharpe risk-return tradeoffs. Empirical evidence is reported that the Leading Economic Indicators (LEI), enhanced by Geoffrey Moore and Victor Zarnowitz, have led real US GDP, 1993-2023. A rising US GDP and stock market have been accompanied by outstanding corporate earnings, corporate earnings per share forecasts, eps, and active portfolio returns during that period. EPS and EPS forecasts in robust regression models drive the portfolio selection process, 1993 -2023. The LEI is an example of US macroeconomics done right!

1. Do Earnings and Earnings Forecasts Matter?

Do earnings matter? The consensus among most economists is yes. Benjamin Graham and David Dodd, in their classical *Security Analysis* (1934), are presently considered by many, including Warren Buffet, the preeminent financial contributors to the theory of stock valuation. In Chapter 27, "The Theory of Common-Stock Investment," Graham and Dodd discussed their explanation for the departure of the public from rational common valuation during the 1927-1929 period. Graham and Dodd attributed much of the valuation departures to the instability of intangibles and the dominant importance of intangibles (p. 301). Graham and Dodd in their various editions of *Security Analysis* considered earnings integral in establishing intrinsic value and stock purchasing opportunities. Graham and Dodd used earnings and intrinsic value determination in the Graham-Newman Corporation portfolio management objectives. [1] John Burr Williams (1938), in his dissertation at Harvard, proposed that the value of a stock should equal the present value of its expected future dividends, which are paid earnings. Williams included the Graham and Dodd low price-to-earnings strategy and the Graham and Dodd net current asset value (buying stocks for their "liquidation" or break-up value) strategy. Harry Markowitz often tells the story of his epiphany, in the basic concepts of portfolio theory came to him one afternoon in the library while reading John Burr Williams' *Theory of Investment Value* [Markowitz (2002)]. [2] Williams proposed that the value of a stock should equal the present value of its future dividends, which is dependent upon corporate earnings. . Since future dividends are uncertain, Harry interpreted Williams' proposal to be to value a stock by its expected future dividends. But if the investor were only interested in expected values of securities, he or she would only be interested in the expected value of the portfolio; and to maximize the expected value of a portfolio one need invest only in a single security. This, Harry knew, was not the way investors did or should act, emphasizing that no one would put all of their eggs in one basket. Investors diversify because they are concerned with risk as well as

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[1] Benjamin Graham and Jerome Newman created the Graham and Newman Corporation in 1936 to buy stocks in companies whose price was less than their intrinsic value. Graham and Newman engaged in hedging these opportunities. In their 1946 letter to stockholders, Benjamin Graham wrote, on January 31, 1946, that their 4 million portfolio composed of $2.18 million of bonds, $0.86 million of preferred stock, and $1.13 million of common stock had produced a return over its 10 years of existence of 17.56 percent while the S&P had produced a corresponding return of 10.1 percent and the Dow has returned 10.0 percent. The Graham-Newman Corporation was liquidated upon the retire of Benjamin Graham as its President in 1955. Clearly Benjamin Graham, as a faculty member at Columbia University, and as President at the Graham-Newman Corporation believed that his valuation techniques, based upon purchasing low PE stocks worked. Earnings mattered.

[2] When it was time to choose a topic for Harry's dissertation, a chance conversation with Professor Marschak led to Markowitz applying mathematical methods to the stock market. Professor Marschak not only thought it reasonable, but explained to Harry that Alfred Cowles, grandson of a part-owner of *The Chicago Tribune* and founder of the Cowles Foundation, himself had been interested in such applications. Professor Marschak sent Harry to Professor Marshall Ketchum who provided a reading list as a guide to the financial theory and practice of the day.

return.[3]. The riskiness of the portfolio was composed not only of the riskiness of the individual securities, as measured by the standard deviation, but also by the relative movements of securities to one another, as measured by the covariance or correlation coefficient of securities. To minimize risk, one seeks to identify securities with lower, if not negative, covariance or correlation coefficient. Since there were two criteria - expected return and risk – the natural approach for an economics student was to imagine the investor selecting a point from the set of Pareto optimal expected return, variance of return combinations, now known as the efficient frontier.[4] Markowitz portfolio analysis has always been concerned with finding the maximum return for a given level of risk, or the minimum risk for a given level of return. The expected returns in portfolio selection would be determined by analysts, preferably based on dividend (and earnings) forecasts.

In 1960, Francis Nicholson, vice president of Provident Tradesmens Bank and Trust Co., Philadelphia, documented the effectiveness of the low price-earnings (PE) strategy during the 1934 -1959 period in the *FAJ.* Using a sample of 100 common stocks of high quality of trust bank investment quality, observed that smaller PE stocks substantially and consistently outperformed higher PE stocks by over 40 percent. James McWilliams (1966) of The Continental Illinois National Bank & Trust Co. reported results of a price-earnings ratio test using data from the Standard & Poor's 900 Industrial Company Compustat tape. The McWilliams sample universe was composed of 390 companies with December fiscal years with complete 12-year histories of April 30 prices, 1952 -1964. McWilliams reported that the lowest decile PE stocks had an average return of 23 percent during the 1952 -1964 period, whereas

[3] James Tobin, of Yale University and The Cowles Foundation, brought Markowitz to New Haven where he produced his Portfolio Selection (1959) monograph.
[4] It was from Koopmans' course on "activity analysis" in which Professor Koopmans distinguished between efficient and inefficient production activities, that Harry decided to label the combinations of risk and return which were not dominated by other combinations as efficient. Hence, the birth of the "Efficient Frontier." The efficient frontier traces out the optimal points along the risk-return frontier. The choice of portfolio expected return and standard deviation is determined by the investor's tolerance of risk. It is important to distinguish between Harry's dissertation and seminal article, entitled "Portfolio Selection", published in 1952, and his Cowles Commission monograph, entitled Portfolio Selection: Efficient Diversification of Investments of 1959. Professor Markowitz makes greater use of the derivation of the "Critical Line Algorithm" in Chapter 8 of this monograph. Moreover, Harry devoted Chapter 9 to "The Semi-Variance", or downside risk measurement avoidance.

decile 10, the highest decile PE stocks had a 15 percent.[5] William Breen (1969) examined the Low PE strategy relative to a high growth set of stocks over time for each year during the 1953 – 1966 time period. During the 1953 -1966 tine period, portfolio one outperformed portfolio two by approximately 14 percent, 37.5 percent to 23.9 percent, on a compounded annualized basis. Victor Niederhoffer and Patrick Reagan (1972) examined 1253 common stocks listed on the New York Stone Exchange (NYSE) during 1970 -1971. The NYSE was far more volatile than the Dow Jones Industrial Average (DJIA) stocks, with almost one-half of the NYSE stocks gaining or losing at least 20 percent, whereas the DJIA stocks averaged a 4.8 percent gain in 1970. Niederhoffer and Reagan selected the 50 best and the 50 worst (price) performers for closer scrutiny, on the assumption that the earnings/performance relationship would be magnified under such a sample. The earnings predictions were taken from the March 31, 1970 edition of the Standard and Poor's "Earnings Forecaster".[6] Profitability was the most important factor separating the best from the worst-performing stocks. In terms of reported 1970 earnings compared to year-earlier results, 45 of the top 50 registered increases, a feat achieved by only four of the bottom 50 stocks. Furthermore, 20 of the top 50 recorded earnings gains of at least 25 per cent, whereas all but six of the bottom 50 suffered declines in excess of 25 per cent. The superior and the inferior performers also differed greatly when actual earnings were compared to the forecasts. [7]

Niederhoffer and Reagan summarized their results that the common characteristics of the companies registering the best price changes included a forecast of moderately increased earnings and a realized profit gain far in excess of analysts' expectations. The worst-performing stocks were characterized by severe earnings declines, combined with unusually optimistic

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[5] In his conclusion, McWilliams offered a unique perspective on quantitative modeling in 1966, “We view this whole area of using the computer as an aid for improving our analytical and portfolio results with enthusiasm at the Continental Bank. The computer offers the financial community the opportunity of becoming increasingly sophisticated in the area of selecting common stocks and blending them into better portfolios for our customers.”.

[6] Prior to the creation of the Institutional Estimate Brokerage Service (IBES) database, the S&P “Earnings Forecaster” was a great resource for academicians, although the database was in print-only. In the early-1980s, Guerard made many trips to 25 Broadway to use the S&P data book.

[7] The Breen and Niederhoffer and Reagan studies were included in an excellent survey of random walk and efficient markets, in Charles Kuehner, “Efficient Markets and Random Walk”, in Sumner N. Levine, Editor, *Financial Analyst’ Handbook I: Methods, Theory, and Portfolio Management* (Homewood, Illinois: Dow Jones-Irvine, Inc., 1975).

forecasts. The four FAJ studies reflected the consensus that earnings mattered from 1934 to 1972. The study authors were a mix of practitioners; bankers and a hedge fund manager; and William Breen was an academician.[8]

Prior to 1976, there was no electronic database of consensus (by brokerage firm) or detailed (by analyst) database. The I/B/E/S database of analysts' earnings per share (eps) forecasts is created in the early 1980s and this resource allows academicians to test larger samples of earnings, forecasted earnings, and over much longer periods of time. Analysts become more accurate as time passes during the year, and quarterly data is reported.

Edwin Elton, Martin Gruber, and Mustafa Gultekin (1981) created a database of 919 one-year-ahead consensus analysts' eps forecasts and 696 two-year-ahead consensus analysts' eps forecasts of 1973, 1974, and 1975 that would evolve into the I/B/E/S database, with (US) data starting in January 1976. Elton, Gruber and Gultekin (EGG, 1981) tested whether analysts' forecasts, their expectations, were incorporated into share prices. EGG asked the question whether excess returns could be earned by selecting stocks on the basis of the highest consensus growth rate. The answer was "no". Share prices were incorporated into stock prices. However, investors with perfect forecasting ability could make risk-adjusted excess returns. An analyst selecting among the top 30% of the firms that have the most underestimated "true" earnings, could earn a 4.54% excess return if selects correctly 50% of the time. In the King's English, the top 30% of the firms of the firms achieving the highest earnings growth, above expectations, could achieve positive and statistically significant excess returns, whereas, the bottom 30% of

[8] Sanjoy Basu (1977) reported the continued effectiveness of the low PE strategy from September 1956 to August 1971, using the Compustat Industrial file and 375 - 400 stocks that had been delisted due to bankruptcies and acquisitions. The 1400 company database, composed of December-fiscal year end firms, contained 753 firms in its largest year of analysis and an average database of 500 firms during the 14-year analysis. The Basu study was important and has been well-cited because of its inclusion of the delisted firms and because of its Capital Asset Pricing Model (CAPM) residual methodology. The Basu results were stunning in that using a much larger sample of firms, including delisted companies over a longer time period, the lower PE portfolios outperformed the higher PE portfolios such that the Treynor and Sharpe ratios, the ratios of excess returns relative to the portfolio betas and standard deviations, respectively. Furthermore, the Jensen alpha was negative for the higher PE portfolios and positive for the lower PE portfolios. The betas, the measure of portfolio systematic risk, was lower in the lower PE portfolios. After adjusting for taxes and transactions costs, Basu reported that the lower PE strategy stocks produced between 2.0 - 3.5 percent higher returns than randomly selected portfolios. Hence, the information of earnings was not perfectly incorporated into share prices and returns of low PE stocks were a statistically verified anomaly. Basu (1983) published a second study of the low PE strategy. Sanjoy Basu again used the Compustat Industrial database and the CRSP data for the December 1962 to 1978 period

the firms of the firms achieving the lowest earnings growth, below expectations, could suffer negative and statistically significant negative excess returns. It is not the eps forecast that allows investors or managers to earn excess returns, but the eps revisions, particularly ss the months approach the end of the fiscal year. The EGG result was very similar to the Niederhoffer and Reagan result, but with a much larger sample and more risk-adjusted excess returns.

In 1988, Bruce Jacobs and Kenneth Levy, published a study of some 25 anomalies previously identified in the financial literature from January 1978 to December 1986 and reported that the low PE, the past three months of EPS estimate revisions, the sales-to-price, the one-month and two-month residual reversal in stock price, and the size variables were highly statistically significant variables. Jacobs and Levy ran generalized least squares regressions on the 108-month anomalies to determine the “naive” effects, using univariate regression analysis, and “pure” effects, using multivariate regression to account for all other anomalies and industry effects. The low PE, the past three month estimate revisions, the sales-to-price, one-month residuals, and size variables were statistically significant in the pure anomaly results. Less than one-half of the previously reported anomalies were statistically significant in the Jacobs and Levy (1988) study.

In 1991, Harry Markowitz developed a quantitative equity management system, Daiwa Portfolio Optimization System (DPOS), at Daiwa Securities Trust Company in Jersey City, NJ. Financial modeling of the expected return used traditional fundamental variables, such as earnings-to-price, book value-to-price, cash flow-to-price, sales-to-price, cash flow-to-price, small size, institutional holdings, earnings forecasts, revisions, recommendations, and breadth, earnings surprises, dividend yield variables identified in Dimson (1988), Jacobs and Levy (1988), and on-going conversations with William (Bill) Ziemba as anomalies.[9] DPOS built stock

[9] Bloch, Guerard, Markowitz, Todd, and Xu (1993), Ziemba and Schwartz (1993), Chan, Hamao, and Lakonishok (1991) specifically addressed many of the earlier reported non-U.S. anomalies and /or compared U.S. and non-U.S. anomalies. Testing and reporting on financial anomalies in October 2019 at The Q-Group meeting, andan earlier version published by Guerard, Deng, Gillam, Markowitz, and Xu, in *Wilmott* (2020), we find that many of the Nerlove (1968), Jacobs and Levy (1988), Levy (2012), Bloch, Guerard, Markowitz, Todd, and Xu (1993), Ziemba and Schwartz (1993), Chan, Hamao, and Lakonishok (1991), and Haugen and Baker (1996) variables have continued to produce statistically significant Active and Specific Returns in the post-publication period, 1995 – 2020 time period. The forecasted earnings acceleration variable has produced statistically significant Active and Specific Returns in the Post-Global Financial Crisis Period. The composite model of earnings, price momentum, and

selection models and created Markowitz Mean-Variance Efficient Frontiers for US and Japanese stock markets. The reader is referred to Guerard, Deng, Gillam, Markowitz, and Xu (2020) for the role of earnings and earnings forecasting in US, international, and global markets, DPOS, and post-DPOS modeling, 2003 -2018.

Langdon Wheeler (1994) developed and tested a strategy in which analyst forecast revision breadth, defined as the number of upward forecast revisions less the number of downward forecast revisions, divided by the total number of estimates, was the criteria for stock selection. Wheeler found statistically significant excess returns from the breadth strategy using the I/B/E/S database from January 1981 to December 1989. The mean information coefficient (IC) of the Wheeler IC of breadth strategy is 0.08, with a standard deviation of 0.07, producing a statistically significant IC.

Bartram and Grinblatt (2019) estimated monthly fair values of 25,000+ stocks from 36 countries for the 1993 -2016 period. A trading strategy based on deviations from fair value earns significant risk-adjusted returns ("alpha") in most regions, especially the Asia Pacific, that are unrelated to known anomalies. The strategy's 40–70 basis point per month alpha difference between emerging and developed markets contrast with Griffin, Kelly, and Nardari (2010) paper mentioned above, concludes that emerging markets have similar or smaller return spreads and thus, are *not* less efficient than developed countries' markets, and Jacobs (2016), finds that profits from 11 anomalies are not more prevalent in emerging markets. A country's pre-transaction-cost alpha is positively related to its trading costs but exceeds country-specific institutional trading costs. Thus, global equity markets are inefficient, particularly in countries with quantifiable market frictions, like trading costs. The Bartram and Grinblatt (2021) variables producing statistically significant were their market mispricing signal, the book-to-price ratio, earnings yield, gross profitability, and momentum.

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fundamental data is a consistent source of alpha in the U.S. and international markets. Excess returns are greater in international stocks than in U.S. stocks.

In summary, yes, over 90 years of financial research suggests that earnings matter. earnings matter,

2. Portfolio Selection in a Changing World, One of Business Cycles

In this section, we introduce the reader to the practitioner-oriented business cycles research works of Geoffery Moore and Victor Zarnowitz, at the National Bureau of Economic Research (NBER) and complementary research of Professor Herman Stekler and David Hendry. Mr. Moore edited a two-volume set of collected NBER studies of the 1938 -1960 period under the title, *Business Cycle Indicators: Contributions to the Analysis of Current Business Conditions* (Princeton, NJ: Princeton University Press, a study by the National Bureau of Economic Research, 1961). Hereafter, we will refer to this volume as Moore, BCI, 1961. Mr. Moore discussed why he included the ten essays of Part One on the selection, testing, and interpretation of business cycle indicators. These essays showed how NBER conducted its research to develop its indicators and underline of importance of continuing the program if further progress is to be made.[10] Volume One included a reprint of the May 28, 1938, NBER Bulletin 69, "Statistical Indicators of Revivals", by Mr. Wesley Clair Mitchell and Mr. Arthur F. Burns.[11] Mr. Mitchell and Mr. Burns proposed a set of 71 series and how they lead, or lagged business cycle revivals. These time series were among the 487-time series discussed in the previous chapter in the Burns

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[10] Moore, *Business Cycle Indicators: Contributions to the Analysis of Current Business Conditions, BCI*, p. xxiv.

[11] Business cycle research in the United States normally begins with Wesley Clair Mitchell *Business Cycles* (University of California Press, 1913). Mr. Mitchell and Mr. Burns listed their requirements for an ideal statistical indicator of cyclical revivals and recessions.

1. The modeling period should cover 50 years or longer under a variety conditions;
2. The series should lead cyclical revival centers by a 3–6-month time interval. Six months is preferred, and the lead time should be in variant;
3. The time series should sweep smoothly upward from each trough and sweep smoothing downward from each peak, showing no erratic movements;
4. The time series movements should be pronounced and recognizable, and its relative amplitude should be consistent;
5. The time series should be related to general business activity such that it establishes confidence that its past behavior in business cycles will be as its past behavior.

Mitchell and Burns identified 71 time series of revivals and recessions, and 49 that led two-thirds of the business revivals that occurred within the months covered by the data, many 1919-1932. The average lead or lag time refers to the average timing of the specific cycle revivals in each series relative to the reference dates of the business cycle revivals.

and Mitchell *Measuring Business Cycles* (1946).

Mr. Moore, in 1950, continued the NBER Burns and Mitchell research, listed seven series as leading indicators for reference cycle patterns of 1919-1938. These time series were (1) residential building contracts, floor space (2) the FRB industrial production index, (3) railroad locomotive shipments, (4) liabilities of business failures, (5) refined copper stocks, (6) NYSE bond sales and (7) agricultural marketing index (Moore, 1961, pp.192-193). Mr. Moore viewed corporate profits over the 1919-1938 period as a coincidental indicator, at troughs, Mr. Moore reports that three times as many time series lead than lag, stating that it is easier to identify indicators of revivals than recessions.[12] Thus, Mr. Moore and the NBER established the Leading Group of economic indicators, now known as the Leading Economic Indicators, or LEI. Mr. Moore created LEI component lists from 1950 -1983. Auerbach (1982) confirmed the Moore LEI variables led US GNP 1950-1979.

Mr. Victor Zarnowitz (1992) continued the Mr. Moore approach to LEI analysis which concentrated on what variables were recommended when for forecasting the economy. In Chapter 11 of his seminal monograph on business cycles, Mr. Zarnowitz listed the 35 economic variables included in the five NBER LEI components of 1950, 1960, 1966, 1975, and 1989. These lists were prepared by Mr. Moore, in 1950 and 1960, Mr. Moore and Mr. Shinkin, in 1966, Mr. Zarnowitz and Mr. Boschan, in 1975, and Mr. Hertzberg and Mr. Beckman, in 1989.[13] Is there consistency among the lists? Yes, and no. The average workweek of production current dollars of workers in manufacturing is the only variable included in all five LEI lists. New orders time series makes all five lists; new orders in durable goods is the 1950, 1960, and 1966 component whereas new orders in consumer goods and materials, in constant dollars, is the LEI component on the 1975 and 1989 lists. Stock prices are included in all five lists, but the Dow Jones Industrial Average is the stock price time series in the 1950 list, whereas, the Standard and Poor's 500 stock price index is included in the 1960, 1966, 1975, and 1989 LEI lists. The money

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[12] Moore, *BCI*, pp. 215-217. Geoffrey H. Moore, "Statistical Indicators Of Cyclical Revivals and Recessions", in Geoffrey H. Moore, Editor, *Business Cycle Indicators: Contributions to the Analysis of Current Business Conditions* (Princeton, NJ: Princeton University Press, a study by the National Bureau of Economic Research, 1961), pp. 184-260.

[13] Zarnowitz, *Business Cycles*, pp. 334-336.

supply is present on two lists, with M1, in constant dollars, on the 1975 list and M2, in constant dollars, on the 1989 list. Several economic time series make two lists: the layoff rate in manufacturing (1960 and 1975); corporate profits after taxes, in current dollars, and current liabilities of business failures are among the LEI components on the 1950 and 1960 lists; and building permits for new private housing, and contracts and orders for plant and equipment, in constant dollars, are among the LEI component on the 1975 and 1989 lists. Thus, about the average workweek, stock prices, and new orders are the most commonly used variables.

3. **Portfolio Selection in a Rapidly Changing World, the Need for *Autometrics***

Mr. Zarnowitz continued the NBER analysis of business cycles in the tradition of Mr. Mitchell, Mr. Burns, and Mr. Moore, his frequent co-author. In Chapter 6, we reviewed the Mr. Zarnowitz econometric model testing, reporting that econometric models, while often beating naïve, no-change models, failed to identify turning points. Mr. Zarnowitz, in his NBER monograph, *Business Cycles: Theory, History, Indictors, and Forecasting*, parts III and IV, verified the statistical significance on the LEI in forecasting, particularly real GDP. Mr. Zarnowitz continued the analysis of Mr, Moore and reported that the NBER LEI continued to be less than satisfactory in predicting turning points in business cycles.

In this section, we report on time series modeling and forecasting using The Conference Board (TCB) U.S. Leading Economic Indicator (LEI) as an input to forecasting real GDP and the unemployment rate. These time series have been addressed before, but our results are more statistically significant using more recently developed time series modeling techniques and software. We employ the automatic time series modeling and forecasting of Hendry and Doornik (2014) and Doornik and Hendry (2015) with its emphasis on structural breaks is very relevant for modeling the MZTT unemployment rate data. Montgomery, Zarnowitz, Tsay, and Tiao (MZTT, 1998) modeled the U.S. unemployment rate as a function of the weekly unemployment claims time series, 1948 – 1993. Xiao, Chen and Guerard (2022) reported similar conclusion is found for the impact of the LEI and weekly unemployment claims series leading the unemployment rate series. We report statistically significant breaks in these data, 1993 to the present, including the COVID period. Our results support the Xia, Chen and Guerard (2022) results using the Hendry *Autometrics* software.

As an introductory example, let us consider the U.S. real GDP as can be represented by an autoregressive integrated moving average (ARIMA) model. The data is differenced to create a process that has a (finite) mean and variance that do not change over time and the covariance between data points of two series depends upon the distance between the data points, not on the time itself – a transformation to stationarity. In economic time series, a first-difference of the data is normally performed.[14] The application of the differencing operator, d, produces a stationary autoregressive moving average ARMA(p, q) model when all parameters are constant across time. Many economics series can be modeled with a simple subset of the class of ARIMA(p, d, q) models, particularly the random walk with drift and a moving average term. The random walk with drift economic time series behavior is not new and can be traced back to Granger and Newbold (1977). Automatic time series models have recently been discussed in Hendry (1986), Hendry and Krolzig (2001, 2005), Hendry and Nielsen (2007), Castle, Doornik, and Hendry (2013), Hendry and Doornik (2014), and Castle and Hendry (2019) and implemented in the *Autometrics* software.[15] Hendry sets the tone for automatic modelling by contrasting how statistically – based his PC-Give and *Autometrics* work in contrast to the "data mining" and "garbage in, garbage out"

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[14] Box and Jenkins, *Time Series Analysis*. Chapter 6; C.W.J. Granger and Paul Newbold, *Forecasting Economic Time Series*. Second Edition (New York: Academic Press, 1986), pp. 109-110, 115-117, 206.

[15] Automatic time series modelling has advocated since the early days of Box and Jenkins (1970). Reilly (1980), with the Autobox System, pioneered early automatic time series model implementation. Tsay (1988) identified outliers, level shifts, and variance change models that were implemented in PC-SCA. SCA was used in modelling time series in MZTT (1998).

routines, citing their forecasting efficiency and performance. If one starts with a large number of predictors, or candidate explanatory variables, say n, then the general model can be written:

$$y_t = \sum_{i=1}^{n} \gamma_i Z_{it} + u_t. \qquad (1)$$

The (conditional) data generating processes is assumed to be given by:

$$y_t = \sum_{i=1}^{n} \beta_i Z_{(i),t} + \epsilon_t, \qquad (2)$$

Where

$$\epsilon_t \cong IN\ (0, \sigma_e^2) \text{ for any } n \leq N.$$

One must select the relevant regressors where $\beta_j \neq 0$ in (2). Hendry and his colleagues refer to equation (16) as the most general, statistical model that can be postulated, given the availability of data and previous empirical and theoretical research as the general unrestricted model (GUM). The Hendry general-to-specific modeling process is referred to as *Gets*. One seeks to identify all relevant variables, the relevant lag structure and cointegrating relations, forming near orthogonal variables, Z. The general unrestricted model, GUM, with s lags of all variables can then be written:

$$y_t = \sum_{i=1}^{n} \sum_{j=0}^{s} \beta_{i,j}\, x_{i,t-j} + \sum_{i=1}^{n} \sum_{j=0}^{s} k_{i,j}\, z_{i,t-j} + \sum_{j=1}^{s} \theta_j y_{t-j} + \sum_{i=1}^{T} \delta_i 1_{\{i=t\}} + e_t\ , \qquad (3)$$

where

$$\varepsilon_t \sim IN(0, \sigma_e^2).$$

Furthermore, outliers and shifts for T observations can be modeled with saturation variables, see Doornik and Hendry (2015) and Hendry and Doornik (2014, Chapters 7 & 14).

Automatic modeling seeks to eliminate irrelevant variables; variables with insignificant estimated coefficients; lag- length reductions; and reducing saturation variables (for each observation); the nonlinearity of the principal components; and combinations of ‘small effects’ represented by principal components.[16] One can consider the orthogonal regressor case in which one ranks the variables by their t-statistics, highest to lowest, and defines m to be the smallest, but statistically significant t-statistic, t_m^2, and discards all variables with t-statistics below the m largest t-values. We seek to select a model of the form:

$$y_t = \sum_{r=1}^{m} \delta_r Z_{\{r\},t} + n_t, \qquad (4)$$

where $Z_{\{r\},t}$ is a subset of the initial N variables.

One progresses from the general unrestricted model to the "final" model in (4) by establishing that model residuals are approximately normal, homoscedastic and independent. Model reduction proceeds by tree searches of insignificant variables. By omitting irrelevant variables, the selection model does not "overfit" the model and the relevant (retained) variables have estimated standard errors close to those from fitting equation (4).

Automatic time series models have recently been discussed in Hendry (1986), Hendry and Krolzig (2001, 2005), Hendry and Nielsen (2007), Castle, Doornik, and Hendry (2013), Hendry and Doornik (2014), and Castle and Hendry (2019) and implemented in the Autometrics software.[17]. Autometrics deals with outliers and breaks in its automatic time series modeling. The Residual Sum of Squares, RSS, decrease as the outlier criteria shrink. Autometrics apply can impulse indicator saturation variables IIS, step indicator saturation variables (SIS), differenced IIS (DIIS), and trend saturation (TIS) to all marginal models. where there are significant indicators.[18] Guerard (2022) applied the SAS and OxMetrics Hendry and Doornik automatic time series

[16] Doornik and Hendry (2013) remind the reader that the data generation process (DGP) is impossible to model, and the best solution that one can achieve is estimate the models to reflect the local DGP, through reduction, described above. The Auotmatic *Gets* algorithm reduces GUM to nest LGDP, the locally relevant variables. Congruency, in which the LGDP has the same shape and size as the GUM; or, models reflect the local DGP.

[17] Automatic time series modeling has advocated since the early days of Box and Jenkins (1970). Reilly (1980), with the Autobox System, pioneered early automatic time series model implementation. Tsay (1988) identified outliers, level shifts, and variance change models that were implemented in PC-SCA. SCA was used in modeling time series in MZTT (1998).

[18] The use of saturation variables avoids the issue of forcing a unit root to capture the shifts, leading to an upward biased estimate of the lagged dependent variable coefficient. The authors are indebted to Jenny Castle for her comments on the application of saturation variables, which she observes addresses this very well.

PCGive (OxMetrics) methodology to several well-studied macroeconomics series, real GDP and the unemployment rate in Guerard (2022), Chapter 7. Guerard, Thomakos, and Kyriazi (2020) reported that the OxMetrics and AutoMetrics system substantially reduced the residual sum of squares measures relative to a traditional variation on the random walk with drift model. Furthermore, the use of rolling window analysis (RWA) confirmed the *Autometrics* forecasts. The transfer function methodology of Ashley, Granger, and Schmalensee (1980) was used in the bivariate modelling of Guerard, Thomakos, and Kyriazi (2020) and Xiao, Chen, and Guerard (2022). The LEI work of Professors Mitchell, Moore, and Zarnowitz has stood the test of time, 1959 -2021.

The author was both an IJF Associate Editor (AE) and friend of Mr. Zarnowitz.[19] In anticipation of future LEI research, I applied for, and received, an updated The Conference Board LEI database as of November 30, 2023, and corresponding LEI data for the UK, China, Japan, Brazil, as the Euro-zone, 1995 -2023, for academic use-only. In that spirit, we updated the LEI models of real GDP, the unemployment rate, and the coincidental indicators reported in Guerard (2022). Furthermore, the author prefers modeling time series data in its raw form, see Table 1 for an Autometrics summary table of raw data, as well as the differenced data transformation, and difference in the logarithmic (DLog or DLOG) transformation of the time series, as found in Jenkins (1979). The reader is referred to Table 2 for an *Autometrics* summary table of the transformed data.

Let us examine the LEI important results using *Autometrics*. First, a traditional AR(1) model of the DLog-transformed quarterly real GDP, 1993 – 11/2023 is not adequately fitted, see Autometrics estimation (1). The model residuals fail the Henry-Doornik econometric diagnostic tests, see particularly the Normality test.

[19] Mr. Zarnowitz came to my Investments class at Rutgers in 2005 and gave a seminar on the LEI and its implications for economic growth and appreciation of stock markets. The author was a US and Euro-zone TCB LEI subscriber while Director of Quantitative Research at McKinley Capital Management, LLC,MCM, in Anchorage, Alaska for 16 years. During those 16 years, I served on the *IJF* and our research department tested the use of LEI in portfolio selection. In 2012, MCM developed a model using automatic time series to that identified dramatic decreases in the LEI were associated with large negative returns, six-to-nine months in the medium-term Axioma factor return. As Professor Dhrymes glibly told me when I mentioned our study, “Congratulations, John. The study is very well done, but it would have been far more profitable had you undertaken the study in 2005, when you joined McKinley, or 2007, when the Global Finance Crisis occurred”. Touche!

Table 1: US Real GDP AR1 *Autometrics* Estimation, 1993-2023

```
Autometrics Estimation (1) Modelling DLogRGDP by OLS

 The estimation sample is: 136 - 259

                  Coefficient  Std.Error  t-value  t-prob Part.R^2
DLogRGDP_1          -0.17039    0.08958     -1.90  0.0600   0.0289
Constant           0.0158234   0.005955      2.66  0.0089   0.0551
Trend          -4.35541e-05   2.922e-05    -1.49  0.1387   0.0180

sigma               0.0115673  RSS              0.0161899835
R^2                 0.0414415  F(2,121) =        2.616 [0.077]
Adj.R^2             0.0255976  log-likelihood        378.558
no. of observations       124  no. of parameters           3
mean(DLogRGDP)     0.00616533  se(DLogRGDP)        0.0117182

AR 1-2 test:      F(2,119)  =  0.23044 [0.7945]
ARCH 1-1 test:    F(1,122)  =   19.173 [0.0000]**
Normality test:   Chi^2(2)  =   115.98 [0.0000]**
Hetero test:      F(4,119)  =   8.7743 [0.0000]**
Hetero-X test:    F(5,118)  =   7.3606 [0.0000]**
```

We proceed to use Autometrics to identify the small real GDP residuals.

The application of the Hendry and colleagues *Autometrics* software produces a better, more statistically significant answer. Note the Residual Sum of Squares, RSS, falls from 0.0162 to 0.0011 in Estimation (2). The reader sees presence of several the differenced impulse-indicator and trend saturation variables during the COVID period. The Zarnowitz LEI, constructed and maintained in the NBER methodology of Mitchell-Burns, and Moore produces positive and statistically significant coefficients on the LEI one-period quarterly lag for the 1993 -2023 period.

Table 2: US Real GDP AR1 with Saturation Variables *Autometrics* Estimation, 1993-2023

```
Automerics Estimation (2) Modelling DLRGDP by OLS
The estimation sample is: 1993-01-01 - 2023-10-01

                  Coefficient  Std.Error  t-value  t-prob Part.R^2
Trend             2.96216e-05  3.904e-06     7.59  0.0000   0.3456
DLLEI_1              0.153934    0.01798     8.56  0.0000   0.4021
DI:2014-07-01     -0.00798389   0.002334    -3.42  0.0009   0.0970
DI:2020-10-01      -0.0862737   0.002550    -33.8  0.0000   0.9130
DI:2022-04-01       0.0100642   0.002336     4.31  0.0000   0.1455
I:2000-10-01        0.0157484   0.003493     4.51  0.0000   0.1572
I:2011-07-01      -0.00934832   0.003395    -2.75  0.0069   0.0650
T1:2000-01-01      0.00791117   0.001699     4.66  0.0000   0.1659
T1:2000-04-01     -0.00779976   0.001693    -4.61  0.0000   0.1630
T1:2008-07-01      0.00904325   0.001520     5.95  0.0000   0.2451
T1:2009-01-01      -0.0135357   0.002490    -5.44  0.0000   0.2133
T1:2009-10-01      0.00457437   0.001089     4.20  0.0001   0.1394
```

```
T1:2020-04-01       0.0100324   0.001783     5.63  0.0000   0.2250
T1:2020-10-01      -0.0316733   0.005082    -6.23  0.0000   0.2627
T1:2021-01-01       0.0216553   0.003408     6.35  0.0000   0.2703

sigma              0.00330028  RSS             0.00118721146
R^2                  0.929731  F(14,109) =     103 [0.000]**
Adj.R^2              0.920705  log-likelihood         540.55
no. of observations       124  no. of parameters          15
mean(DLRGDP)       0.00616533  se(DLRGDP)          0.0117182

AR 1-2 test:      F(2,107)  =   2.6439 [0.0757]
ARCH 1-1 test:    F(1,122)  =   1.3744 [0.2433]
Normality test:   Chi^2(2)  =   4.6713 [0.0967]
Hetero test:      F(20,99)  =  0.72836 [0.7883]
Hetero-X test:    F(28,91)  =  0.54968 [0.9631]
RESET23 test:     F(2,107)  =  0.33124 [0.7188]
```

The residuals in Estimation (2) are more consistent with the *Autometrics* diagnostic tests.

Mr. Zarnowitz modeled real GDP in his (1992) magnum opus on business cycles. Mr, Zarnowitz moved from modeling real GDP to a composite Coincident Economic Indicator, CEI, that included real GDP. In *Autometrics* Estimation (3), we report that the DLOG-transformed LEI significantly leads the DLOG-transformed CEI at lag two, 1993-2023.

Table 3: TCB CEI AR1 with LEI and Saturation Variables *Autometrics* Estimation, 1993-2023

```
Autometrics Estimation(3) Modelling DLCEI by OLS
The estimation sample is: 1993-01-01 - 2023-10-01

                  Coefficient  Std.Error  t-value  t-prob Part.R^2
Trend             1.76620e-05  3.610e-06     4.89  0.0000   0.1828
DLLEI_2              0.110922    0.01896     5.85  0.0000   0.2423
DI:2005-10-01     -0.00707362   0.002237    -3.16  0.0020   0.0855
DI:2008-04-01      -0.0125269   0.003264    -3.84  0.0002   0.1210
DI:2008-07-01       0.0760036   0.006501     11.7  0.0000   0.5609
DI:2008-10-01       0.0576289   0.005133     11.2  0.0000   0.5408
DI:2009-01-01       0.0202465   0.003500     5.78  0.0000   0.2382
DI:2020-04-01       -0.138064   0.003290    -42.0  0.0000   0.9427
DI:2020-07-01      -0.0305645   0.003894    -7.85  0.0000   0.3654
I:1995-04-01       -0.0105491   0.003243    -3.25  0.0015   0.0900
I:2008-07-01        -0.102787   0.008779    -11.7  0.0000   0.5616
T1:1999-10-01      0.00248674  0.0003686     6.75  0.0000   0.2984
T1:2001-01-01     -0.00267145  0.0003748    -7.13  0.0000   0.3219
T1:2006-07-01     0.000387900  8.811e-05     4.40  0.0000   0.1534
T1:2020-01-01       0.0221190   0.006344     3.49  0.0007   0.1020
T1:2020-04-01      -0.0458995    0.01261    -3.64  0.0004   0.1101
T1:2020-07-01       0.0236992   0.006333     3.74  0.0003   0.1157

sigma               0.0031631  RSS            0.00107055809
R^2                  0.967682  F(16,107) =   200.2 [0.000]**
Adj.R^2              0.962849  log-likelihood        546.963
no. of observations       124  no. of parameters          17
mean(DLCEI)         0.0045788  se(DLCEI)           0.0164186

AR 1-2 test:      F(2,105)  =  0.10190 [0.9032]
```

```
ARCH 1-1 test:     F(1,122)  =0.0048424 [0.9446]
Normality test:    Chi^2(2)  =  0.36490 [0.8332]
Hetero test:       F(15,99)  =  0.50267 [0.9340]
Hetero-X test:     F(21,93)  =  0.54926 [0.9409]
RESET23 test:      F(2,105)  =  0.97649 [0.3800]
```

The two-quarter lagged LEI variable lead the CI time series and are positive and statistically significant, with reported t-statistic of 5.85. The model is adequately fitted, as reported in the diagnostics.[20]

Finally, we report quarterly Montgomery, Zarnowitz, Tsay, and Tiao (MZTT, *JASA*, 1998) unemployment rate replication analyses for the 1993 -2023Q3 period in *Autometrics.* The analysis follows Guerard, Thomakos, and Kyriazi (2020) and Guerard (2022). We report results of modeling Weekly Unemployment Claims derived from Autometrics analysis of The Conference Board (TCB) database, as of November 2023.

Table 4: The US Unemployment Rate AR1 *Autometrics* Least Squares Estimation, 1993-2023

```
Autometrics Estimation EQ(4) Modelling DUER by OLS

The estimation sample is: 1993-01-01 - 2023-10-01

                  Coefficient  Std.Error  t-value  t-prob Part.R^2
DUER_1              -0.167129    0.08964    -1.86  0.0647   0.0279
Constant          -0.00778855     0.5897  -0.0132  0.9895   0.0000
Trend            -0.000127414   0.002924  -0.0436  0.9653   0.0000

sigma                 1.16542  RSS                 164.344045
R^2                 0.0279341  F(2,121) =      1.739 [0.180]
Adj.R^2             0.0118669  log-likelihood       -193.413
no. of observations       124  no. of parameters           3
mean(DUER)         -0.0274194  se(DUER)               1.1724

AR 1-2 test:       F(2,119)  =   2.5399 [0.0831]
ARCH 1-1 test:     F(1,122)  =  0.27926 [0.5981]
Normality test:    Chi^2(2)  =   1086.5 [0.0000]**
Hetero test:       F(4,119)  =  0.94838 [0.4387]
Hetero-X test:     F(5,118)  =  0.77791 [0.5675]
RESET23 test:      F(2,119)  =   12.967 [0.0000]**
```

The *Autometrics* estimation (4) with Least Squares, OLS, is our benchmark for post-1993 Victor Zarnowitz validation. The model residuals suffer my outliers or structural breaks, see Figure 1.

[20] I believe Mr. Zarnowitz would be very pleased with both al GDP and CEI analysis results, as he was with the author's LEI work in 2001 and 2004

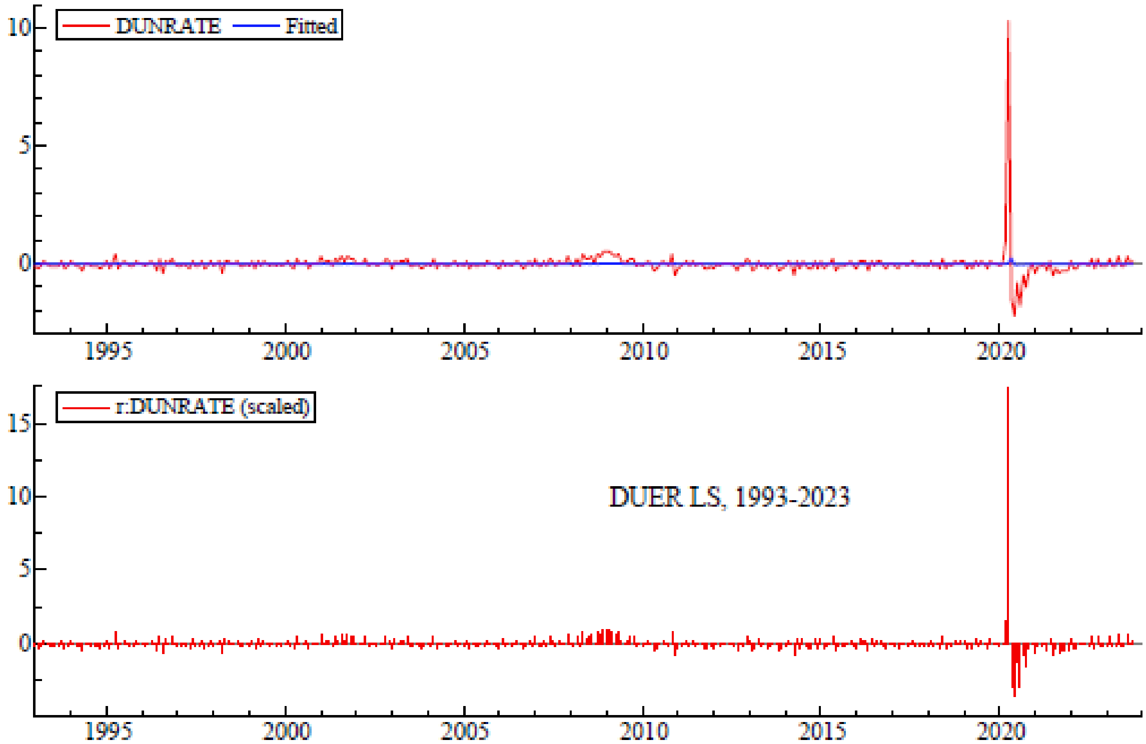

Figure 1

We report that Weekly Unemployment Claims derived from *Autometrics* analysis of The Conference Board (TCB) database, as of November 2023 lead the Unemployment Rate, as reported by MZTT in 1998, with data ending in 1993. We report two and three-quarters lags of unemployment claims lead the Unemployment Rate. Note the RSS falls from 164 to 3.67 in *Autometrics* Estimation (5). Clearly *Autometrics* estimation with saturation variables is necessary.

Table 5: The US Unemployment Rate AR1 with Weekly Unemployment Claims and Saturation Variables *Autometrics* Estimation, 1993-2023

Autometrics EQ(5) Modelling DUER by OLS

The estimation sample is: 1993-01-01 - 2023-10-01

	Coefficient	Std.Error	t-value	t-prob	Part.R^2
DLWkUNCL_2	1.19413	0.08925	13.4	0.0000	0.6259
DLWkUNCL_3	1.60892	0.2824	5.70	0.0000	0.2328
DI:2008-07-01	-2.40831	0.3298	-7.30	0.0000	0.3327
DI:2008-10-01	-1.84421	0.2698	-6.84	0.0000	0.3040
DI:2009-01-01	-0.817508	0.1899	-4.31	0.0000	0.1477
DI:2019-01-01	0.346961	0.1311	2.65	0.0094	0.0614
DI:2020-04-01	11.2516	0.1736	64.8	0.0000	0.9752
DI:2020-07-01	6.72376	0.2285	29.4	0.0000	0.8900
DI:2021-01-01	-3.96212	0.8311	-4.77	0.0000	0.1752

```
DI:2021-04-01        -1.84332     0.5531    -3.33  0.0012   0.0941
DI:2021-07-01        -1.82597     0.4420    -4.13  0.0001   0.1375
DI:2021-10-01        -2.31926     0.4537    -5.11  0.0000   0.1963
DI:2022-01-01        -1.66711     0.3591    -4.64  0.0000   0.1677
DI:2022-04-01        -1.06333     0.2626    -4.05  0.0001   0.1329
DI:2022-07-01       -0.555415     0.1805    -3.08  0.0027   0.0813
I:2008-07-01          3.09195     0.3812     8.11  0.0000   0.3808
I:2014-01-01        -0.571611     0.1854    -3.08  0.0026   0.0816

sigma                0.185357  RSS               3.67621789
log-likelihood        42.1922
no. of observations       124  no. of parameters          17
mean(DUER)         -0.0274194  se(DUER)              1.1724

AR 1-2 test:      F(2,105)  =   1.8216 [0.1668]
ARCH 1-1 test:    F(1,122)  =  0.17974 [0.6723]
Normality test:   Chi^2(2)  =0.0010455 [0.9995]
Hetero test:      F(17,101) =  0.52401 [0.9352]
Hetero-X test:    F(18,100) =  0.50236 [0.9515]
RESET23 test:     F(2,105)  =   1.0270 [0.3617]
```

The estimated residuals of Autometrics Estimation (5) pass all diagnostic tests. The saturation variables were reported for their statistically significance in Dhrymes (2017), when no one foresaw the pandemic.

We added the TCB LEI variable to the Weekly Unemployment Claims variable in The Conference Board (TCB) database, as of November 2023, and report that only the LEI leads the Unemployment Rate, with two-quarter and four-quarter lags during the 1993 -2023 period. We report two and three-quarters lags of unemployment claims lead the Unemployment Rate. The estimated residuals pass the normality test. See Figure 2 below.

Table 6: The US Unemployment Rate AR1 with Weekly Unemployment Claims and Saturation Variables *Autometrics* Estimation, 1993-2023

```
Autometrics EQ(6) Modelling DUER by OLS
The estimation sample is: 1993-01-01 - 2023-10-01

                  Coefficient  Std.Error  t-value  t-prob Part.R^2
DLLEI_2              -5.95501      1.288    -4.62  0.0000   0.1590
DLLEI_4              -3.11995     0.9888    -3.16  0.0021   0.0810
DI:2020-04-01         8.95877     0.1463     61.2  0.0000   0.9707
I:2020-10-01         -5.91088     0.2694    -21.9  0.0000   0.8099
T1:2008-01-01       -0.215167    0.04351    -4.95  0.0000   0.1779
T1:2009-01-01         1.27593     0.2124     6.01  0.0000   0.2421
T1:2009-04-01        -1.06135     0.1732    -6.13  0.0000   0.2495
T1:2019-10-01        -2.24354     0.1010    -22.2  0.0000   0.8138
T1:2020-04-01         4.74619     0.2019     23.5  0.0000   0.8302
T1:2020-10-01        -2.57817     0.1242    -20.8  0.0000   0.7923
T1:2022-07-01       0.0775306    0.01802     4.30  0.0000   0.1407

sigma                0.193804  RSS               4.24426613
log-likelihood        33.2838
```

```
no. of observations        124  no. of parameters          11
mean(DUER)          -0.0274194  se(DUER)               1.1724

AR 1-2 test:       F(2,111)  =   3.3705 [0.0379]*
ARCH 1-1 test:     F(1,122)  =  0.31691 [0.5745]
Normality test:    Chi^2(2)  =  0.79846 [0.6708]
Hetero test:       F(14,106) =  0.67583 [0.7932]
Hetero-X test:     F(27,93)  =   1.2026 [0.2544]
RESET23 test:      F(2,111)  =   2.7932 [0.0655]
```

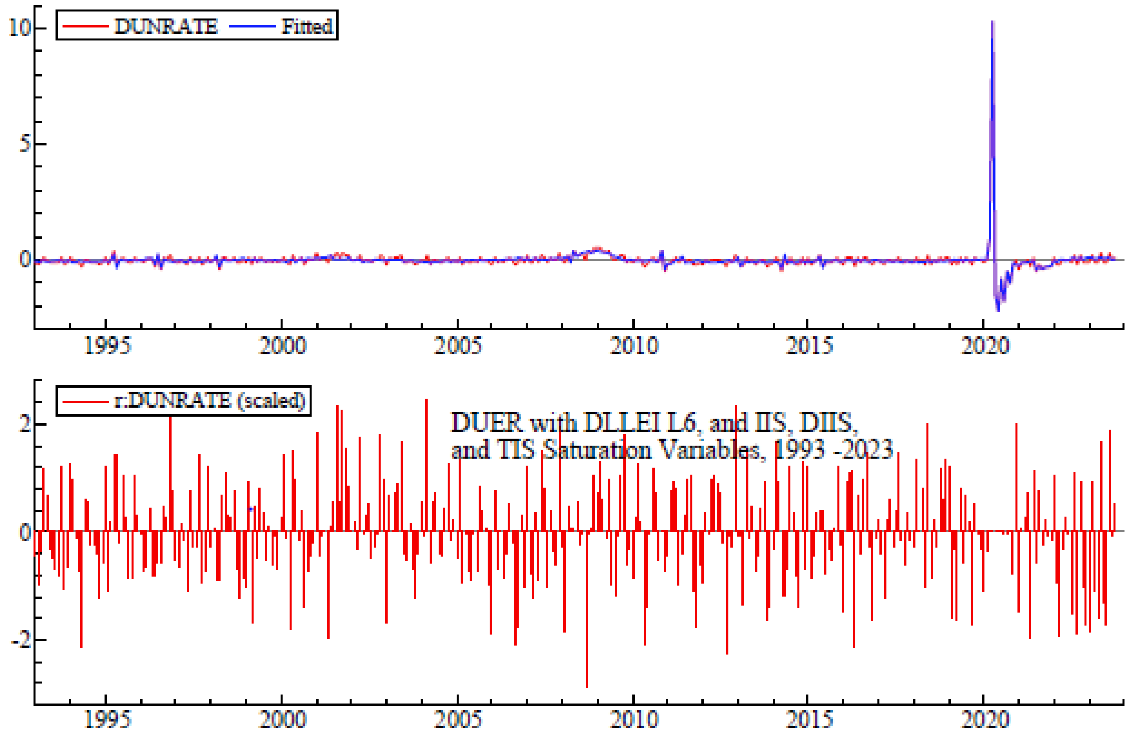

Figure 2

In Section 3, we used the latest Conference Board database and reported *Autometrics* estimations of real US GDP and the unemployment rate as a function if the Leading Economic Indicators, LEI, and one of its components, the weekly unemployment claims time series. We applied the Hendry and Doornik (2014) and Castle and Hendry (2019) automatic time series PCGive (OxMetrics) methodology to widely covered macroeconomic time series. We report that the OxMetrics and *Autometrics* system substantially reduce regression sum of squares measures relative to a traditional variation on the random walk with drift model. The modeling process of including the Leading Economic Indicator in forecasting real GDP has been addressed before, but our results are more statistically significant, using the latest data for model verification. A similar conclusion is found for the impact of the LEI and weekly unemployment claims series leading the unemployment rate series.

4. Empirical Verification of Risk and Return Models, Thirty Years of Markowitz and Ziemba Models

In this section, we use FactSet data, commercially available, as we reported to the reader in Guerard, Gillam, Deng, Markowitz, Xu, and Wang (2018). In this section, we use the FactSet data universe for the Russell 3000 (R3) Index constituents, for the January 1995 – December 2023 time-period.[21] The US portfolio selection problem can be solved by the "one button" approach within FactSet, see Beheshti, Guerard, and Mercs (2021). Within the Russell 3000 the REG10, CP, RCP, CTEF, REG8, and the I/B/E/S FEP1 and FEP2 factors produce the largest, and highly statistically significant, the REG10 Information Coefficients, ICs. The reader is referred to Table 7.

In optimized portfolios, using a 20% quarterly turnover, the REG8, REG10, and CTEF portfolios produce excess returns, subtracting 125 basis points of round-trip transactions costs, in the range of 100 (REG8) to 200-350 basis points, annualized, for CTEF and REG10 portfolios. The reader is referred to Table 8. The WLRR and forecasted earnings portfolios. portfolios of 1993 work to outperform the benchmark during the 1995-2023 period. Sharpe and Information Ratios often rise with higher tracking errors 6-8 %, as opposed to 4 %, more of an index-enhanced level. The authors have always pushed to maximize the Sharpe Ratios and geometric means, as

[21] In 2010, Stone and Guerard presented an update to the Guerard and Takano model at the CRSP Forum. The Japanese stock returns were from the Tokyo Stock Exchange from January 1975 through December 2005. The database used for both stock returns and financial statement data is the PACAP Research Center database of University of Rhode Island. The Stone and Guerard universe used all securities in the United States covered by the Center for Research in Security Prices (CRSP) database and had Compustat data on the Wharton Research Data Services (WRDS) files, 1980 - 2005.

advocated in Markowitz (1959) and Bloch et al. (1993). The original Markowitz Model presented in REG8 by John Guerard at the BPF in 1991 performs very well during the 1995 -2022 period! The REG8 and REG9 models contained many of the Ziemba (1991) fundamental factors.

5. Summary and Conclusions and Recommendations for Better Portfolio Selection in a Rapidly Changing World

In summary, early studies in the *Financial Analysts Journal* (*FAJ)* reported that the Graham and Dodd low PE strategy continued. Recent studies in the *FAJ* reported that academic and practitioner research using the I/B/E/S database, domestically and internationally, established that the low PE, or high EP, strategy continues to be statistically associated with stockholder returns. Do earnings matter? Yes!

. We applied the Hendry and Doornik (2014) and Castle and Hendry (2019) automatic time series PCGive (OxMetrics and *Autometrics*) methodology to widely covered macroeconomic time series, US real GDP, the US unemployment rate, and The Conference Board Coincidental Indicators Index, using the TCB LEI as an input. We report that the OxMetrics and *Autometrics* system substantially reduce regression sum of squares measures relative to a traditional variation on the random walk with drift model. . We report statistically significant coefficients on the TCB LEI variable and substantial residual sum of squares, RSS, reductions! Yes, The *Autometrics* software was a most effective tool for macroeconomic modelling. Furthermore, the Mitchell, Moore, and Zarnowitz LEI reduced modelling errors and the saturation variables were particularly effective during COVID! Surely this is macroeconomics done correctly!

Happy 80th birthday, Sir David Hendry.

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Table 7. FactSet US Russell 3000 alpha Factors. January 1995 -December 2023

Factor	Universe Return						Excess vs. Bench					Information Coefficients				t-Statistics (ICs)			
	F1-FN	1	2	3	4	5	1	2	3	4	5	1 Month	3 Month	6 Month	12 Month	1 Month	3 Month	6 Month	12 Month
REG10	13.09	15.63	12.21	11.14	8.04	-1.78	5.31	1.89	0.89	-1.50	-9.90	0.049	0.072	0.097	0.122	2.797	4.065	5.520	6.863
REG9	11.24	15.14	11.61	10.82	7.34	0.24	5.00	1.39	0.63	-2.22	-8.19	0.046	0.065	0.088	0.115	2.579	3.701	5.008	6.478
CTEF	10.69	15.62	12.84	10.06	5.24	2.37	5.06	2.52	0.21	-3.98	-6.54	0.045	0.057	0.070	0.082	2.476	3.138	3.833	4.428
CP	10.25	14.12	12.33	11.34	6.59	0.33	4.28	1.85	0.90	-3.02	-8.00	0.040	0.062	0.087	0.113	2.235	3.509	4.861	6.320
REG8	9.60	13.96	11.74	10.62	7.73	0.95	4.00	1.49	0.43	-1.90	-7.54	0.037	0.056	0.078	0.105	2.121	3.177	4.441	5.931
RDP	#N/A	12.60	10.71	9.59	7.03	#N/A	2.26	-0.07	-0.74	-2.03	#N/A	0.032	0.050	0.075	0.100	1.819	2.853	4.211	5.574
RCP	9.59	12.53	12.77	12.03	9.28	0.60	2.97	2.31	1.39	-0.86	-7.72	0.039	0.059	0.079	0.103	2.157	3.277	4.350	5.664
FY2_EP	9.08	14.04	12.37	9.91	6.48	2.02	4.17	1.89	-0.40	-2.91	-6.63	0.044	0.058	0.073	0.086	2.472	3.249	4.082	4.763
SP	8.48	12.18	11.98	11.37	7.81	1.57	2.74	1.83	1.08	-2.15	-7.28	0.026	0.041	0.059	0.078	1.479	2.333	3.311	4.390
FY1_EP	8.23	14.37	11.76	9.58	6.74	2.20	4.23	1.23	-0.67	-2.50	-6.34	0.047	0.063	0.081	0.098	2.608	3.535	4.519	5.407
FY2_BREADTH	8.05	14.24	11.64	9.86	6.85	4.90	3.95	1.45	-0.58	-2.51	-4.55	0.028	0.032	0.039	0.043	1.517	1.715	2.085	2.293
FY1_BREADTH	8.05	14.52	11.12	8.73	6.93	5.30	4.25	1.11	-1.00	-2.44	-4.19	0.027	0.032	0.040	0.045	1.469	1.719	2.155	2.389
EP	6.48	13.69	12.18	9.99	6.15	2.45	3.61	1.58	-0.38	-3.30	-5.73	0.041	0.062	0.087	0.114	2.315	3.501	4.847	6.355
FY2_REVISION	5.33	11.86	10.63	7.33	8.36	5.17	2.04	-0.71	-2.19	-1.41	-3.92	0.017	0.021	0.019	0.018	0.946	1.117	1.038	0.986
PM71	4.81	12.51	10.90	10.93	9.76	0.37	2.29	0.44	0.57	-0.06	-7.55	0.026	0.040	0.056	0.049	1.435	2.178	3.008	2.572
REP	4.47	12.29	13.13	11.03	7.06	4.93	2.41	2.41	0.38	-2.73	-3.66	0.040	0.059	0.080	0.103	2.212	3.297	4.418	5.674
BP	4.30	10.64	11.30	9.27	8.27	5.51	1.28	1.11	-0.82	-1.55	-3.75	0.010	0.017	0.028	0.043	0.555	0.982	1.572	2.429
FY1_REVISION	4.14	11.09	10.02	8.61	7.99	5.74	1.33	-0.34	-1.03	-1.63	-3.47	0.014	0.015	0.014	0.012	0.737	0.819	0.785	0.664
DP	3.06	11.67	11.38	10.18	7.16	2.73	1.07	0.78	0.02	-1.90	-5.95	0.031	0.049	0.074	0.100	1.756	2.795	4.189	5.581
RSP	0.58	4.75	11.83	12.23	10.91	5.00	-3.60	1.77	1.74	0.43	-4.38	-0.002	-0.005	-0.005	0.004	-0.099	-0.252	-0.212	0.272
RBP	0.23	5.53	11.55	10.96	10.85	5.90	-2.96	1.47	0.52	0.40	-3.40	-0.001	-0.004	-0.005	0.003	-0.032	-0.201	-0.237	0.216

Table 8. FactSet US Russell 3000 Portfolio Selection. January 1995 -December 2023

Table 8 US Russell 3000 Portfolio Dashboard, 1995 -2023
Portfolio Weighing: EAW4

Portfolios	Risk Stock Specific Effect	Risk Stock Specific Effect T-Stat	Risk Factors Effect	Risk Factors Effect T-Stat	Total Effect	Dividend Yield	Earnings Yield	Growth	Medium-Term Momentum	Profitability	Size	Value
CTEF_6TE	6.20	5.44	1.08	3.36	7.28	-0.04	1.64	0.02	1.35	-0.12	2.22	0.20
REG10_8TE	7.43	5.42	-0.21	2.08	7.22	-0.10	1.69	-0.06	0.16	-0.26	2.47	1.21
REG9_6TE	7.20	6.42	-0.38	1.96	6.82	0.06	1.61	-0.02	-0.82	-0.52	2.64	1.05
REG9_4TE	6.58	8.92	0.22	2.40	6.80	-0.09	1.48	0.01	-0.71	-0.57	2.00	0.82
CTEF_8TE	6.23	4.24	0.54	2.75	6.77	-0.10	1.80	0.00	1.48	-0.17	2.61	0.33
REG10_6TE	6.63	5.88	0.11	2.48	6.75	-0.20	1.61	-0.05	0.12	-0.44	2.55	1.04
CTEF_4TE	5.53	7.11	1.09	3.95	6.62	-0.09	1.28	0.00	0.94	-0.20	1.56	0.17
REG8_4TE	7.63	9.95	-1.43	1.07	6.19	-0.11	0.95	0.03	-1.26	-0.56	2.04	0.86
CTEF_2TE	5.11	13.47	1.03	5.05	6.14	-0.11	0.80	0.03	0.53	-0.11	0.78	0.10
REG9_8TE	6.43	4.93	-0.30	1.63	6.13	0.10	1.55	-0.07	-0.87	-0.47	3.00	1.35
REG10_4TE	5.53	7.54	0.54	2.72	6.07	-0.11	1.41	-0.04	0.07	-0.51	2.01	0.82
REG9_2TE	5.39	15.29	0.19	2.18	5.58	-0.05	0.99	-0.01	-0.48	-0.35	1.14	0.54
REG8_2TE	5.91	16.80	-0.34	1.23	5.57	-0.05	0.79	-0.01	-0.76	-0.35	1.16	0.58
REG8_6TE	7.77	6.87	-2.26	0.56	5.51	-0.06	0.76	-0.03	-1.47	-0.51	2.54	0.98
REG10_2TE	4.82	13.81	0.60	2.92	5.41	-0.06	0.97	-0.02	0.01	-0.32	1.11	0.50
REG8_8TE	5.78	4.42	-2.68	0.02	3.09	0.02	0.39	-0.04	-1.55	-0.49	2.98	1.29

In using the Axioma optimization software, one must define several risk measure terms. The statistical significance of two of these effects, factor, and stock specific, are also presented as *t*-Statistics.

Risk Factors Effect: The overall excess return explained by the active exposures to the factors in the risk model. It is calculated by compounding the calculation period results for the sum of each factor's Active Exposure multiplied by its Factor Return. This effect can be further decomposed down to individual risk model factors.

Risk Stock Specific Effect: The portion of the active return that is not explained by the risk model, often referred to as stock selection skill:

Risk Total Effect – Risk Factors Effect

Risk Total Effect or Total Active Returns: The overall active performance of the portfolio gross of transaction costs. It is equal to:

Risk Stock Specific Effect + Risk Factors Effect

At the asset level, this can be expressed by the following formula:

$$r_i = r_f + \epsilon_i = \sum_{k=1}^{K} x_{i,k} f_k + \epsilon_i$$

r_i: Standalone asset total return
r_f: Standalone factors effect
ϵ_i: Asset specific returns
$x_{i,k}$: Asset raw factor exposure to factor k
f_k: Raw factor return of factor k

Risk Transaction Effect: The performance impact of fees, trading costs, and execution price relative to close price.

Risk Stock Specific & Factors Effect T-Stat: Tests whether the average return is statistically different than zero.