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Cointegration analysis of the Fed model [☆]

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Abstract

The Fed model postulates that the equity earnings yield follows the bond yield in the long run. Our tests based on a cointegration analysis of the United States, United Kingdom and German data indicate that the Fed model has predictive power in forecasting changes in the equity prices, earnings and bond yields. The predictions are better in the US than in other countries. Our approach consists of building a Vector Equilibrium Correction model which provides a quantitative dynamic version of the Fed model.

JEL classification: G12; G15; C32; C52; C53

Keywords: Cointegration analysis; Vector equilibrium correction; VAR; Stock markets

☆ The views expressed in this paper are those of the authors' and may not necessarily be shared by the European Central Bank.

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1. Introduction

The Fed model postulates that the earnings yield E/P of a stock index tends to move in the same direction as the treasury bond yield Y thus giving a way to predict price movements in the equity market: if E/P is much less than Y one might expect a decrease in the equity prices P. This effect was studied already in Ziemba and Schwartz (1991) and it became widely known with the Humphrey–Hawkins Report Board of Governors of the Federal Reserve System (1997). The idea is that bonds and stocks compete for investment funds and those funds tend to move towards the more attractive investment. Ziemba and Schwartz (1991) used the difference $Y - E/P$ as a stock market danger indicator. They showed that this was accurate in predicting major crashes in the stock markets of US and Japan during 1948–1989. Berge and Ziemba (2003) made a further study of the predictive ability of this indicator for predicting stock price rises and declines with various data estimation techniques for the US, Japan, Germany, Canada and the UK. For 1970–2003 Berge and Ziemba (2003) found that the measure provided signals to enter and exit the stock markets superior to buy and hold strategy and provided signals that predicted large declines. Practitioners such as Yardeni (2003) have also used this measure to try signal large stock market moves. Ziemba (2003) details many successful applications of the idea in various equity markets. Campbell and Vuolteenaho (2004) show that during 1927–2002 the bond yield and proxies of the risk premium are strongly statistically significant in explaining variations in the log stock yield (either the earnings-price ratio or the dividends-price ratio). Despite the empirical success in describing the behavior of stock prices and its popularity among practitioners the Fed model has also been criticized for being theoretically invalid; see, e.g., Asness (2003) and Campbell and Vuolteenaho (2004). The main criticism is that the Fed model compares a nominal quantity Y to the real quantity E/P.

This paper studies the Fed model from statistical point of view with a focus on the ability of the Fed model to forecast changes in equity prices, earnings and bond yields. This is done through studying the *logarithmic indicator* defined by

$$I_t = \ln\left(\frac{Y_t}{E_t/P_t}\right) = \ln Y_t - \ln E_t + \ln P_t. \tag{1}$$

Taking logarithms of positive quantities is common practice in econometrics and it has two important advantages. First, proportional variations in the values of strictly positive variables are often more meaningful than absolute ones. Second, logarithmic variables often fit statistical models better than original ones. Figure 1 displays the logarithmic indicator together with logarithmic values of the general equity market index for the US. During 2001 stock market prices fell and the indicator moved to a lower level indicating less danger in the market. However, in late 2001, the fall in stock market prices was exceeded by the fall in earnings. This lead to the indicator moving even higher which anticipated the 22% fall in the stock prices in 2002. In late 2002 the indicator moved to a low level which is consistent with the rise in stock prices in 2003.

The main idea of the paper is to develop a linear time series model around the log indicator and to test whether the indicator improves the predictive power of the model. Being linear in all the logarithmic variables suggests that I_t might serve as an *equilibrium correction term* in a Vector Equilibrium Correction (VEC) model for the logarithmic vari-

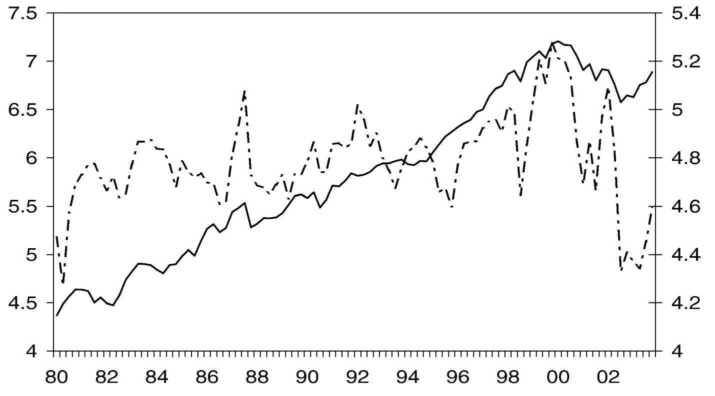


Fig. 1. Datastream log US market index and the log indicator (right scale, dotted line) during 1980/1–2003/4.

ables; see Engle and Granger (1987) and Johansen (1995). The resulting time series model provides a quantitative version of the FED-model and it gives predictions not only of the equity price index but all the variables in the model.

Out-of-sample forecast tests in the US, the UK, and Germany indicate that VEC-models with the logarithmic indicator outperform Vector autoregressive (VAR) models, without the indicator.

The paper is organized as follows. Section 2 describes the data used in the tests. In Section 3, we study the stationary properties of the time series, and in particular of the log indicator. In Section 4, we develop and analyze VEC-models for markets in the US, the UK and Germany. Section 5 compares the predictive ability of the VEC-models against VAR-models in out-of-sample forecast tests. Section 6 concludes.

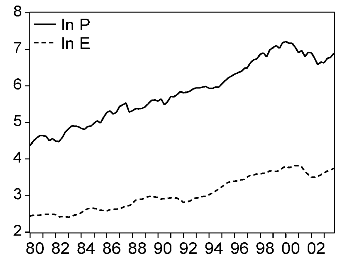
2. Data

The stock market price and earnings data as well as the bond yields for the three markets are from Datastream. Datastream total market price indices for the United States, United Kingdom and Germany represent the behavior of the stock prices in all three markets. The earnings (past) corresponding to the indices are calculated from the reported price earnings (P/E) ratios. The bond yields represent the yields on ten-year government benchmark bonds and are calculated by Datastream. Our dataset covers quarterly observations from January 1980 to December 2003.

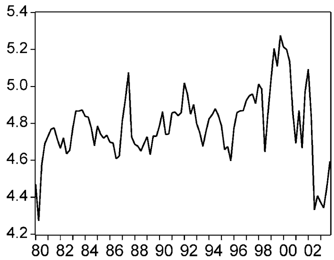
3. Tests for cointegration

This section studies the stationarity properties of the time series. Figures 2–4 display the historical values of $\ln Y_t^i$, $\ln P_t^i$, $\ln E_t^i$ and I_t^i from 1980/1 to 2003/4, where $i = US, UK$ and GER, respectively. Even though the log bond yield, stock price index and earnings appear non-stationary, their linear combinations (I_t^i) are stationary in all three markets; see Figs. 2–4.

(a) $\ln P_t^{US}$.



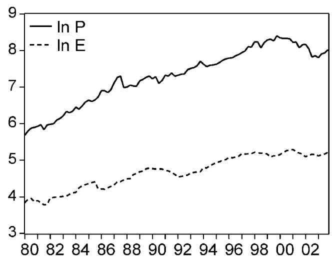
(b) $\ln P_t^{US}$ (solid line) and $\ln E_t^{US}$.



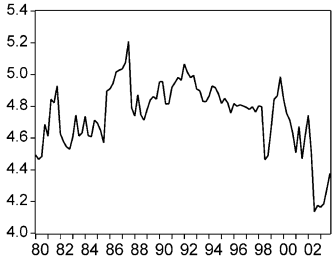
(c) I_t^{US}.

Fig. 2. Logarithmic time series for the United States, 1980/1–2003/4.

(a) $\ln Y_t^{UK}$.



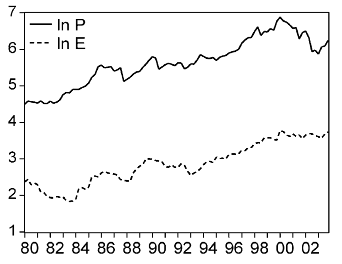
(b) $\ln P_t^{UK}$ (solid line) and $\ln E_t^{UK}$.



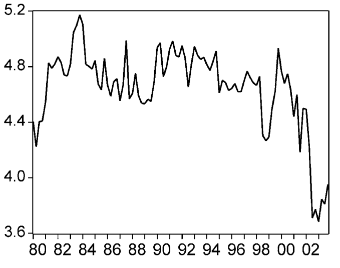
(c) I_t^{UK}.

Fig. 3. Logarithmic time series for the United Kingdom, 1980/1–2003/4.

(a) $\ln Y_t^{GER}$.



(b) $\ln P_t^{GER}$ (solid line) and $\ln E_t^{GER}$.



(c) I_t^{GER}.

Fig. 4. Logarithmic time series for Germany, 1980/1–2003/4.

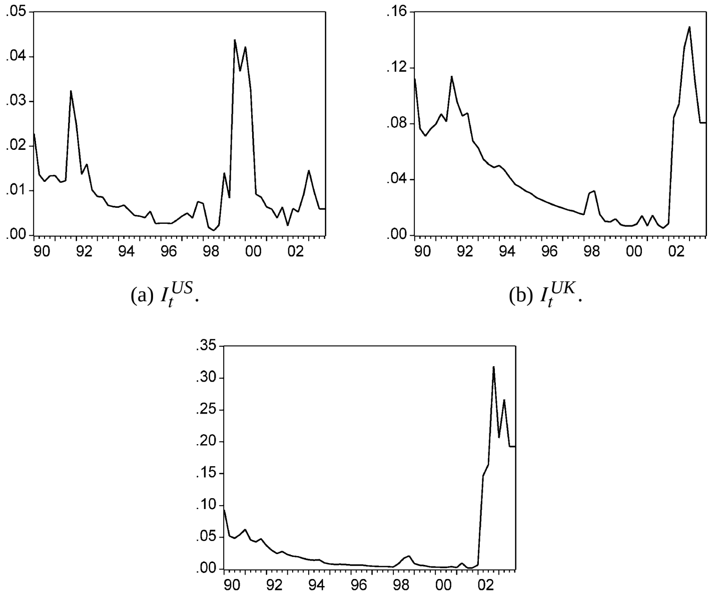
Table 1
Unit root test statistics of the time series between 1980/1 and 2003/4

	US			UK			GER		
Time series	nl	$z(t)$	t-statistic	nl	$z(t)$	t-statistic	nl	$z(t)$	t-statistic
$\ln Y$	0	(1)	−1.30	0	(1)	−0.97	0	(1)	−1.28
$\ln P$	0	$(1, t)$	−1.75	0	$(1, t)$	−1.49	0	$(1, t)$	−1.94
$\ln E$	1	$(1, t)$	−2.96	2	$(1, t)$	−2.37	0	$(1, t)$	−2.91
$\Delta \ln Y$	0	(0)	−10.02*	0	(0)	−9.37*	0	(0)	−8.23*
$\Delta \ln P$	0	(1)	−9.36*	0	(1)	−9.95*	0	(1)	−9.40*
$\Delta \ln E$	0	(1)	−4.93*	1	(1)	−5.47*	0	(1)	−8.60*

Notes. The table reports results of the augmented Dickey–Fuller tests for all the time series. The number of lags (nl) in the tests have been selected using the Schwarz information criterion with a maximum of twelve lags. The value of $z(t)$ indicates the deterministic terms included in the unit root regressions. When $z(t) = 0$ the deterministic terms are omitted, with $z(t) = 1$ a constant is included and with $z(t) = (1, t)$ a constant and a trend are included.

* Indicate the rejection of the unit root null at the 1% significance level.

We study, using data from 1980/1 to 2003/4, the stationarity properties of $\ln Y_t^i$, $\ln P_t^i$ and $\ln E_t^i$ by performing augmented Dickey–Fuller (Dickey and Fuller, 1981) tests for all the time series. The results of the unit root tests in Table 1 are very similar across the markets. The log bond yield, log stock price index and log earnings are non-stationary and their first differences are stationary.



(a) I_t^{US}.

(b) I_t^{UK}.

(c) I_t^{GER}.

Fig. 5. Unit root test results for the logarithmic indicators. *Notes*. Figures display the p-values of augmented Dickey–Fuller tests for the logarithmic indicator on subsamples ranging from 1980/1–1990/1 to 1980/1–2003/4 for the three markets. Low p-values, e.g., below 5%, indicate the rejection of the unit root null.

Next we test the stationarity of the indicator, $\ln I_t^i$, using different subsamples of our data set. Figure 5 displays the p-values of augmented Dickey–Fuller tests for the logarithmic indicator on different subsamples for all the three markets. The initial estimation period used in the unit root tests is $t = 1980/1, \ldots, 1990/1$. After this, the sample size is expanded by one observation at a time and the test statistic is recomputed for each subsample ($t = 1980/1$ to $1990/2$, $t = 1980/1$ to $1990/3$, etc.). The results in Fig. 5, where low p-values (e.g., below 5%) indicate the rejection of the unit root null, confirm the stationarity of the log indicator in the US over all the considered subsamples. In the UK and Germany the indicator is fairly stationary until the end of 2001, since the p-values are below 10% over most of the subsamples. Figures 3–4 show that the rapid decline of the log indicator towards the end of year 2001 causes the p-values of the ADF tests to increase to over 10% and 20% in the UK and Germany, respectively. Since, the indicator appears fairly stationary over most of the subsamples in all the markets, thus implying cointegration between the time series, we estimate VEC models to test whether the indicator can be used to explain the observed variations in the time series and especially in equity prices. To study how the recent market developments affect the resulting parameter estimates, we analyze all the estimation results using two different samples. The first subsample covers observations before the latest market turmoil, from 1980/1 to 2000/4, where the indicator appears very stationary, and the second sample uses the whole dataset, 1980/1 to 2003/4.

4. Statistical analysis of the Fed model

To test the predictive ability of the indicator, we estimate a Vector Equilibrium Correction (VEC) model popularized by Engle and Granger (1987) and Johansen (1995) for the vector process

$$x_t = \begin{bmatrix} \ln Y_t \\ \ln P_t \\ \ln E_t \end{bmatrix}.$$

This approach is similar to the Vector autoregression (VAR) approach used in Campbell and Shiller (1988), and it has similar advantages. A VEC model is obtained from a VAR model by adding an "equilibrium correction" term to it. It is a linear time series model of the form

$$\Delta x_t = c + \sum_{i=1}^{k} A_i \Delta x_{t-i} + \alpha(\beta' x_{t-1} - \mu) + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma), \tag{2}$$

where $c \in \mathbb{R}^3$, $A_i \in \mathbb{R}^{3\times3}$, $\beta \in \mathbb{R}^{3\times l}$, $\mu \in \mathbb{R}^l$, $\alpha \in \mathbb{R}^{3\times l}$ and $\Sigma \in \mathbb{R}^{3\times3}$ is the covariance matrix for the normally distributed random innovations. The third term on the right takes into account the long-term behavior of x_t around statistical equilibria described by the linear equations $\beta' x = \mu$. It is assumed that, in the long run,

$$E[\beta' x_t] = \mu, \tag{3}$$

and that if x_t deviates from the equilibria (due to shocks in economic conditions) it will tend to move back to them. The matrix α determines the speed of adjustment towards the equilibria. In this sense, VEC-models incorporate long-run equilibrium relationships (often derived from economic theory) with short-run dynamic characteristics deduced from historical data.

We are interested in whether or not the indicator I_t could serve as an equilibrium term in a VEC-model for x_t, and whether it explains the variations in x_t, and particularly on P_t as the Fed model stipulates. As described in Section 3, we assume that the indicator is stationary, i.e., choose $\beta' = [1, -1, 1]$, and estimate the remaining parameters of (2) from historical data. Although our approach resembles the method of Engle and Granger (1987) it is not a valid statistical approach. If there is actually no cointegration between the time series, i.e., the indicator is nonstationary, our model will be incorrectly specified and the t-statistic inference of the VEC model will be invalid. However, VEC model offers a natural way for modeling the phenomenon and testing the predictive ability of the indicator.

Following the findings of the unit root tests in Section 3, we present the estimation results for two different samples. The first subsample covers observations from 1980/1 to 2000/4 and the second the whole dataset, 1980/1 to 2003/4. The resulting parameter estimates and the corresponding t-values (in parenthesis) are given in Tables 2–4 for the three markets. Tables 2–4 also report as summary equation statistics the R-squared (R^2) and adjusted R^2 values, equation standard errors (S.E.), p-values of F-statistic, values of the log likelihood function as well as mean and standard deviation of the dependent variables. The R^2 statistic measures the success of the regression in predicting the values

Table 2
Parameter estimates, t-values and summary statistics for the United States

	1980/1–2000/4			1980/1–2003/4		
	$\Delta \ln P_t$	$\Delta \ln E_t$	$\Delta \ln Y_t$	$\Delta \ln P_t$	$\Delta \ln E_t$	$\Delta \ln Y_t$
$\Delta \ln P_{t-1}$	−0.046	−0.071	0.140	0.040	−0.068	0.137
	(−0.413)	(−1.724)	(1.038)	(0.393)	(−1.801)	(1.176)
$\Delta \ln E_{t-1}$	0.196	0.504	−0.008	0.148	0.608	−0.149
	(0.735)	(5.168)	(−0.026)	(0.635)	(6.911)	(−0.551)
$\Delta \ln Y_{t-1}$	−0.124	0.000	0.146	−0.071	0.002	0.102
	(−1.284)	(0.008)	(1.257)	(−0.782)	(0.067)	(0.976)
$\ln I_{t-1}$	−0.123	0.025	−0.142	−0.139	0.009	−0.150
	(−2.311)	(1.271)	(−2.227)	(−2.915)	(0.481)	(−2.723)
c	0.618	−0.108	0.671	0.687	−0.034	0.710
	(2.421)	(−1.154)	(2.190)	(2.999)	(−0.394)	(2.686)
R^2	0.126	0.285	0.069	0.132	0.353	0.085
Adj. R^2	0.081	0.248	0.021	0.093	0.324	0.044
S.E. equation	0.072	0.026	0.086	0.078	0.030	0.091
Prob(F-statistic)	0.032	0.000	0.231	0.013	0.000	0.091
Log likelihood	102.000	184.700	87.014	108.447	200.220	94.883
Mean dependent	0.031	0.017	−0.007	0.026	0.014	−0.008
S.D. dependent	0.075	0.030	0.087	0.082	0.036	0.093

Notes. The table reports parameter estimates and t-statistics (in parenthesis) from the VEC model for two different subsamples, 1980/1–2000/4 and 1980/1–2003/4. As summary equation statistics the table reports R-squared (R^2) and adjusted R^2 values, equation standard errors (S.E.), p-values of F-statistic for testing the joint significance of the regressors, log likelihood function values as well as mean and standard deviation of the dependent variables. If the reported p-value of the F-statistic is less than a specified significance level, say 0.05, the null hypothesis that all equation coefficients are equal to zero is rejected. The datastream US market price index is used to represent the equity prices and the earnings are calculated from the reported P/E ratios. The bond yields correspond to the Datastream US ten-year government benchmark bond index.

of the dependent variable and may be interpreted as the fraction of the variance of the dependent variable explained by the regressors. One problem with using R^2 as a measure of goodness of fit is that R^2 will never decrease as more regressors are added. The adjusted R^2 penalizes for the addition of regressors which do not contribute to the explanatory power of the model, can decrease as regressors are added, and for poorly fitting models, may be negative. The reported F-statistic p-values are from a test of the hypothesis that all of the coefficients (excluding the constant) in a regression are zero. If the p-value is less than a specified significance level, say 0.05, the null hypothesis that all equation coefficients are equal to zero is rejected.

In the US the results are similar across the considered samples. The indicator, I_t, has a statistically significant negative effect on the equity prices, as the Fed model postulates, but it also enters the bond yield equation with a significant negative coefficient. Thus, the indicator pushes the equity prices and bond yields to the same direction, which can be interpreted as a two way correction to an observed disequilibrium between the current bond yields and equity earnings. The changes in log earnings are well explained by its lagged values which account for a high proportion of the variation in the time series, as is apparent from the relatively high R^2 for the earnings equation. This is in line with the findings of Campbell and Shiller (1988) for predicting equity earnings.

Table 3
Parameter estimates, t-values and summary statistics for the United Kingdom

	1980/1–2000/4			1980/1–2003/4		
	$\Delta \ln P_t$	$\Delta \ln E_t$	$\Delta \ln Y_t$	$\Delta \ln P_t$	$\Delta \ln E_t$	$\Delta \ln Y_t$
$\Delta \ln P_{t-1}$	−0.129	0.057	0.192	−0.036	0.043	0.179
	(−1.121)	(0.811)	(1.724)	(−0.328)	(0.715)	(1.897)
$\Delta \ln E_{t-1}$	−0.079	0.202	0.152	0.047	0.176	0.160
	(−0.438)	(1.841)	(0.870)	(0.255)	(1.734)	(1.012)
$\Delta \ln Y_{t-1}$	−0.132	0.042	0.127	−0.142	0.043	0.104
	(−1.028)	(0.541)	(1.026)	(−1.112)	(0.611)	(0.941)
$\ln I_{t-1}$	−0.138	0.079	−0.059	−0.042	0.049	−0.067
	(−2.296)	(2.166)	(−1.019)	(−0.925)	(1.921)	(−1.709)
c	0.700	−0.370	0.266	0.224	−0.220	0.304
	(2.410)	(−2.096)	(0.947)	(1.026)	(−1.831)	(1.622)
R^2	0.107	0.099	0.055	0.035	0.086	0.065
Adj. R^2	0.061	0.052	0.006	−0.009	0.045	0.023
S.E. equation	0.078	0.048	0.076	0.086	0.047	0.074
Prob(F-statistic)	0.065	0.088	0.355	0.529	0.088	0.193
Log likelihood	95.029	135.888	97.838	99.687	155.617	113.833
Mean dependent	0.031	0.016	−0.012	0.024	0.014	−0.011
S.D. dependent	0.081	0.049	0.076	0.086	0.049	0.075

Notes. The table reports parameter estimates and t-statistics (in parenthesis) from the VEC model for two different subsamples, 1980/1–2000/4 and 1980/1–2003/4. As summary equation statistics the table reports R-squared (R^2) and adjusted R^2 values, equation standard errors (S.E.), p-values of F-statistic for testing the joint significance of the regressors, log likelihood function values as well as mean and standard deviation of the dependent variables. If the reported p-value of the F-statistic is less than a specified significance level, say 0.05, the null hypothesis that all equation coefficients are equal to zero is rejected. The datastream UK market price index is used to present the equity prices and the earnings are calculated from the reported P/E ratios. The bond yields correspond to the Datastream UK ten-year government benchmark bond index.

In the UK, the indicator is the only significant regressor explaining the variations of the equity prices and earnings during the first considered sample. However, this effect is alleviated when the whole dataset is used for estimation. The model does not explain the observed variations in the time series very well, which is highlighted by the low adjusted R^2 and high p-values of the F-statistics, see Table 3.

In Germany, the indicator is again the most significant regressor in the model, by entering the earnings and bond yield equations with significant coefficients in the 1980/1–2000/4 sample, and the bond yield equation in the full sample. The earnings' fluctuations are explained by the changes in equity prices and the bond yields are strongly autocorrelated in both samples.

Table 5 reports multivariate residual test statistics for the regressions. The tests reveal no autocorrelation or heteroskedasticity problems in the residual time series. However, the normality assumption of the residuals is rejected at a 1% significance level in the first subsample of the UK data and for the whole sample the residuals seem to be non-normally distributed in all the three countries.

The indicator is able to explain some of the observed variations in the time series in all three markets. Especially, in the US and UK the indicator predicts the changes in equity prices, but it also appears as a significant regressor for bond yields in the US and Germany

Table 4
Parameter estimates, t-values and summary statistics for Germany

	1980/1–2000/4			1980/1–2003/4		
	$\Delta \ln P_t$	$\Delta \ln E_t$	$\Delta \ln Y_t$	$\Delta \ln P_t$	$\Delta \ln E_t$	$\Delta \ln Y_t$
$\Delta \ln P_{t-1}$	0.045	0.161	0.040	0.060	0.215	0.046
	(0.395)	(1.556)	(0.552)	(0.540)	(2.596)	(0.732)
$\Delta \ln E_{t-1}$	0.031	0.156	−0.076	0.093	0.087	−0.028
	(0.254)	(1.391)	(−0.969)	(0.685)	(0.859)	(−0.363)
$\Delta \ln Y_{t-1}$	−0.256	−0.105	0.272	−0.291	−0.078	0.224
	(−1.617)	(−0.730)	(2.691)	(−1.638)	(−0.588)	(2.234)
$\ln I_{t-1}$	−0.111	0.113	−0.136	−0.037	0.031	−0.052
	(−1.814)	(2.017)	(−3.479)	(−0.848)	(0.962)	(−2.140)
c	0.549	−0.526	0.639	0.184	−0.137	0.239
	(1.888)	(−1.990)	(3.456)	(0.909)	(−0.906)	(2.092)
R^2	0.093	0.118	0.178	0.052	0.112	0.086
Adj. R^2	0.046	0.072	0.135	0.009	0.072	0.045
S.E. equation	0.095	0.087	0.061	0.112	0.084	0.063
Prob(F-statistic)	0.105	0.044	0.004	0.312	0.031	0.088
Log likelihood	78.966	86.809	116.036	74.680	101.851	128.508
Mean dependent	0.025	0.014	−0.006	0.018	0.014	−0.007
S.D. dependent	0.098	0.090	0.065	0.113	0.087	0.065

Notes. The table reports parameter estimates and t-statistics (in parenthesis) from the VEC model for two different subsamples, 1980/1–2000/4 and 1980/1–2003/4. As summary equation statistics the table reports R-squared (R^2) and adjusted R^2 values, equation standard errors (S.E.), p-values of F-statistic for testing the joint significance of the regressors, log likelihood function values as well as mean and standard deviation of the dependent variables. If the reported p-value of the F-statistic is less than a specified significance level, say 0.05, the null hypothesis that all equation coefficients are equal to zero is rejected. The datastream Germany market price index is used to present the equity prices and the earnings are calculated from the reported P/E ratios. The bond yields correspond to the Datastream Germany ten-year government benchmark bond index.

Table 5
Multivariate residual test statistics

	1980/1–2000/4			1980/1–2003/4		
	US	UK	GER	US	UK	GER
Autocorrelation LM(4)	0.943	0.483	0.631	0.628	0.812	0.519
Normality	0.096	0.001	0.014	0.003	0.000	0.004
Heteroskedasticity	0.243	0.444	0.286	0.148	0.726	0.604

Notes. The table reports multivariate residual test statistics for the regressions. The numbers are p-values of the statistics in the first column. The Lagrange multiplier (LM) test reports the multivariate test statistics for residual autocorrelation up to the specified order, $h = 4$. Under the null hypothesis of no serial correlation of order h, the LM statistic is asymptotically χ^2 distributed with k^2 degrees of freedom (Johansen, 1995). The normality test reports the multivariate extensions of the Jarque–Bera residual test (Doornik and Hansen, 1994), which compares the third and fourth moments of the residuals to those from the normal distribution. The reported value is the probability that a Jarque–Bera statistic exceeds (in absolute value) the observed value under the null hypothesis. A small probability value leads to the rejection of the null hypothesis of a normal distribution. Heteroskedasticity test is the extension of White's (1980) test to systems of equations as discussed, e.g., by Doornik (1995). The test regression is run by regressing each cross product of the residuals on the cross products of the regressors and testing the joint significance of the regression. Under the null of no heteroskedasticity, the non-constant regressors should not be jointly significant, see Doornik (1995).

as well as for earnings in the UK and Germany. However, the extent of its forecasting power is somewhat questionable due to the low adjusted R^2 values reported in Tables 2–4. To further analyze the forecast ability of the indicator we compare the developed VEC model against VAR models in out-of-sample forecast tests in the next section.

5. Forecast tests with the Fed model

We compare the predictive ability of the VEC-models in out-of-sample tests against VAR-models for differences. The VAR-models are obtained by dropping the equilibrium correction term (the FED-indicator), so the focus is on the predictive ability of the log indicator. The models' forecast performance is tested in a 1-step ahead forecast comparison using recursive estimation, where the models are re-estimated each time a new prediction has to be constructed. Initially, the models are estimated using a data sample $t = 1980/1$ to 1989/4, and a 1-step ahead forecast is constructed using the estimated parameters. After this, the estimation period is expanded by one observation at a time (i.e., $t = 1980/1$ to 1990/1, $t = 1980/1$ to 1990/2, etc.) and a new 1-step prediction is constructed using the re-estimated parameters. We use the root mean squared forecast error (RMSE) (see, e.g., Makridakis et al., 1998) as a criterion for measuring the forecast accuracy of the different models. The VAR and VEC models' RMSEs on two different subsamples, 1990/1 to 2000/4 and 1990/1 to 2003/4, are given in Table 6.

In the first subsample, 1990/1 to 2000/4, the VEC models outperform the VAR models by producing smaller forecast errors for the log differences of all the forecasted time series in all the three markets. The same general observation applies also in the second sample, 1990/1 to 2003/4, although the prediction errors generated by the models are slightly larger when the observations from 2001/1 to 2003/4 are included in the forecast test. Apart from forecasting the changes in the German log earnings, VEC models outperform VAR models by generating smaller or equal forecast errors for all the time series. It appears that the indicator has predictive power in forecasting quarterly differences of equity prices, earnings

Table 6
Root mean squared errors for 1-step ahead forecasts

Forecasted variable	US		UK		GER	
	VAR	VEC	VAR	VEC	VAR	VEC
Forecast sample 1990/1–2000/4						
$\Delta \ln P$	0.068	0.067	0.072	0.068	0.098	0.094
$\Delta \ln E$	0.025	0.024	0.039	0.038	0.073	0.073
$\Delta \ln Y$	0.082	0.079	0.074	0.073	0.064	0.061
Forecast sample 1990/1–2003/4						
$\Delta \ln P$	0.080	0.077	0.082	0.082	0.120	0.117
$\Delta \ln E$	0.030	0.029	0.040	0.039	0.068	0.071
$\Delta \ln Y$	0.091	0.086	0.073	0.070	0.063	0.063

Notes. The table reports 1-step ahead RMSEs of VAR and VEC models for two different out-of-sample forecast periods. The model parameters are re-estimated every time a new prediction has to be constructed.

and bond yields, even though the reductions in the forecast errors produced by the indicator are somewhat limited.

6. Conclusion

This paper developed a logarithmic Vector Equilibrium Correction version of the Fed model. The results of Section 4 show that the model is statistically significant in explaining variations in the logarithmic values of stock prices, earnings and bond yields. Moreover, in the forecast tests of Section 5, the VEC-model outperforms the VAR-model obtained by dropping the log indicator from the VEC-model (and re-estimating the parameters). These results support the earlier findings of Ziemba and Schwartz (1991), Berge and Ziemba (2003), Ziemba (2003) and Campbell and Vuolteenaho (2004). Consistent with Berge and Ziemba (2003), our results indicate that the Fed model is more successful in the US than in the other markets. Our results do not validate the logic behind the Fed model but they do show that during 1980–2003 the Fed model has had some predictive power in the US, the UK and German markets.

References

Asness, C., 2003. Fight the fed model: The relationship between future returns and stock and bond market yields. Journal of Portfolio Management (Fall), 11–24.

Berge, K., Ziemba, W.T., 2003. The predictive ability of the bond stock earnings yield differential in world-wide equity markets. Manuscript. University of British Columbia.

Board of Governors of the Federal Reserve System, 1997. Monetary policy report to the congress pursuant to the full employment and balanced growth act of 1978. Technical report. URL www.federalreserve.gov/boarddocs/hh/1997/july/fullreport.htm.

Campbell, J., Shiller, R., 1988. Stock prices, earnings and expected dividends. Journal of Finance 43, 661–676.

Campbell, J.Y., Vuolteenaho, T., 2004. Inflation illusion and stock prices. American Economic Review, Papers and Proceedings 94 (May), 19–23.

Dickey, D.A., Fuller, W.A., 1981. Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica 49, 1057–1072.

Doornik, J.A., 1995. Testing general restrictions on the cointegrating space. Technical report. Nuffield College, Oxford. URL http://www.doornik.com/research/coigen.pdf.

Doornik, J.A., Hansen, H., 1994. An omnibus test for univariate and multivariate normality. Technical report. Nuffield College, Oxford. URL http://www.doornik.com/research/normal2.pdf.

Engle, R.F., Granger, C.W.J., 1987. Co-integration and error correction: Representation, estimation, and testing. Econometrica 55, 251–276.

Johansen, S., 1995. Likelihood-based Inference in Cointegrated Vector Autoregressive Models. Oxford University Press, New York.

Makridakis, S., Wheelwright, S.C., Hyndman, R.C., 1998. Forecasting: Methods and Applications, third ed. Wiley, New York.

White, H., 1980. A heteroskedasticity-consistent covariance matrix and a direct test for heteroskedasticity. Econometrica 48, 817–838.

Yardeni, E., 2003. Stock valuation models. Topical study 58. Prudential Financial Research. URL www.cm1.prusec.com/yardweb.nsf/Yardeni.

Ziemba, W.T., 2003. The Stochastic Programming Approach to Asset Liability and Wealth Management. AIMR, Charlottesville, Virginia.

Ziemba, W.T., Schwartz, S.L., 1991. Invest Japan: The Structure, Performance and Opportunities of Japan's Stock, Bond and Fund Markets. Probus Publishing, Chicago.