View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by Research Papers in Economics

ISSN 1750-4171

DEPARTMENT OF ECONOMICS

DISCUSSION PAPER SERIES

Generating Innovations in Economic Variables

Vitor Leone and Lawrence A. Leger

WP 2007 - 19

Dept Economics
Loughborough University
Loughborough
LE11 3TU United Kingdom
Tel: + 44 (0) 1509 222701
Fax: + 44 (0) 1509 223910
http://www.lboro.ac.uk/departments/ec

Loughborough University

Abstract

Stock prices should respond only to unpredictable components of economic news ('innovations') in efficient markets. While innovations used in empirical investigations of the economic underpinnings of stock market risk should at least satisfy this basic requirement this may not guarantee satisfactory research results. Three methods of generating innovations are evaluated for a variety of economic variables. First differencing produces unsatisfactory serially correlated innovations in general. Both ARIMA and Kalman Filter innovations are unpredictable, but in a further evaluation the component scores from Principal Components Analysis are regressed against economic innovations using PcGets. The results are far less noisy when Kalman Filter innovations are used.

JEL Classification: G1 General Financial Markets

Keywords: Macroeconomic variables, innovations, stock returns, principal components analysis.

Vitor.Leone@dtz.com. DTZ, 3-5 Swallow Place, London, UK.

Corresponding author: L.A.Leger@lboro.ac.uk. Telephone: (+44) (0)1509 222716

Fax: (+44) (0)1509 223910

Department of Economics, Loughborough University, Leicestershire, LE11 3TU, UK.

Generating Innovations in Economic Variables

Introduction

Empirical tests and applications of multi-factor asset pricing models are often focused on the relationship between stock prices and economic variables, in the belief that valuation is underpinned by real economic activity. As Chen *et al.* (1986), Priestley (1996) and others have argued, it is only the unpredictable component of economic news ('innovations') that should have any impact on asset prices in efficient markets. Innovations that are genuine shocks should be serially uncorrelated processes, so the method used to generate them is critical in empirical work. Three techniques have been reported: first differencing (rate of change when applied to log transformations) (Chen, *et al.,* 1986; Cheng, 1995; Priestley, 1996), ARIMA autoregressive methods (Beenstock and Chan, 1988; Clare and Thomas, 1994; Priestley, 1996; Clare *et al.*, 1997), and the Kalman Filter (Priestley, 1996, Garrett and Priestley, 1997; Antoniou *et al.*, 1998; Cauchie *et al*., 2004). There is an intuitive case for preferring the Kalman Filter (because this embodies an updating process by which expectations are revised in response to economic news) but this needs further empirical evaluation. The issue has been partly addressed by Priestley (1996) who found (i) that the pricing of risk factors in cross-sectional tests of the APT on UK data was sensitive to the innovations methodology and (ii) that the Kalman Filter and Autoregressive Distributed Lag models (up to 12 lags) outperformed first differencing as an innovations-generating method. We have been unable to find any other published comparative evaluation of methods for generating innovations. This paper therefore contributes to the literature by evaluating Kalman Filter against ARIMA innovations in a time-series investigation of the economic underpinnings of a Principal Components Analysis of stock prices. The evaluation is based on the Ljung-Box test for serial correlation (Ljung and Box, 1978) in the innovations series, and on performance in identifying the economic determinants of market risk. With respect to the latter, we use an approach to the economic interpretation of risk factors similar to that of Chen and Jordan (1993)[1], regressing PCA component scores against economic variables in time-series. We assume that underlying sources of risk can be identified by the pattern of economic variables to which the components are related and we examine whether any particular method of generating innovations leads to a clearer economic interpretation of risk factors.

Selecting Economic Variables

As in previous studies for the UK, such as Beenstock and Chan (1988), Clare and Thomas (1994), Cheng (1995) and Priestley (1996), our selection of economic variables is based on a present value model relating the real stock price, p_t, to discounted expected future real dividends, d_t:

$$p_t = E_t\left[\sum_{j=1}^{\infty}(1+r)^{-j} d_{t+j}\right] \quad (1)$$

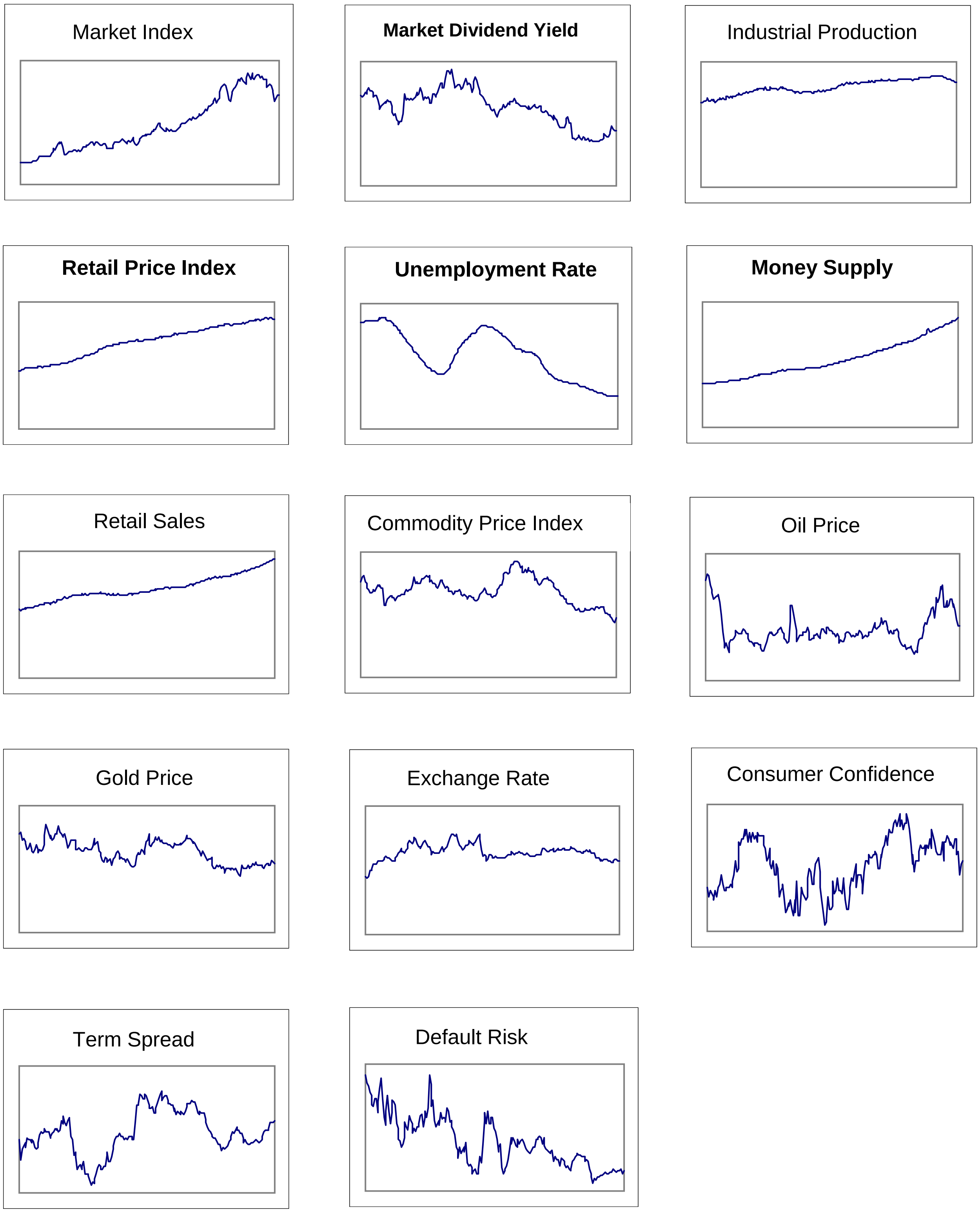
Discount rate r is the rate of return required by the investor. This valuation model implies that share prices respond to anything that changes the expected value of dividends or the required rate of return. In the absence of a full structural model of the economic valuation it is impossible to identify the precise influence of any particular economic variable and we follow standard practice in not attempting to do so. The selected variables are presented in Table 1 and graphs of the raw data are given in Figure 1.

Table 1. UK Economic Series 1976-2001 and Stationarity Tests: (Augmented Dickey-Fuller and Phillips-Perron)

Variable	**Flag**	**ADF**	**PP**
Market Index (FT All Share)	*MR*	-2.440353	-2.374062
Market Index Dividend Yield	*DY*	**-3.598385**	**-3.586866**
Industrial Production	*IP*	-1.774295	-2.502807
Retail Price Index	*RP*	-1.867845	-0.577145
Unemployment Rate	*UN*	-2.562944	-1.281972
Money Supply M0	*MS*	4.542591	4.311323
Retail Sales	*RS*	0.030188	-1.469234
Reuters Commodity Price Index	*CP*	-2.073329	-2.239606
Oil Price (£)	*OP*	-3.099109	-2.623361
Gold Price (£)	*GP*	-2.215364	-2.249221
US$ Exchange Rate	*ER*	-2.639840	-2.318235
UK Consumer Confidence Indicator	*CC*	-3.141102	-3.289767
20-Year Gilts Redemption Yield (Gilts)			
3 Month Treasury Bill Yield (TBill)			
Corporate Debenture and Loan Redemption Yield (Corp)			
Default Risk (Gilts – TBill)	*DR*	**-3.434464**	-3.206298
Term Spread (Gilts – Corp)	*TS*	-2.382905	-2.743641

No values show significant rejection of a unit root at the 5% level or better except those in bold type.

Figure 1. Raw Data 01/1985 to 12/2001



UK data were collected from Datastream for each series. Changes in Retail Prices and Money Supply may affect both cash flows and interest rates (M0 was the only money supply series spanning the full sample period). The Oil Price and Commodity Prices may influence industry costs, revenues and profits, and consequently dividends. Gold is often viewed as a portfolio balancing asset providing an investment alternative. Exchange rates (represented here by the Dollar/Sterling rate) may influence the value of foreign earnings and net export performance, affecting profits and dividends. Real economic activity, as reflected in business cycle variables (Unemployment, Industrial Production and Retail Sales) should also have an influence on expected future cash flows. Changes in any of these variables could also alter the outlook for interest rates and consequently the discount rate. Since the latter may be adjusted for risk, we define Default Risk as the difference between the Corporate Debenture and Loan Redemption Yield and the Gross Redemption Yield on 20-year Gilts. We also use Term Spread, a commonly-used measure of the market risk premium defined as the difference between the Gross Redemption Yield on 20-year Gilts and the 3-month Treasury Bill rate. Retail Sales may also be a proxy for real consumption, reflecting the marginal utility of real wealth and hence the risk premium. We include the FTA All Share index and its Dividend Yield, since the market return seems to explain a significant proportion of asset returns in time-series factor models and its exclusion is likely to lead to an omitted variables bias. This also allows us to examine the incremental impact from other sources of economic news. Finally, in a departure from tradition we include a Consumer Confidence Indicator which can be thought of as a psychological variable reflecting investors' expectations of investment performance, wealth and the state of the economy, with consequent effects on required rates of return and stock prices.

Table 1 also shows the results of Augmented Dickey-Fuller (ADF: Dickey and Fuller, 1981) and Phillips-Perron (PP: Phillipps and Perron, 1988) stationarity tests applied to the raw series, assuming models containing trend and constant, using 14 lags, showing that most of the basic economic series contain a unit root. The null hypothesis of unit root was rejected at the 5% level or better only for the UK FTA all share index dividend yield (both ADF and PP tests) and Default Risk (ADF test).

Generating and Comparing Innovations

First differencing in logs (rate of change) was done for all variables except Default Risk, Term Spread, Unemployment rate and Consumer Confidence (where the untransformed variables were differenced). This produced stationary time series of innovations but did not prevent serial correlation. The ARIMA models were specified by choosing optimal values for the autoregressive and moving average components of the first-differenced series. This was done by (i) examining the autocorrelation and partial autocorrelation functions (ii) estimating the parameters of the model by maximum likelihood, and (iii) evaluating the models using residual diagnostics based on the Ljung-Box test, the information criterion (AIC) of Akaike (1974) and the Bayesian information criterion (SBIC) of Schwarz (1978). These models were initially examined using three lags on each component and the most parsimonious model was subsequently selected. Any parsimonious model that showed the presence of serial autocorrelation in the ARIMA residuals was re-modelled with more components until the serial correlation was removed. Tables 2 and 3 show the initial and final models. The residuals of the final models constitute the ARIMA innovations.

Table 2. Initial Arima Model Selected by AIC and SBIC Criteria

Defining the AR and MA Components for the Derived Series Using AIC and SBIC Criteria			
Index	**Model** (p,q)	**AIC**	**SBIC**
Market Capital Gain	(0,0)	-3.148891	-3.136866
Market Index Dividend Yield	(0,1)	-3.334925	-3.3100875
Industrial Production*	(1,0)	-4.056867	-4.030632
Retail Price Index *	(0,2)	-7.599025	-7.562865
Unemployment*	(3,0)	-4.206941	-4.154471
Money Supply*	(1,3)	-7.56148	-7.500881
Retail Sales	(3,3)	-4.215538	-4.130763
Commodity Price Index	(1,0)	-4.9066	-4.882531
Gold Price	(0,0)	-1.688277	-1.676252
Oil Price	(0,1)	-2.348386	-2.324336
Exchange Rate	(0,1)	-4.624723	-4.600673
Consumer Confidence	(1,0)	5.152115	5.176222
Default Risk	(1,2)	0.890841	0.939054
Term Spread	(2,2)	1.638801	1.699211

* Serial correlation was present in the residuals of the initial models for these variables. The models were refined until serial correlation was eliminated

Table 3. Final Parsimonious Model using Arima Modelling

Market Index	No AR or MA Components	
Market Index Dividend Yield	$DY = \underset{(-0.0689)}{-0.002} + \underset{(3.871)}{0.215}MA(1)$	$R^2 = 0.0402$
Industrial Production	$IP = \underset{(1.0999)}{0.0007} - \underset{(-5.061)}{0.285}AR(1) + \underset{(2.515)}{0.142}AR(3) + \underset{(2.546)}{0.142}AR(8)$	$R^2 = 0.1228$
Retail Price Index	$RP = \underset{(3.297)}{0.0038} + \underset{(14.071)}{0.623}AR(12) + \underset{(5.377)}{0.294}MA(1) + \underset{(3.3087)}{0.182}MA(2) + \underset{(5.0338)}{0.274}MA(6)$	$R^2 = 0.4964$
Unemployment	$UN = \underset{(0.0002)}{-0.0003} + \underset{(0.135)}{0.182}AR(1) + \underset{(0.283)}{0.261}AR(2) + \underset{(0.379)}{0.378}AR(3) + \underset{(0.125)}{0.833}AR(4) + \underset{(0.197)}{0.15}AR(5) - \underset{(-0.27)}{0.202}AR(10)$	$R^2 = 0.7263$
Money Supply	$MS = \underset{(5.297)}{0.005} + \underset{(40.71)}{0.957}AR(1) - \underset{(-24.13)}{1.031}MA(1) + \underset{(3.96)}{0.154}MA(3)$	$R^2 = 0.1205$
Retail Sales	$RS = \underset{(6.257)}{0.0024} + \underset{(7.370)}{0.393}AR(1) - \underset{(-16.364)}{0.679}AR(2) - \underset{(-7.007)}{0.363}AR(3) - \underset{(-94.09)}{0.894}MA(1) + \underset{(1439)}{1.088}MA(2) - \underset{(-22.68)}{0.120}MA(3)$	$R^2 = 0.2758$
Commodity Price Index	$CP = \underset{(0.328)}{0.0006} + \underset{(5.798)}{0.313}AR(1)$	$R^2 = 0.0984$
Oil Price	$OP = \underset{(0.239)}{0.0014} + \underset{(7.127)}{0.376}MA(1)$	$R^2 = 0.1131$
Gold Price	No AR or MA Components	
Exchange Rate	$ER = \underset{(-0.568)}{-0.0011} + \underset{(7.966)}{0.413}MA(1)$	$R^2 = 0.1382$
Consumer Confidence	$CC = \underset{(0.099)}{0.0164} - \underset{(-1.692)}{0.096}AR(1)$	$R^2 = 0.0092$
Default Risk	$DR = \underset{(1.067)}{0.332} + \underset{(60.59)}{0.973}AR(1) - \underset{(-6.109)}{0.359}MA(1) - \underset{(-4.208)}{0.245}MA(2)$	$R^2 = 0.7242$
Term Spread	$TS = \underset{(-0.409)}{-0.014} + \underset{(3.811)}{0.496}AR(1) - \underset{(-8.434)}{0.734}AR(2) - \underset{(-4.068)}{0.465}MA(1) + \underset{(9.665)}{0.795}MA(2)$	$R^2 = 0.0615$

The Kalman Filter (Harvey, 1989) is a very general approach to the modelling of economic information that allows for optimal updating in the underlying structure. The ‘Structural Time Series Analyser, Modeller and Predictor’ software (STAMP) of Koopman, *et al*. (1999) was used to apply the Kalman Filter, specifying stochastic level, stochastic slope, stochastic trigonometric seasonal and irregular components, and estimating by maximum likelihood. Unlike the ARIMA models, the variables were not initially adjusted by first differencing. The models were re-estimated until convergence was reached, with insignificant components being eliminated and lags of the explanatory variables included if necessary. Table 4 gives the final Kalman Filter models, showing the number of iterations necessary to achieve converge and the strength of convergence. ‘Very strong’ convergence signalled by STAMP indicates successful maximum likelihood estimation. Failure to achieve convergence may be an indication of a poorly specified model. The residuals from the final models constitute the Kalman Filter innovations.

The innovations derived from first-differencing, ARIMA models and the Kalman Filter were evaluated as innovations by checking for serial correlation using the Ljung-Box test with 24 lags. The Q-statistic sample starts in 1979 but data were collected from 1974, to allow 5 years of data for initialising the Kalman Filter algorithm. The Ljung-Box test results are given in Table 5.

Table 4: Time Series Models of Economic Variables (Kalman Filter)

Variable	Model	Convergence	
Market Index	Trend (Level plus slope) + Lags (2, 3, 5, 6, 7, 10) + Irregular	Very strong, 8 iterations	$R^2 = 0.$
Dividend Yield	Trend (Level plus slope) + Trig seasonal + Lags (1, 2, 11) + Irregular	Very strong, 13 iterations	$R^2 = 0.$
Industrial Production	Level + Lags (1, 3, 8) + Irregular	Very strong, 4 iterations	$R^2 = 0.$
Retail Price Index	Trend (Level plus slope) + Trig seasonal + Lags (1, 6) + Irregular	Very strong, 17 iterations	$R^2 = 0.$
Unemployment	Level + Lags (1, 2, 3, 5, 10) + Irregular	Very strong, 8 iterations	$R^2 = 0.$
Money Supply	Trend (Level plus slope) + Lags (1, 2) + Irregular	Very strong, 6 iterations	$R^2 = 0.$
Retail Sales	Trend (Level plus slope) + Irregular	Very strong, 6 iterations	$R^2 = 0.$
Commodity Prices	Trend (Level plus slope) + Lags (1, 2, 4, 7)+ Irregular	Very strong, 2 iterations	$R^2 = 0.$
Oil Prices	Level + Trig seasonal + Lags (1, 2, 3, 4) + Irregular	Very strong, 5 iterations	$R^2 = 0.$
Gold Price	Level + Irregular	Very strong, 9 iterations	$R^2 = 0.$
Exchange Rate	Trend (Level plus slope) + Lags (1, 2, 3, 5, 12) + Irregular	Very strong, 3 iterations	$R^2 = 0.$
Consumer Confidence	Level + Irregular	Very strong, 5 iterations	$R^2 = 0.$
Default Risk	Level + Trig seasonal + Lags (1) + Irregular	Very strong, 6 iterations	$R^2 = 0.$
Term Spread	Level + Fixed seasonal + Lags (1, 10, 11) + Irregular	Very strong in 2 iterations	$R^2 = 0.$

Table 5. Serial Correlation in the Derived Innovations Series

Ljung-Box* test for serial correlation Q-Statistic (24 lags)			
Innovation Series	**First Differences**	**Arima**	**Kalman Filter**
Market Index	28.901 (0.2239)	28.901 (0.2239)	10.944 (0.9844)
Dividend Yield	37.012 **(0.0436)**	24.291 (0.4451)	18.573 (0.7744)
Industrial Production	53.325 **(0.0005)**	22.735 (0.5355)	21.499 (0.6091)
Retail Price Index	332.72 **(0.0000)**	24.940 (0.4090)	21.809 (0.5907)
Unemployment	1335.10 **(0.0000)**	23.314 (0.5013)	20.564 (0.6643)
Money Supply	30.501 (0.1687)	24.121 (0.4547)	14.935 (0.8514)
Retail Sales	89.164 **(0.0000)**	32.517 (0.1147)	21.004 (0.6385)
Commodity Prices	70.191 **(0.0000)**	21.085 (0.6338)	14.069 (0.8856)
Oil Prices	70.940 **(0.0000)**	30.859 (0.1579)	19.115 (0.7458)
Gold Price	29.370 (0.2065)	29.370 (0.2065)	31.703 (0.1345)
Exchange Rate	52.550 **(0.0007)**	19.882 (0.7635)	22.307 (0.5609)
Consumer Confidence	29.733 (0.1938)	22.228 (0.5657)	22.897 (0.5259)
Default Risk	2238.0 **(0.0000)**	23.962 (0.4638)	29.248(0.2109)
Market Index	38.427 **(0.0313)**	12.255 (0.9769)	24.484 (0.3291)

Probability values in bold indicate significant presence of serial correlation.

Table 5 shows that first differencing does not in general produce generate serially uncorrelated series and is generally unsuitable as a method for generating innovations. This rejection reflects the results of Priestley (1996) who found a greater degree of annual mispricing for the first-difference method. On the other hand, both the ARIMA and Kalman Filter innovations are serially uncorrelated and there is apparently little to choose between them. Given their similar statistical characteristics we evaluate these innovations further by examining their performance in explaining the scores of the first component of Principal Components Analysis (PCA).

Interpreting Principal Components using ARIMA and Kalman Filter Innovations

Component scores from a PCA of stock returns were regressed in time series against the economic innovations. The components, c_k, are written as N linear combinations of returns, x_i, on N individual stocks ($i = 1 \ldots N$), with 'loadings', b_{ik}:

$$\begin{aligned} c_1 &= b_{11}x_1 + \cdots + b_{1N}x_N \\ &\vdots \\ c_N &= b_{N1}x_1 + \cdots + b_{NN}x_N . \end{aligned} \tag{2}$$

By construction (see Morrison, 1990) the components are independent of each other and a small number of components are used to explain the majority of systematic covariation in the raw data (stock returns in this case).

Over a 20-year period we expect fairly strong co-movements between the time series of prices for different individual stocks – implying a linear factor model of returns in which the return to a well-diversified market index is an important factor (the well-known 'Market Model'). Put another way, we expect 'market risk' to be the dominant 'explanatory' variable underlying the first principal component of a PCA, aggregating the influence of other economic variables. While other systematic sources of risk (if any) might underpin other extracted components, there is no reason to suppose that the underlying sources of risk remain stable over a 20-year period (a very long time in politics, international relations, technology and the business cycle) and it seems unlikely that patterns of economic influence on different PCA components would be replicated in repeated sampling. Indeed, there was no replicated pattern of explanatory variables across different samples for any other than the first principal component so we restrict our discussion to the latter. In any case, the identity of the ‘true’ underpinnings of the risk components is not at issue here, since we are concerned with evaluating Kalman Filter and ARIMA methods of generating innovations, not with explaining the different components. Under our criterion, the method that filters out sample-specific results to produce stronger cross-sample consistency in explaining the first component is to be preferred.

While over a 20-year period we expect an efficient modelling procedure to filter out any association between the first principal component and innovations in variables other than the market index and its dividend yield, this is not a required result. *A priori* any well-replicated pattern of explanatory variables is acceptable – what is important is that the replicated pattern is as free from sample-specific noise as possible.

The sample of stock returns, corrected for dividends and capital changes, was taken from the London Share Price Database (LSPD) and included all UK stocks traded throughout the period 1975 to 2001, excluding investment trusts and financials. Joliffe (1986) asserts that the excessive presence of zero data influences the results of a principal components analysis, so thinly traded stocks with a high proportion (more than 20%) of zero returns or missing observations were also excluded. Occasional missing returns were otherwise assigned a value of zero. This reduced the sample from 516 to 240 stocks. To provide replication, this sample was split by alphabetical order into 10 groups of 24 stocks each and for each group the PCA was performed on the correlation matrix of returns. The eigenvalues from the PCA revealed that between 23% and 32% of the total variation was captured by the first component (an average of 29.5% across all 10 sample groups) with roughly an additional 5% captured by the second component.

The loadings for the first component were used to generate a time series of component scores for each group across the sample period 1979-2001 that were regressed against the ARIMA and Kalman Filter innovations in the economic variables using the LSE general-to-specific approach to economic modelling (Hendry 1995, Hendry and Krolzig, 2001) of PcGets (OxMetrics™). In this approach, a general unrestricted model (GUM) is formulated from the theoretical and empirical framework under consideration (in our case the relations between economic innovations and principal components).The GUM for stock sample *i* is represented by the regression

$$c_{it} = \gamma_{i0} + \sum_{k=1}^{K} \gamma_{ik} z_{kt} + \varepsilon_{it} \qquad (3)$$

where the c_{it} are scores for the first component for sample group *i* and z_{kt} are time-series observations for each of the *K* innovations. The GUM is automatically simplified by PcGets to a parsimonious congruent model containing individually significant regressors, with each simplification stage being checked automatically by the diagnostic testing procedures of the programme.

Table 6. Explanatory Economic Variables, First PCA Component (PCGets), Replicated over 10 Stock Samples

Kalman Filter				**Arima**								
Sample 1	*MR(+)*	*DY(-)*		Sample 1	*Const(-)*	*MR(+)*	*DY(-)*		*RP(+)*			
Sample 2	*MR(+)*	*DY(-)*		Sample 2	*Const(-)*	*MR(+)*	*DY(-)*			*DF(+)*		
Sample 3	*MR(+)*	*DY(-)*		Sample 3	*Const(-)*	*MR(+)*	*DY(-)*					
Sample 4	*MR(+)*	*DY(-)*		Sample 4	*Const(-)*	*MR(+)*						*OP(-)*
Sample 5	*MR(+)*	*DY(-)*		Sample 5	*Const(-)*	*MR(+)*	*DY(-)*					
Sample 6	*MR(+)*	*DY(-)*		Sample 6	*Const(-)*	*MR(+)*	*DY(-)*					
Sample 7	*MR(+)*	*DY(-)*		Sample 7	*Const(-)*	*MR(+)*	*DY(-)*	*CC(+)*	*RP(+)*		*MS(+)*	
Sample 8	*MR(+)*	*DY(-)*		Sample 8	*Const(-)*	*MR(+)*	*DY(-)*					
Sample 9	*MR(+)*	*DY(-)*		Sample 9	*Const(-)*	*MR(+)*	*DY(-)*	*CC(+)*				
Sample 10	*MR(+)*	*DY(-)*		Sample 10	*Const(-)*	*MR(+)*	*DY(-)*	*CC(+)*		*DF(+)*		

Const=Constant, *MR*=Market Index, *DY*=Market Dividend Yield, *CC*=Consumer Confidence, *RP*=Retail Price Index, *DF*=Default Risk, *GP*=Gold Price, *OP*=Oil Price, *MS*=Money Supply, *UN*=Unemployment,

The results for the final parsimonious models are given in Table 6, where striking differences between the two innovation methods can be observed. Market Return and Dividend Yield are significant in every case for the Kalman Filter and in all cases but one for ARIMA. However, while no other variable is significant when using the Kalman Filter, there is a general tendency for a significant constant term (an undesirable result) plus occasional other variables when using ARIMA innovations. There is no obvious pattern to the other variables detected when using the ARIMA innovations and no reason to expect them to contribute significantly to an explanation of the first principal component. We therefore conclude that the Kalman Filter outperforms ARIMA modelling in generating innovations for applications of this sort.

References

Akaike, H. (1974). “A new look at the statistical model identification”. *IEEE Trans. on Automatic Control*, 19(6), 716-723.

Antoniou, A., I. Garrett and R. Priestley (1998). “Macroeconomic Variables as Common Pervasive Risk Factors and the Empirical Content of the Arbitrage Pricing Theory”, *Journal of Empirical Finance*, 5, 221-240.

Beenstock, M. and K-F. Chan (1988). “Economic Forces in the London Stock Market”, *Oxford Bulletin of Economics and Statistics*, 50, 27-39.

Cauchie, S., M. Hoesli and D. Isakov (2004). “The Determinants of Stock Returns in a Small Open Economy”, *International Review of Economics and Finance*, 13, 167-185.

Chen, N-F., R. Roll and S.A. Ross (1986). “Economic Forces and the Stock Market”, *Journal of Business*, 59, 383-403.

Chen, S.J. and B.D. Jordan (1993). “Some Empirical Tests in the Arbitrage Pricing Theory: Macrovariables vs Derived Factors”, *Journal of Banking and Finance*, 17, 65-89.

Cheng, A.C.S. (1996). “Economic Factors and Stock Markets: Empirical Evidence from the UK and the US”, *International Journal of Finance and Economics*, 1, 287-302.

Clare, A.D. and S.H. Thomas (1994). “Macroeconomic Factors, the APT, and the UK Stock Market”, *Journal of Business Finance and Accounting*, 21, 309-330.

Clare, A.D., R. Priestley and S.H. Thomas (1997). “The Robustness of the APT to Alternative Estimators”, *Journal of Business Finance and Accounting*, 24, 645-655.

Dickey D.A. and W.A. Fuller (1981). “Likelhood Ratio Statistics for Autoregressive Time Series with a Unit Root”, *Econometirca*, 49, 1057-1072.

Garrett, I. and R. Priestley (1997). “Do Assumptions about Factor Structure matter in Empirical Tests of the APT?” *Journal of Business Finance and Accounting*, 24, 249-260.

Harvey, A.C. (1989). *Forecasting Structural Time-Series Models and the Kalman Filter*, Cambridge University Press.

Hendry, D.F. (1995). *Dynamic Econometrics*, Oxford University Press.

Hendry, D.F. and H.M. Krolzig (2001). *Automatic Econometric Selection using PcGets,* 4th Edition, Timberlake Consultants Press.

Joliffe, I.T. (1986). *Principal Components Analysis*, Springer-Verlag, New York.

Koopman, S.J., A.C. Harvey, J.A. Doornik, and N. Shephard (2000). *STAMP 6.0: Structural Time Series Analyser, Modeller and Predictor*, Timberlake Consultants Press.

Ljung, G.M. and G.E.P. Box (1978). "On a measure of lack of fit in time series models", *Biometrika*, 65, 297-303.

Morrison, D.F. (1990). *Multivariate Statistical Methods*, 3rd Edition, McGraw-Hill, New York.

Phillips, P.C.B. and P. Perron (1988). "Testing for a Unit Root in Time Series Regression", *Biometrika*, 75, 335-346.

Priestley, R. (1996). "The Arbitrage Pricing Theory, Macroeconomic and Financial Factors, and Expectations Generating Process", *Journal of Banking and Finance*, 20, pp 869-890.

Schwarz, G. (1978). "Estimating the Dimension of a Model", *The Annals of Statistics*, 6, 461-464.

---

[1] Chen and Jordan used a factor analysis of returns on portfolios of stocks.