Pergamon

Journal of International Money and Finance, Vol. 16, No. 6, pp. 821–836, 1997

Printed in Great Britain
0261-5606/97 $17.00 + 0.00

PII: S0261-5606(97)00031-4

What are the global sources of rational variation in international equity returns?

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This paper uses multivariate statistical approaches to investigate the global sources of international real return variation. These approaches allow us to take into account the widely-documented evidence that stock market returns from different countries move in tandem with each other. In the spirit of Fama [Fama, E. F. (1990) Stock returns, expected returns, and real activity. *Journal of Finance* **45**, 89–108.] we examine two potential sources of international real return variation: changes in expected future cash flows and changes in discount rates. In this study, common global economic variables that relate to changes in the global economy or to international business conditions serve as proxies for the two sources of variation. Our results show that these two sources of variation capture a statistically significant fraction of stock price variability; their explanatory power, however, differs across holding period horizons. While proxies for changes in discount rates have an incremental impact on both monthly and quarterly real returns, proxies for changes in expected future cash flows have only an incremental impact on quarterly real returns. Our results are also generally robust to the different methodologies employed. (JEL G12, G15, C32).

*The authors would like to thank Andy Lo, Steve Magee, Tim Opler, Raman Uppal, and workshop participants at the 1995 Winter Econometric Society Meetings in Washington, DC, University of Houston, the 1995 Asia-Pacific Basin Conference, and the University of Texas at Austin for helpful comments and suggestions.

In standard financial valuation models, stock price variability stems from a combination of shocks to expected cash flows, time-varying expected returns, and shocks to expected returns. The latter two measures induce changes in discount rates that affect stock prices. Thus, markets are said to be rational if prices reflect these fundamental variables. Some existing studies have shown that variables such as real gross national product and future production growth reflect information about future cash flows that is impounded in stock prices. Other studies have provided evidence suggesting that a large proportion of stock return variances is attributable to changing expected returns, which are generally captured by dividend yields on stocks, default spreads, and term spreads. In contrast, Fama (1990) has examined the combined explanatory power of the three sources of return variation and shown that these variables can explain about 58% of the annual return variance.[1] Nevertheless, the evidence has thus far focused mainly on the US stock market, and very little evidence on the other markets across the world.

This study attempts to offer evidence of global sources of rational variation in different national stock market prices. In particular, we use financial evaluation models examined in, for example, Fama (1990) and Schwert (1990), to investigate whether the above US phenomenon extends more generally to other markets, and whether the effect varies across holding period horizons.

This paper also contributes to the current literature in that it focuses on the maximum degree of global shared variation in 18 national stock markets and uses the multivariate maximal R^2 (γ) statistical methodology developed by Lo and MacKinlay (1995). Common global economic variables that relate to changes in the global economy or to international business conditions serve as proxies for the three sources of return variation.

Further, we propose a multivariate latent-root-test statistic, which is a generalization of the maximal R^2 approach, to evaluate the relative information found in the three global measures of real return variation. We test whether these different measures have any incremental explanatory power in the presence of each other. Our results offer insights into the effects on international real equity returns. In particular, we assess the relative importance of the role of these three stock fundamental variables in explaining expected real returns. Finally, we employ a Wald test with less restricted assumptions to examine the robustness of our results to the different methodologies employed.

We use the monthly and quarterly data of 18 national stock markets for the period January 1970–December 1991. We find evidence that the combination of shocks to expected cash flows, time-varying expected returns, and shocks to expected returns has significant explanatory power for stock price variability. The fractions of real return variation explained by global variables, separately or jointly, increase as the holding period lengthens. The strength of the explanatory power of these three types of fundamental variables increases at least two-fold from monthly to quarterly horizons.

Global economic variables proxying for both changing expected returns and shocks to expected returns capture up to 18% of the monthly portfolio stock variance and 48% of the quarterly variance. Current and future world-production growth rates explain a maximum of 13% of the monthly stock price variability and 37% of the quarterly variability. The maximum joint explanatory power of the three measures is 23% using monthly observations and 59% using quarterly observations. These results thus indicate a strong cross correlation among the selected global variables as well as among the national equity returns, suggesting that similar international economic forces influence variations in stock market fundamentals.

Results further show that shocks to expected cash flows have statistically significant incremental explanatory power only for quarterly real returns, while both time-varying expected returns and shocks to expected returns exhibit statistically significant incremental power for explaining both monthly and quarterly real returns. Even though the latter explain the largest component of the real return variation, their explanatory power, combined with that of cash-flow effects, captures a more significant fraction of the total variation in real returns.

In the next section we describe the data. The empirical models and methodologies are discussed in Section II. Section III reports the results, and the fourth section contains some concluding remarks.

I. Data

I.A. Real stock market returns

Our stock-market data come from Morgan Stanley Capital International (MSCI) and relate to countries including Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore/Malaysia, Spain, Sweden, Switzerland, the United Kingdom, and the United States. These market indexes are value-weighted with inclusive dividends and are measured in US dollars. They exclude the market value of investment companies and of foreign-domiciled companies and thus avoid the problem of double-counting. We convert stock market returns to real returns using inflation rates computed from the US consumer price index. In our analyses, we use continuously compounded real returns for monthly and quarterly return horizons.

I.B. Systematic global measures of country stock return variation

In our study we construct global information variables that are proxies for time-varying expected returns and for shocks to both expected returns and expected future cash flows. The choice of these proxy variables shares the similar motivation as those used by Fama (1990).

Drawing evidence from existing studies, the global variation in expected real returns on international stocks is reflected in dividend yields of the MSCI world index (WDY), term spreads (TERM, defined as the difference between the 10-year US government bond yield and the yield on short-term US Treasury bills),[2] and Eurodollar-Treasury yield spreads (TED, defined as the difference between the 3-month Eurodollar rate and the 90-day yield on the US Treasury bill).[3] Many existing studies, such as Keim and Stambaugh (1986), Fama and French (1989) and Fama (1990), show that dividend yields and term spreads predict equity returns quite well. Fama and French further show that these two variables relate to changes in business conditions. A recent study by Chen (1991) finds that dividend yields measure the current health of the economy, while term spreads reflect the future health of the economy. World dividend yields and term spreads therefore reflect changes in the international business environment due to fluctuations in world business conditions. TED is a proxy for movements in expected stock market returns in response to changes in world political risk.[4]

Similarly to Fama (1990), our study interprets the residuals from first-order autoregressions fitted to TED and TERM as proxies for shocks to expected returns, and we denote the residuals as TEDSH and TERMSH. These two variables measure world economic news affecting future expected returns.

Finally, we use quarterly growth in industrial production over the next 12 months to proxy for expected future cash flows. According to studies such as Fama (1990) and Chen (1991), a 12-month period is sufficient to capture the cyclical behavior in business conditions and provide adequate information about the future state of the economy.[5] Except for Hong Kong and Singapore/Malaysia, all the countries in our study are members of the OECD, so we use future growth rates of the OECD industrial production index (P_t), provided by Citibase, to proxy for investors' changing expectations of future worldwide real economic activity.[6]

The cross correlation coefficients between these selected variables are reported in Table 1. The elements in the upper diagonal block matrix represent monthly correlation coefficients between the variables, while those in the lower diagonal are the quarterly correlation coefficients. Notice that the strengths of the monthly and quarterly correlations are different. For the monthly figures, the largest correlation coefficient of -0.45 is between TED and TERM, while the smallest correlation coefficient of -0.02 is between TERM and TERMSH or between TED and TEDSH. For the quarterly figures, the largest correlation coefficient of -0.48 is between TED and TERM, while the smallest correlation coefficient of zero is between WDY and P_{t+6}.

II. Empirical models and methodologies

II.A. Empirical models

We examine the effects of global shocks to expected future cash flows and the effects of expected-return variables on international real returns using the following relationships:

$$\langle 1 \rangle \qquad r_{j,t} = \alpha_j + \alpha_{1,j} P_t + \alpha_{2,j} P_{t+3} + \alpha_{3,j} P_{t+6} + \alpha_{4,j} P_{t+9} + \nu^1_{j,t},$$

$$\langle 2 \rangle \qquad r_{j,t} = a_j + a_{1,j} WDY_{t-1} + a_{2,j} TED_{t-1} + a_{3,j} TERM_{t-1} + a_{4,j} TEDSH_t + a_{5,j} TERMSH_t + \nu^2_{j,t},$$

TABLE 1. Cross correlation statistics

	WDY	TED	TERM	TEDSH	TERMSH	P_t	P_{t+3}	P_{t+6}	P_{t+9}
WDY		0.35	−0.14	0.14	0.02	−0.28	−0.18	−0.12	−0.14
TED	0.34		−0.45	−0.02	0.07	−0.30	−0.27	−0.18	−0.06
TERM	−0.08	−0.48		−0.16	−0.02	0.12	0.27	0.32	0.31
TEDSH	0.15	−0.02	−0.17		−0.25	−0.04	−0.16	−0.03	−0.13
TERMSH	−0.06	0.16	−0.01	−0.41		−0.12	−0.08	0.02	0.08
P_t	−0.15	−0.35	0.22	−0.21	−0.05		0.15	0.13	0.04
P_{t+3}	−0.06	−0.18	0.34	−0.28	−0.08	0.12		0.14	0.14
P_{t+6}	0.00	−0.04	0.26	−0.19	0.21	0.20	0.14		0.13
P_{t+9}	0.02	−0.02	0.35	−0.05	−0.01	0.05	0.19	0.13	

Cross correlations between the world dividend yield(WDY), the Eurodollar spread (TED), the term spread (TERM), shocks to TED (TEDSH) and to TERM (TERMSH), and current and future OECD industrial production growth rates (P_t, P_{t+3}, P_{t+6}, P_{t+9}). The elements in the upper diagonal block matrix represent monthly correlation coefficients, while those in the lower diagonal are the quarterly correlation coefficients between the variables as indicated in the legends. The sample period is 1970:2–1991:12.

and

$$\langle 3 \rangle\ r_{j,t} = \alpha_j + \alpha_{1,j}P_t + \alpha_{2,j}P_{t+3} + \alpha_{3,j}P_{t+6} + \alpha_{4,j}P_{t+9} + \alpha_{5,j}WDY_{t-1} + \alpha_{6,j}TED_{t-1} + \alpha_{7,j}TERM_{t-1} + \alpha_{8,j}TEDSH_t + \alpha_{9,j}TERMSH_t + \nu^3_{j,t},$$

where $r_{j,t}$ is the jth country real return, $\nu^i_{j,t}$s are random error terms, and the remaining variables are defined as in Section I. Relation $\langle 1 \rangle$ describes the relationship between real returns and expected future global production growth rates; relation $\langle 2 \rangle$ describes the relationship between real returns and the proxies for time-varying global expected returns and for global shocks to expected returns. Equation $\langle 3 \rangle$ dictates the combined explanatory power of the two global information variables. Financial valuation models similar to $\langle 1 \rangle$, $\langle 2 \rangle$ and $\langle 3 \rangle$ are also used by, for example, Fama (1990), Schwert (1990) and Harris and Opler (1993), to investigate real stock return variation in the US and other industrialized countries. Unlike these studies which use the standard univariate regression analysis, we will investigate these three relationships using both univariate and multivariate statistical methodologies described in the following subsection.

II.B. Methodologies

Suppose $Z_t = (r_{1t}, \ldots, r_{Nt})'$ is the vector of N country real stock returns; X_{1t} and X_{2t} are vectors of $K1$ and $K2$ explanatory variables; B_1 and B_2 are the $K1 \times N$ and $K2 \times N$ coefficient matrices; b is the vector of constants; and $\varepsilon_t = (\nu_{1t}, \ldots \nu_{Nt})'$ is the vector of disturbance terms. Assuming $E_{t-1}[\varepsilon_t] = 0$ and

$\text{Var}_{t-1}[\varepsilon_t] = \Sigma$, the regression model can be written as

$$\langle 4\rangle \qquad Z_t = B_1'X_{1,t} + B_2'X_{2,t} + b + \varepsilon_t, \\ \equiv B'X_t + \varepsilon_t.$$

Any incremental explanatory power of $X_{1,t}$ conditioned on $X_{2,t}$ can be determined using a linear restriction test on the multivariate linear model. Specifically, the null hypothesis $RB = 0$, where $R = [I_{K1}\ 0]$, tests the incremental predictability of $X_{1,t}$. A similar argument applies for testing the incremental explanatory power of $X_{2,t}$ conditioned on $X_{1,t}$.

For notational convenience, we define $Z = (Z_1, \ldots, Z_T)'$, $X = (X_1, \ldots, X_T)'$, and $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_T)'$. Then, from $\langle 4\rangle$, we have $Z = XB + \varepsilon$. Let $\hat{\Sigma}$ and $\hat{B}$ be the maximum likelihood estimates of Σ and B, and let the matrices S and Q be defined as:

$$\langle 5\rangle \qquad S \equiv \hat{B}'R'\left[R(X'X)^{-1}R'\right]^{-1}R\hat{B} = Z_1^*{}'Z_1^*,$$

and,

$$\langle 6\rangle \qquad Q \equiv T\hat{\Sigma} = Z'Z - \hat{B}'X'Z = Z_3^*{}'Z_3^*.$$

Q represents the matrix due to the error and measures the fraction of Z_t that is not explained by X_t. Also S denotes the matrix due to the hypothesis and measures the increased unexplained component attributed to the constraint of $B_1 = 0$. If $B_1 = 0$, then S will be small relative to Q. Under the normality assumption, the distributions of Z_1^* and Z_3^* are given by $Z_1^* \sim N(M_1, I_{K1} \otimes \Sigma)$ and $Z_3^* \sim N(0, I_{(T-K1-K2-1)} \otimes \Sigma)$, where M_1 is the expected value of Z_1^* and T is the sample size (see, for example, Muirhead, 1982, p. 436).

Suppose $\gamma = (\gamma_1, \ldots, \gamma_N)$ is the vector of portfolio weights that sum to one,[7] and γZ_t is the real return on a portfolio based on the linear combination of N international real equity returns. Conditional on $X_{2,t}$ the incremental proportion of variation in γZ_t due to $X_{1,t}$ is given by

$$\langle 7\rangle \qquad R^2(\gamma) \equiv \frac{\gamma' S \gamma}{\gamma'(Q+S)\gamma}.$$

The maximum value of $R^2(\gamma)$ in $\langle 7\rangle$ and the corresponding portfolio γ^* are given by l, the largest latent root of the matrix $(Q+S)^{-1}S$, and the latent vector associated with this latent root.[8] This maximum latent root l therefore yields the greatest possible incremental predictable power of $X_{1,t}$.

The maximum-latent-root approach generalizes the maximal R^2 method proposed by Lo and MacKinlay (1995). For instance, by eliminating $X_{2,t}$ from $\langle 4\rangle$, the $R^2(\gamma)$ in $\langle 7\rangle$ yields the conventional coefficient of determination from regressing γZ_t on $X_{1,t}$ and a constant. In this case, the l statistic measures the maximum proportion of variation in γZ_t that is explained by $X_{1,t}$. Thus the Lo-MacKinlay maximal R^2 procedure is a special case of the maximum-latent-root method, since the latter admits a more general conditional information set in calculating the maximum incremental explanatory power of the variables.

The l statistic allows us to test the significance of the restriction $RB = 0$. When the computed statistic is large relative to its critical value, which is obtained from the distribution of l under the null hypothesis $RB = 0$, we reject the validity of this restriction. Analytically, the distribution of l under the normality assumption can be obtained as follows:[9] under the null, the distribution of λ (the maximum latent root of SQ^{-1}) is given by Theorem 10.6.8 and Corollary 10.6.9 of Muirhead (1982); based on this result, we derive the distribution of l under the null by observing that $\lambda = l/(1-l)$, which is a monotone function of l.[10]

While we can analytically derive the null distribution of l, the resulting distribution is computationally intractable and, hence, we use Monte Carlo methods to generate the required critical values. For each model specification, we generate T independent vectors of N normal variates with zero means and identity covariance matrices as the left-hand-side variables, where T is the sample size. We then compute the l statistics from these random vectors and X_ts. For a given combination of sample size, international equities, and explanatory variables, we replicate this procedure 10 000 times to tabulate the empirical distribution of l.

These two proposed multivariate test statistics are in the spirit of the Roll (1988) R^2 and offer many advantages. Firstly, the multivariate tests incorporate cross-sectional effects among the national real equity returns and among the explanatory variables. Secondly, they allow us to attain the maximum power, or the maximum incremental power, of the world economic variables used for explaining the cross section of national real stock returns. Unlike statistics used in many existing studies that focus on univariate analyses, the maximum-latent-root test statistic and the maximal $R^2(\gamma)$ in our study build on a multivariate information set. Thirdly, these statistics also allow us to evaluate and compare the statistical significance of the variables proxying for shocks to future cash flows and proxying for variations in future discount rates.

Additionally, we employ an alternative multivariate approach with less restricted assumptions that allows us to check the robustness of our results. Unlike the maximal $R^2(\gamma)$ and the l statistic, the asymptotic result of this alternative approach does not depend on the normality assumption. Following Gourieroux *et al.* (1991), we use the canonical analysis framework to examine the null hypothesis $RB = 0$. It is shown that the Wald statistic for testing $RB = 0$ is given by

$$W = T \sum_{i=1}^{N} \omega_i/(1-\omega_i), \tag{8}$$

where ω_is are the latent roots of the matrix $(Q+S)^{-1}S$. Under the null hypothesis, W has an asymptotic chi-square distribution with $K1 \times N$ degrees of freedom.

As the construction of the W statistic is different from the l statistic, the former offers some additional information on the incremental explanatory power of the variables and also provides a means to assess the robustness of the results derived from the maximal $\bar{R}^2(\gamma)$ and l test statistics.[11] In contrast, however, the maximal $\bar{R}^2(\gamma)$ and l statistics allow us to gauge the extent to which the total variance of real return variation can be explained by the proxies for cash-flow and discount-rate variables.

III. Empirical results

III.A. Univariate analyses

Table 2 presents both the monthly and quarterly $\bar{R}^2$s for the models specified by relations ⟨1⟩–⟨3⟩. Since parameter estimates of each model formulation are essentially the same as those found in the literature, we do not report them.[12] We also check the adequacy of the full model specification ⟨3⟩ by performing a number of diagnostic statistics. In examining the first 12 lags of the resulting residuals, we reject three of the 18 cases that there exists no serial correlation as well as no autoregressive conditional heteroskedasticity. Both tests are evaluated at the 5% significance level. Overall, these statistics suggest that the

TABLE 2. Adjusted R^2s from regressing monthly and quarterly country stock real returns on proxies for time-varying expected returns and global shocks to both expected returns and expected cash flows

Country	$\bar{R}^{2,F}_M$	$\bar{R}^{2,1}_M$	$\bar{R}^{2,2}_M$	$\bar{R}^{2,F}_Q$	$\bar{R}^{2,1}_Q$	$\bar{R}^{2,2}_Q$
Australia	0.07	0.03	0.05	0.26	0.11	0.21
Austria	0.07	0.01	0.06	0.18	0.05	0.15
Belgium	0.10	0.04	0.09	0.24	0.09	0.21
Canada	0.06	0.03	0.05	0.27	0.17	0.17
Denmark	0.11	0.06	0.07	0.23	0.15	0.15
France	0.10	0.02	0.09	0.19	0.10	0.13
Germany	0.11	0.03	0.08	0.22	0.04	0.18
Hong Kong	0.07	0.03	0.05	0.10	0.05	0.09
Italy	0.03	0.01	0.03	0.13	0.02	0.12
Japan	0.10	0.06	0.07	0.20	0.12	0.16
Netherlands	0.12	0.04	0.10	0.31	0.09	0.27
Norway	0.06	0.03	0.05	0.13	0.07	0.10
S'pore/M'sia	0.08	0.06	0.02	0.18	0.10	0.11
Spain	0.05	0.02	0.04	0.09	0.04	0.06
Sweden	0.06	0.02	0.05	0.14	0.04	0.11
Switzerland	0.13	0.04	0.11	0.35	0.09	0.31
United Kingdom	0.10	0.04	0.07	0.28	0.13	0.17
United States	0.08	0.04	0.06	0.30	0.10	0.27

$\bar{R}^{2,F}_M$, $\bar{R}^{2,1}_M$ and $\bar{R}^{2,2}_M$ are the $\bar{R}^2$s obtained from the regressions of monthly r_t on: (1) P_t, P_{t+3}, P_{t+6}, P_{t+9}, WDY_{t-1}, TED_{t-1}, TERM_{t-1}, TEDSH_t, and TERMSH_t; (2) P_t, P_{t+3}, P_{t+6}, and P_{t+9}; and (3) WDY_{t-1}, TED_{t-1}, TERM_{t-1}, TEDSH_t, and TERMSH_t, respectively. The $\bar{R}^{2,F}_Q$, $\bar{R}^{2,1}_Q$, and $\bar{R}^{2,2}_Q$ are their quarterly counterparts. r is the real return, WDY is the World dividend yield (over the past 12 months) on the MSCI World index, TED is the Eurodollar-Treasury yield spread, TERM is the term structure of interest rates, TEDSH and TERMSH are the residuals from first-order autoregression fitted to TED and TERM, and P_{t+g} is the growth rate of IPOECD (the industrial production index of the OECD countries). The sample period is 1970:2–1991:12.

model reasonably captures the temporal dynamics and the potential ARCH effect documented in the stock price literature. On the other hand, however, most individual country regressions fail the Jarque–Bera normality test. This makes the robust Wald test a good complement to the maximal R^2 and the maximum-latent root approaches in evaluating the explanatory power of the variables employed.

Several interesting observations emerge from Table 2. Firstly, we find that much of the variability of real stock returns is better explained by both time-varying expected returns and shocks to expected returns than by global shocks to expected future cash flows.[13] The monthly $\bar{R}^2$s from regressing real stock returns against OECD future production growth rates are mostly smaller than the quarterly $\bar{R}^2$s. This finding is mainly due to the fact that fluctuations in expected future cash flows influencing stock prices are generally not immediate because output from investment usually takes a long time to materialize. The result thus suggests that effects due to time-varying expected returns and to shocks to expected returns contribute substantially to the increased strength in the explanatory power.

Secondly, 32 of the 36 $\bar{R}^2$s from the model $\langle 3 \rangle$ are less than the sum of the separate explanatory powers of the two sets of variables, while the remaining $\bar{R}^2$s are equal to the sum. This finding indicates a strong interaction among the countries' real returns, the proxies for time-varying global discount-rate variables, and the global shocks to expected future cash flows. Lastly, the combined explanatory power of the two groups of information variables generally becomes greater as the horizon increases. For the monthly horizon, the average $\bar{R}^2$ is 8.3%, while for the quarterly horizon, it is 21.1%.

So far, this analysis has not accounted for the widely documented strong cross correlation in international stock returns (see, for example, King and Wadhwani, 1990; Bekaert and Hodrick, 1992; Campbell and Hamao, 1992). Although our results provide comparisons with those of the existing studies using univariate analyses, the estimators are likely to be inefficient and statistical inferences drawn may be misleading. In subsequent subsections we will apply multivariate statistical methods to adjust for cross correlation in international stock returns.

III.B. Global sources of rational variation — their maximum explanatory power

This section uses the Lo and MacKinlay (1995) multivariate method to exploit the co-movement among international stock market returns and among the proxies for discount-rate and cash-flow effects. Here we estimate the maximum explained proportion of common variation in stock market returns attributed to the two selected groups of proxy variables. The combined and separate maximal $\bar{R}^2(\gamma)$s estimated, together with the W statistics, using this representative world portfolio (henceforth called the 'maximal world portfolio') are reported in Table 3. This maximal world portfolio is constructed by maximizing the $\bar{R}^2$ according to the procedure described in Section IIB. The largest latent vector at which $\bar{R}^2$ is maximized determines the asset weights in the world maximal portfolio.

The maximal $\bar{R}^2(\gamma)$s in Table 3 are always larger than the conventional $\bar{R}^2$s for each nation's stock market, as reported in Table 2. The maximal $\bar{R}^2(\gamma)$s, which are evaluated based on the simulated critical values of the $\bar{R}^2$s reported in Table A.1 in the Appendix, are all significant at the 5% level, and so are the W statistics. This finding provides strong evidence of cross effects between countries' stock returns and world economic variables. When we consider only cash-flow variables in the regression, all the coefficients on the future OECD production growth rates, except for the two on the monthly P_{t+3} and P_{t+3}, are positive. This result is generally consistent with an equilibrium asset pricing model. Since financial securities are claims against future outputs, any increase in expected future levels of economic activity will induce a higher expected equity return. We observe, however, that growth rates in industrial production proxying for expected future cash flows can explain a larger fraction of the variance of quarterly real returns than of monthly real returns. The quarterly

TABLE 3. Monthly and quarterly regressions of the representative maximal world portfolio against the proxies for time-varying global expected returns, global shocks to expected returns, and shocks to expected global future cash flows

α_1	α_2	α_3	α_4	α_5	α_6	α_7	α_8	α_9	$\bar{R}^2(\gamma)$	W
					Monthly					
−1.41	−9.92	3.55	10.55						0.13*	96.18*
(2.82)	(2.42)	(2.58)	(2.30)							
				21.59	−23.00	12.31	−15.33	14.56	0.18*	153.72*
				(5.86)	(5.48)	(4.66)	(6.17)	(14.08)		
26.27	−34.56	13.50	−15.99	14.75	−1.24	−0.24	−0.22	1.04	0.23*	244.93*
(7.56)	(7.45)	(6.63)	(7.84)	(16.89)	(0.42)	(0.39)	(0.33)	(0.36)		
					Quarterly					
1.06	0.37	4.56	0.58						0.37*	116.60*
(0.80)	(0.71)	(0.75)	(0.73)							
				11.76	−4.16	37.34	−32.72	−14.33	0.48*	185.20*
				(4.13)	(5.15)	(10.84)	(5.52)	(16.85)		
17.66	−21.05	83.69	−52.32	8.73	−4.56	−2.67	−3.66	3.04	0.59*	339.27*
(7.04)	(7.91)	(19.68)	(10.23)	(28.55)	(1.14)	(1.10)	(0.93)	(1.17)		

The fitted model is $r_t = \alpha + \alpha_1 P_t + \alpha_2 P_{t+3} + \alpha_3 P_{t+6} + \alpha_4 P_{t+9} + \alpha_5 \mathrm{WDY}_{t-1} + \alpha_6 \mathrm{TED}_{t-1} + \alpha_7 \mathrm{TERM}_{t-1} + \alpha_8 \mathrm{TEDSH}_t + \alpha_9 \mathrm{TERMSH}_t + \nu_t$, where r is the real return, WDY is the world dividend yield (over the past 12 months) on the MSCI World index, TED is the Eurodollar-Treasury yield spread, TERM is the term structure of interest rates, TEDSH and TERMSH are the residuals from first-order autoregression fitted to TED and TERM, and P_{t+g} is the growth rate of IPOECD (the industrial production index of the OECD countries). Heteroskedastic-consistent standard errors are in parentheses. *Denotes significance at the 5% level. $\bar{R}^2(\gamma)$ and W are the adjusted maximal R^2 and the Wald statistics, respectively. The sample period is 1970:2–1991:12.

maximal $\bar{R}^2(\gamma)$ is 37%, while the monthly maximal $\bar{R}^2(\gamma)$ is only 13%. But both are significant at the 5% level.

When we use proxies for time-varying discount-rate variables alone in the regression, the quarterly maximal $\bar{R}^2(\gamma)$ is almost three times larger than the monthly maximal $\bar{R}^2(\gamma)$. The two commonly used forecasting variables — dividend yields and term spreads — are found to be positively related to expected real return on the maximal portfolio. Positive coefficients on WDY and TERM are consistent with asset pricing models such as Breeden (1979), Cox et al. (1985), and Constantinides (1990). These models imply that a depressed state of economy with low consumption is associated with a high relative risk aversion and hence a high expected market return.

When we consider the measures of return variation jointly, the monthly maximal $\bar{R}^2(\gamma)$ is 23%; the separate maximal $\bar{R}^2(\gamma)$s for the proxies of global shocks to expected future cash flows, and for the expected return variables, are 13% and 18%, respectively. For quarterly horizons, the values of the maximal $\bar{R}^2(\gamma)$s are substantially larger and are also significant at the 5% level. The explanatory power of the global measures of return variability improves with the holding period horizon. The combined maximum explanatory power of these variables increases from 23% for the monthly horizon to 59% for the quarterly horizon.

Interestingly, all the monthly and quarterly shocks to expected future global cash flows have significant effects on real return. In contrast, the discount-rate variables for different horizons demonstrate different effects on real return variation. While some of the coefficients on monthly measures for time-varying expected returns and shocks to expected returns are significant, almost all of those quarterly variables (except for WDY) are significant. Thus, information about the world real sector does provide a rational explanation for the cross section of countries' stock market movements. Overall, evidence suggests that proxies for global time-varying expected returns, global shocks to expected returns, and for global shocks to cash flows share some common information that is useful for explaining real return movements.

III.C. What the global sources of rational variation are

In this section we compare the information contained in the two sets of selected variables. Specifically, we address the following issues:

1. whether the two global sources of variation contain non-overlapping information about the real equity return, and
2. whether the cash-flow effect and the discount-rate effect provide incremental information about the global real equity variation in the presence of each other.

Here we use the multivariate maximum-latent-root test and the robust Wald test to measure and compare the information contained in the proxy variables with respect to the real return on the maximal world portfolio. There are three possible cases. If one source of variation contains some unique information about the real return on the maximal portfolio, then it will have significant

TABLE 4. Results for the incremental explanatory power of the two sources of real return variation

Incremental explanatory power of $X_{2,t-1}$	Monthly		Quarterly	
	l	W	l	W
Global shocks to expected cash flows (H1)	0.12	86.62	0.46*	134.86*
Global expected-return variables (H2)	0.18	144.23*	0.53*	203.86*

The reported incremental explanatory power of one measure of variation is evaluated in the presence of the other. The sample period is 1970:2—1991:12. Proxies for global shocks to expected cash flows include P_t, P_{t+3}, P_{t+6}, and P_{t+9}, while those for global expected-return variables are WDY_{t-1}, TED_{t-1}, $TERM_{t-1}$, $TEDSH_t$, and $TERMSH_t$. WDY is the world dividend yield (over the past 12 months) on the MSCI world index, TED is the Eurodollar-Treasury yield spread, TERM is the term structure of interest rates, TEDSH and TERMSH are the residuals from first-order autoregression fitted to TED and TERM, and P_{t+g} is the growth rate of IPOECD, the industrial production index of the OECD countries. *Denotes significance at the 5% level; l and W are the maximum latent root and Wald statistics.

incremental explanatory power in the presence of another source of variation. In other words, the resulting l and W statistics will be significant. If both sources of return variation contain essentially the same information, the l and W statistics for both measures will be insignificant. Finally, if the information contained in one source of variation is already contained in another, then only the latter source will yield significant l and W statistics.

Table 4 reports the maximum-latent-root and the Wald test results using monthly and quarterly observations. The former's statistical significance is evaluated based on the simulated critical values reported in Table A.2. Table 4 shows an interesting pattern in the calculated l and W statistics. Both the monthly l and W statistics are all smaller than the quarterly ones, and the proxies for global shocks to expected future cash flows always generate lower l and W statistics than do the proxies for discount-rate variables.

Generally, the results are robust to the different methodologies used. Only in the case of monthly observations where discount-rate variables are evaluated in the presence of shocks to expected future cash flows that the l and W statistics produce different results. Based only on the Wald test that is robust to non-normal errors, the discount-rate variables contain significant incremental explanatory power beyond that already contained in the global shocks to expected future cash flows, but not vice versa. In contrast, when we use quarterly observations, both sets of proxy variables play an important role in explaining the real return on the maximal world portfolio. Shocks to expected future cash flows do contain incremental information about quarterly real returns, while proxies for discount-rate variables exhibit incremental explanatory power for both monthly and quarterly returns.

Our findings therefore demonstrate that future growth rates in industrial production are better at explaining longer horizon returns. Other studies such as Fama (1990) and Chen (1991) have also reached this conclusion. In summary, evidence suggests that proxies for discount-rate variables are the major source of short-horizon return variation and that both discount-rate and cash-flow variables contribute to longer-horizon return variation. Given that these selected variables are related to the current and future state of the world economy, we infer that the variation in real return is rational.

IV. Concluding remarks

This paper has proposed multivariate statistical methodologies to examine whether there exist systematic global sources of rational variation in 18 different aggregate stock indexes around the world. We have found evidence that the selected global economic variables that proxy for time-varying global expected returns and for global shocks to both expected returns and expected future cash flows can jointly and reliably explain stock market returns. The global economic variables proxying for time-varying expected returns and for shocks to expected returns capture up to a maximum of 18% of monthly stock return variance and 48% of quarterly variance. Current and future global production growth rates that incorporate information about global economic real activity capture up to a maximum of 13% of monthly variation and 37% of quarterly variation. The fractions of the total explained portion of price variability are 23% and 59% for the monthly and quarterly horizons. The explanatory power of the two different global measures has increased at least two-fold when quarterly return observations are used in the place of monthly observations.

Our findings show that the discount-rate effect contains incremental information useful for explaining monthly and quarterly real equity price movements, and that the cash-flow effect only plays an important role in quarterly return variation. Evidence thus suggests that global economic and business conditions do have an impact on real equity return variation. And proxies for future global economic activity tend to have a greater impact on longer real return variation. Overall, real equity return movements reflect the rational behavior of investors as a substantial amount of return variation can be explained by the fundamental variables.

Appendix

The distribution is based on Monte Carlo simulations consisting of 10000 independent replications of 251 and 83 i.i.d. Gaussian observations for the monthly and quarterly horizons, respectively. The regressors are (1) for $R9$: WDY_{t-1}, TED_{t-1}, TERM_{t-1}, SHD_t, SHM_t, P_t, P_{t+3}, P_{t+6}, and P_{t+9}; (2) for $R5$: WDY_{t-1}, TED_{t-1}, TERM_{t-1}, TEDSH_t, and TERMSH_t; and (3) for $R4$: P_t, P_{t+3}, P_{t+6}, and P_{t+9}. A constant is included in these regressions. WDY is the world dividend yield (over the past 12 months) on the MSCI world index, TED is the Eurodollar-Treasury yield spread, TERM is the term structure of interest rate, TEDSH and TERMSH are the residuals from first-order autoregression fitted to TED and TERM, and P_{t+g} is the growth rate of IPOECD, the industrial production index of the OECD countries.

TABLE A.1. Simulated sample distributions of the maximal $\bar{R}^2$ under the null hypothesis of no relation

	Mean	S.D.	Min	Max	1%	5%	10%	50%	90%	95%	99%
	Monthly horizons — sample period (January 1970–December 1991)										
$R9$	0.052	0.021	0.002	0.166	0.014	0.022	0.027	0.049	0.079	0.089	0.107
$R5$	0.041	0.017	0.003	0.144	0.012	0.017	0.021	0.039	0.064	0.072	0.091
$R4$	0.037	0.016	0.003	0.130	0.010	0.016	0.019	0.035	0.059	0.067	0.083
	Quarterly horizons — sample period (January 1970–December 1991)										
$R9$	0.156	0.058	−0.003	0.410	0.044	0.071	0.086	0.152	0.234	0.260	0.305
$R5$	0.124	0.049	0.005	0.392	0.038	0.055	0.065	0.118	0.189	0.211	0.256
$R4$	0.114	0.047	0.009	0.344	0.032	0.050	0.059	0.108	0.178	0.201	0.246

TABLE A.2. Simulated sample distributions of the maximal-latent-root test statistic l in the presence of $X_{2,t-1}$

	Mean	S.D.	Min	Max	1%	5%	10%	50%	90%	95%	99%
	Monthly horizons — sample period (January 1970–December 1991)										
$H1$	0.256	0.046	0.123	0.453	0.155	0.175	0.186	0.224	0.248	0.251	0.253
$H2$	0.277	0.045	0.144	0.499	0.175	0.195	0.207	0.245	0.269	0.271	0.274
	Quarterly horizons — sample period (January 1970–December 1991)										
$H1$	0.373	0.061	0.185	0.611	0.239	0.264	0.277	0.330	0.363	0.367	0.370
$H2$	0.397	0.058	0.219	0.633	0.265	0.292	0.307	0.355	0.387	0.391	0.394

The distribution is based on Monte Carlo simulations consisting of 10 000 independent replications of 251 and 83 i.i.d. Gaussian observations for the monthly and quarterly horizons, respectively.

Notes

1. Schwert (1990) extends the sample period from 1889 to 1988 and finds that Fama's results are robust even with a much longer sample period.
2. US Treasury bill yields come from the CRSP bond files, while US long-term government bond yields come from Citibase.
3. Notice that the selection of global variables proxying for time-varying expected returns contrasts with that of Harris and Opler (1993), who use country-specific dividend yields and the term structure of interest rates as proxies for time-varying expected returns. Thus Harris and Opler's study uses a univariate approach that contrasts with our multivariate method. Our approach is, however, consistent with the Ferson and Harvey (1993) findings that global variables such as TERM and TED can better capture time variation in the global risk premiums. See, also, Cheung *et al.* (1997).
4. According to Aliber (1978), the Eurodollar yield spread can be generally viewed as a political risk premium that reflects either actual or anticipated barriers to arbitrage across national borders.
5. Future growth rates up to 24 months ahead were also considered in our preliminary analysis. However, industrial production growth rates beyond 12 months ahead were typically insignificant and, hence, were not incorporated in our subsequent analyses.

6. We also performed the same regressions using the United State's industrial production and found that the results were qualitatively similar.
7. For practical purposes, one may want to consider portfolio weights that are constrained to be non-negative. In this case, one can obtain the desired portfolio weights numerically by incorporating the restriction $\gamma \geq 0$ in the algorithm used to maximize $R^2(\gamma)$. We estimated both the unconstrained and constrained maximal portfolios. Since the results are qualitatively similar, we present the unconstrained maximal portfolio results, while the constrained portfolio results are available upon request.
8. This result can be derived using the method employed by Lo and MacKinlay (1995) to obtain their maximal $R^2(\gamma)$.
9. The conditional homoskedasticity and normality assumptions of ε_ts do not imply that R_ts are conditionally homoskedastic and normal. When ε_ts are conditionally heteroskedastic, a general central limit theorem can be used to show that the distribution given in the text is still valid in large samples. Also see the related discussion by Lo and MacKinlay (1995).
10. The distribution function of λ is given by, for example, Muirhead (1982, $\langle 37 \rangle$ on page 483). Because l is a monotone function of λ, its distribution function can be obtained from that of λ by direct substitution.
11. Throughout this paper, we use the adjusted coefficient of determination $\bar{R}^2(\gamma)$ instead of $R^2(\gamma)$. $\bar{R}^2(\gamma)$ provides a better comparison across different model specifications, because it accounts for the number of regressors in the model. Since $\bar{R}2(\gamma)$ is proportional to $R^2(\gamma)$, the portfolio that maximizes $R^2(\gamma)$ also maximizes $\bar{R}^2(\gamma)$.
12. Detailed results are available upon request.
13. We found similar results when regressing the real stock market returns of the G-7 countries against their respective growth rates in industrial production. However, we did not conduct the analysis in the case of Singapore/Malaysia and Hong Kong since data on the latter's IPs were not available.

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