

Functional Form of Stock Return Model: Some International Evidence

M.M.CHAUDHURY

Southern Methodist University and University of Saskatchewan

G.F.LEE

Rutgers University and Nanyang Technological University

A linear (loglinear) empirical return model is rejected for more than half (one-third) of an international sample of 425 stocks. A generalized functional form improves explanatory power and enhances the role of a global index in the stock return model. Additionally, the inclusion of a lagged dependent variable seems desirable for many stocks to allow incomplete price response to domestic and global market variations.

I. INTRODUCTION

The Sharpe-Lintner-Mossin Capital Asset Pricing Model (CAPM) asserts that in market equilibrium, the expected return on a security is a linear function of its systematic risk (beta) with respect to the market portfolio. In testing CAPM and its numerous other applications, a linear or loglinear ex post return generation model is used almost universally. There is, however, an emerging body of evidence that the estimation of a generalized nonlinear functional form for the ex post return process is perhaps more appropriate. In this paper, we produce further evidence from an international sample of stocks which support the use of a generalized functional form. Such evidence has hitherto been lacking in the literature.

A nonlinear functional form may arise when returns are measured over an interval different from the "true" homogeneous investment horizon of investors assumed by CAPM (Jensen, 1969; Cheng and Deets, 1973).¹ Levy (1972) and Levhari and Levy (1977) have demonstrated that the assumption of a holding period different from the "true" horizon leads to systematic bias of the performance measurement index as well as the beta estimate.

Using quadratic preferences, and stationary and serially independent return distribution, Lee, Wu, and Wei (1990) derive a generalized CAPM under heterogeneous investment horizon. The risk-return relationship is shown to be a nonlinear function of beta. Levy and Samuelson (1992), however, show that a linear CAPM holds if portfolio revisions are allowed in every period. Lee, Wu and Wei (1990) cite several reasons why investors may avoid frequent portfolio revisions.

On the empirical front, Lee (1976) proposed and tested generalized functional forms for finite horizon return generation model. His findings indicate that, for observed returns, a nonlinear functional form should be estimated even if the theoretical functional form of risk-return relationship is linear. At minimum, a nonlinear return model improves the explanatory power of CAPM. McDonald (1983) also found a generalized model to be appropriate in a significant number of cases of his sample of 1164 securities, especially so in the case of low capitalization securities; but the bias of the traditional market model beta did not appear to be material. Further, in a sample of 76 electric utility firms, Bubnys and Lee (1989) found neither CAPM linearity nor log-linearity to be borne out.

While the above studies have made significant contribution to our knowledge about the probable sources and effects of nonlinearity in the empirical stock return models, all of the empirical evidence relate to the U.S. In this paper, we examine if a generalized market model is relevant in countries other than the U.S. and if the degree of relevance varies across countries. This should benefit researchers and practitioners in those countries as well as international users (multinationals, global investors and researchers).

A generalized market model attempts to improve specification of functional form for the ex post or empirical return generation process. In this paper, we additionally investigate two other areas of specification for the empirical return model.

First. We wish to examine if the generalized market model should be extended to include a global market index in addition to the domestic market index. In the context of international asset pricing, a linear two factor (country and global) return generation model has been commonly used by researchers to test integration vs. segmentation of the international capital market, and the benefits of international diversification (Sölnik, 1974b, c), Lessard (1974), Jorion and Schwartz (1986), Errunza and Losque (1985), Errunza, Losque and Padmanabhan (1989)). In this paper, we estimate the linear two-factor model and its generalized form for our international sample of stocks. While the dominance of a national factor in the return process has been documented previously (Sölnik (1974 b, c); Lessard, 1974), it would be interesting to see if the relevance of a global factor (index) is affected by the choice of a functional form. We also address a related empirical issue of whether to use a value-weighted or an equally-weighted global index. The recent findings of Fama and French (1992) call into question the validity of a single market index stock return model, and make

tests of nonlinear models with multiple and different market portfolios particularly timely.

Second, A generalized market model and its extended two factor version are both static in nature in the sense that stocks are assumed to respond to the domestic and the global market variations without any adjustment delay. To allow price adjustment lags, Cartwright and Lee (1987) proposed a dynamic version of the linear (domestic) market model in which the lagged value of stock return appears as an additional regressor. They found the dynamic model to be a better specification for a portion of their sample of U.S. stocks.

In this paper, we estimate the dynamic version of both linear and generalized market model, and the linear and generalized two factor model. Our objective is to evaluate the relevance of a dynamic version in the context of a more general specification search than Cartwright and Lee (1987). If a dynamic model is appropriate, static model parameter estimates would be biased, and may lead to erroneous conclusions in further uses of these estimates and lower explanatory power of domestic or international asset pricing model. Moreover, any serial correlation in index returns would lead to lower precision and thus statistically insignificant OLS estimates of static model coefficients.²

The rest of this paper is organized as follows. In section II, we explain the return generation models that we estimate. Section III describes the data and methodology. Results are then discussed in Section IV. We conclude with a summary of important findings in Section V.

II. MODELS ESTIMATED

A. Domestic Asset Pricing

For security pricing in the domestic context, we estimate the standard market model of Sharpe (1963), and a generalized market model based upon Box-Cox transformation of returns.

Dropping the time subscript, the market model (MM) is defined as:

$$R_{ik} = A_{ik} + B_{ik}R_k + E_{ik} \quad (1)$$

where over time interval $t - 1$ to t :

- R_{ik} = 1 + the rate of return for stock i of country k ,
- R_k = 1 + the rate of return for country k 's national market index,
- E_{ik} = the i.i.d. error term having zero expectation,
- A_{ik} = the regression intercept for stock i of country k , and
- B_{ik} = the regression slope coefficient and is intended to estimate the systematic risk (beta) of stock i with respect to the national market portfolio of country k .

The generalized market model (GMM) based upon Box-Cox transformation is defined as:

$$r_{ik} = a_{ik} + b_{ik}r_k + \epsilon_{ik} \quad (1a)$$

where the lower case letters indicate that the returns have been transformed according to:

$$\begin{aligned} r_{ik} &= (R_{ik}^{1/L} - 1)/L_{ik} \text{ and } r_k = (R_k^{1/L_k} - 1)/L_{ik}, L_{ik} \neq 0 \\ r_{ik} &= \ln(R_{ik}) \text{ and } r_k = \ln(R_k), L_{ik} = 0 \end{aligned}$$

The standard market model in Equation 1 is a special case of the generalized market model in Equation 1a with $L_{ik} = 1$. For $L_{ik} = 0$, the generalized market model becomes a loglinear model as suggested by Jensen (1969) in the context of instantaneous horizon.

Note that our transformation parameter L is stock-specific. If the CAPM holds but nonlinearity arises due to the observed return interval being different from the "true" homogeneous horizon, the transformation parameter L is equal to the ratio of true horizon to observed interval, and L should not be stock-specific. On the other hand, if the heterogeneous horizon CAPM of Lee et al. (1990) is appropriate, then the transformation parameter would be stock-specific. Of course, a nonlinear model such as Equation 1a may be suitable due to reasons other than the horizon, e.g., serial correlation (Gilster, 1979), heteroskedasticity (Fabozzi, Francis and Lee, 1980), and skewness in returns (Lee, 1977). In that case, it is likely that the transformation parameter would be stock-specific.

Although the heterogeneous horizon CAPM calls for a more general functional form than Equation 1a where stock returns and market returns are to be transformed using different parameters, the results of McDonald (1983) suggest that the statistical improvements from doing so are at best meager. Hence we do not pursue the multiple parameter transformation in this paper.

The models in Equations 1 and 1a are static in nature in the sense that there is no adjustment lag in the stocks' response to the market. Cartwright and Lee (1987) proposed the following dynamic market model (DMM) version of the static model in Equation 1:

$$R_{ik}(t) = A_{ik}^D + B_{ik}^DR_k(t) + H_{ik}^DR_{ik}(t-1) + E_{ik}^D(t) \quad (2)$$

In the above equation and throughout the rest of this paper, we use superscript D to indicate that the variable or parameter in question is from a dynamic model.

The distinguishing feature of the dynamic market model in Equation 2 as compared to the static market model in Equation 1 is the presence of the lagged value of the security return as a regressor (the lagged dependent variable); the

associated slope coefficient H_{ik}^D captures the dynamics of the return generation process. By repeated substitution of the lagged dependent variable from the same dynamic market model, we arrive at:

$$R_{ik}(t) = A_{ik}^D + \sum_{l=0}^{\infty} B_{ik}^D (H_{ik}^D)^l R_k(t-l) + E_{ik}^D(t) \quad (2A)$$

The infinite geometric lag structure in Equation 2A shows in a clearer fashion the dependence of the security return on the current as well as the lagged values of the market return. However, for estimation purposes, the lagged dependent form of the dynamic market model in Equation 2 is preferred for two reasons. First, if the market returns exhibit serial correlation, we would run into a multicollinearity problem using past market returns as regressors. Second, the detailed version in Equation 2A offers no practical guidance as to how many lags of the market return should be included as regressors to capture most of the systematic risk. The number of lags to include in the regression equation becomes an extra parameter to be estimated.

For the adjustment process in Equations 2 and 2A to be non-explosive, the absolute value of H_{ik}^D should be less than 1.0 i.e., the speed of adjustment, which equals $1.0 - H_{ik}^D$, should be between 0.0 and 2.0. Otherwise, the more distant values of the market return will have greater influence on the current security return than the nearer ones. Alternatively, the effect of the current market index variation on the security will tend to increase as we move further into the future. This, of course, would be a destabilizing situation.

Assuming that the adjustment process is stable, the lag structure in Equation 2A implies that the effect of the past market returns decays at the rate H_{ik}^D as one moves away from the current period. Such an assumption seems plausible for the stock returns.

A positive H_{ik}^D indicates that the security does not fully adjust to changes in the national index in the current period. The full sensitivity (beta) to the national index, $B_{ik}^D / (1 - H_{ik}^D)$, is thus higher than the contemporaneous or immediate impact, B_{ik}^D .² On the other hand, a negative H_{ik}^D indicates over-adjustment in the current period. In other words, the total impact is less than the immediate one.

The concept of incomplete price adjustment in the current period can be accommodated within the framework of a generalized dynamic market model (*GDMM*):

$$r_{ik}(t) = a_{ik}^D + b_{ik}^D r_k(t) + h_{ik}^D r_{ik}(t-1) + e_{ik}^D(t) \quad (2a)$$

As before, lower-case letters indicate that the returns have been transformed according to the Box-Cox procedure. *GDMM* says that not only is security return nonlinearly related to contemporaneous market return, it is also affected by past market returns albeit in a similar nonlinear fashion. Of course, *GDMM* contains *MM*($h_{ik}^D = 0$, $L_{ik}^D = 1$), *GMM*($h_{ik}^D = 0$), and *DMM*($L_{ik}^D = 1$) as special cases.

B. International Asset Pricing

In the context of international asset pricing, if the world capital market is integrated, ex ante risk premium on a security equals ex ante risk premium on the global market portfolio times the security's systematic risk (global beta) with respect to the global portfolio (Solnik, 1974a).

A direct extension of the domestic asset pricing arguments would lead us to the international market model used by Solnik (1974b,c) among others:

$$R_{ik}(t) = C_{ik} + G_{ik}R_G(t) + U_{ik}(t),$$

where $R_G(t)$ is the return on the global market portfolio and is commonly proxied by the return on a global stock index; G_{ik} is intended to measure the security's global systematic risk, and U_{ik} is an i.i.d. error term.

Solnik (1974b,c) and Lessard (1974), however, report that there are strong national factors present in the price process of individual securities. The national market model in Equation 1 explains more of individual security return variations than the international market model. Hence the authors suggest the use of a two-factor model for individual securities:

Solnik (1974c):

$$R_{ik}(t) = F_{ik} + M_{ik}R_k(t) + N_{ik}R_G(t) + \Phi_{ik}(t)$$

Lessard (1974):

$$R_{ik}(t) = Q_{ik} + Z_{ik}U_k(t) + G_{ik}R_G(t) + \eta_{ik}(t)$$

where $\Phi_{ik}(t)$ and $\eta_{ik}(t)$ are i.i.d. error terms, M_{ik} and Z_{ik} are alternative estimates of the security's pure national risk, N_{ik} is an estimate of the security's pure global risk (ignores indirect impact felt through the national market), G_{ik} is an estimate of the security's global risk (includes indirect impact felt through the national market); $U_k(t)$ is that component of the national market return which is uncorrelated to the global market return and is estimated from the following regression:

$$R_k(t) = C_k + G_kR_G(t) + U_k(t)$$

This is in fact the static international market model as applied to the national portfolio. The models of Solnik (1974c) and Lessard (1974) are related in the following manner:

$$G_{ik} = N_{ik} + M_{ik}G_k$$

In an integrated world market, the pure national risk M_{ik} would not be priced since it can be diversified away through international investments. On the

other hand, if the security belongs to a segmented national market, the pure international risk N_{ik} would not be priced (Errunza and Losq, 1985; Jorion and Schwartz, 1986). In a mildly segmented market (Errunza and Losq, 1985, 1989), pure national risk of securities in which foreign investment is not allowed would be priced as in the case of complete segmentation, but their global systematic risk would also be priced as in the case of complete integration.³

In this paper, we focus on the specification of the empirical return generation model in the context of international asset pricing. Specifically, given the reported dominance of a national factor in a linear and static model, we explore if it is worthwhile to include a global index (equally-weighted or value-weighted) in a generalized two factor model or a generalized dynamic two factor model. Stated otherwise, we examine if the global variations are an important source of risk other than through their effect on the national market. To this end, we estimate the following two factor models:

1. *Two Factor Equally-Weighted Model (TTEWM):*

$$R_{ik}(t) = F_{ik}^E + M_{ik}^E R_k(t) + N_{ik}^E R_G(t) + \Phi_{ik}^E(t) \quad (3)$$

2. *Generalized Two Factor Equally-Weighted Model (GTFEWM):*

$$r_{ik}(t) = f_{ik}^G + n_{ik}^G r_k(t) + n_{ik}^G r_G(t) + \phi_{ik}^G(t) \quad (3a)$$

3. *Dynamic Two Factor Equally-Weighted Model (DTFEWM):*

$$R_{ik}(t) = F_{ik}^{ED} + M_{ik}^{ED} R_k(t) + N_{ik}^{ED} R_G(t) + H_{ik}^{ED} R_{ik}(t-1) + \Phi_{ik}^{ED}(t) \quad (4)$$

4. *Generalized Dynamic Two Factor Equally-Weighted Model (GDTFEWM):*

$$r_{ik}(t) = f_{ik}^{ED} + n_{ik}^{ED} r_k(t) + n_{ik}^{ED} r_G(t) + h_{ik}^{ED} r_{ik}(t-1) + \phi_{ik}^{ED}(t) \quad (4a)$$

5. *Two Factor Value-Weighted Model (TFVWM):*

$$R_{ik}(t) = F_{ik}^V + M_{ik}^V R_k(t) + N_{ik}^V R_G(t) + \Phi_{ik}^V(t) \quad (5)$$

6. *Generalized Two Factor Value-Weighted Model (GTFVWM):*

$$r_{ik}(t) = f_{ik}^V + n_{ik}^V r_k(t) + n_{ik}^V r_G(t) + \phi_{ik}^V(t) \quad (5a)$$

7. *Dynamic Two Factor Value-Weighted Model (DTFVWM):*

$$R_{ik}(t) = F_{ik}^{VD} + M_{ik}^{VD} R_k(t) + N_{ik}^{VD} R_G(t) + H_{ik}^{VD} R_{ik}(t-1) + \Phi_{ik}^{VD}(t) \quad (6)$$

8. *Generalized Dynamic Two Factor Value-Weighted Model (GDTFVWM):*

$$r_{ik}(t) = f_{ik}^{VD} + n_{ik}^{VD} r_k(t) + n_{ik}^{VD} r_G(t) + h_{ik}^{VD} r_{ik}(t-1) + \phi_{ik}^{VD}(t) \quad (6a)$$

As before, we use superscript D to indicate that a dynamic model is involved. Similarly, superscript E/V denotes the presence of the equally-weighted (value-weighted) global index. Variables and parameters in lower-case of course symbolize the use of transformed returns.

Depending upon whether the global index is equally-weighted or value-weighted, $GDTFEWM$ or $GDTFVWM$ contains all other models as special cases. Whether such a degree of generality is called for is of course an empirical issue we wish to examine.

III. DATA AND METHODOLOGY

A. Data

The data for this study were provided by the New York brokerage firm Goldman Sachs. Month-end values for 24 national indexes and the prices (adjusted for capital changes) of 481 stocks over the 60-month period of July 1984 through July 1989 were available to us. All series that did not have complete data over the period and all countries which had fewer than 7 stocks in the original data base were excluded from the sample of individual stocks. We further screened out stocks which appeared to have unusually large price quotations. This gave us a final sample of 425 stocks from 10 countries, viz., Japan (139), Australia (7), France (11), Germany (20), Italy (8), Netherlands (7), Switzerland (7), U.K. (36), U.S. (180), and Canada (10).

The national equity indexes are the "FT Actuaries/Goldman Sachs International Indexes" and have been used by Roll (1992) among others. These are broadly-based equally-weighted stock market indexes for each country. For example, the Japanese index has 455 constituent stocks from the Tokyo and the Osaka Exchanges. The U.S. index is calculated using a total of 546 stocks from the NYSE, the AMEX, and the NASDAQ.

We used an equally-weighted as well as a value-weighted global index in our estimations. The equally-weighted global index return in a given month is a simple average of the returns on 25 national indexes which had complete data over our sample period. For the value-weighted global index return, we weighted each country's national index return by its average share of the world market capitalization over the 60 month sample period.

The individual stocks in the Goldman Sachs data base are among the largest and the most liquid stocks in their respective countries. As such, problems related to low volume or infrequency of trading are expected to be minimal.

B. Methodology

Our aim in this paper is to undertake specification search for the empirical return model in three directions: (1) functional form (linear, loglinear, or non-

linear); (2) factor structure (include or omit a global index, equally-weighted or value-weighted); and (3) price adjustment patterns (static vs. dynamic).¹⁷ While the three specification issues could be related and as such a joint search may be called for, we initially entertain them separately to gain insights into each area, especially the functional form area. In the final stage, all three issues are brought together in the course of our search for the best overall model.

B.1. Functional Form

To determine the appropriate functional form, for each of our 425 stocks, we follow the steps below for each of *GMM*, *GDMM*, *GTFEW*, *GDTFEW*, *GTFVWM*, *GDTFVWM*:

1. Assuming a normal distribution for the error term, use maximum likelihood estimation (*MLE*) procedure to estimate unrestricted log-likelihood of the model; call it *MLLF*.
2. Use *MLE* to estimate log-likelihood of a restricted version of the model where the Box-Cox transformation parameter *L* is set to 1.0 to correspond to a linear model; call it *LLF*.
3. Use *MLE* to estimate log-likelihood of a restricted version of the model where the Box-Cox transformation parameter *L* is set to 0.0 to correspond to a loglinear model; call it *ZLLF*.
4. A likelihood ratio test statistic, $CHIL = 2(MLLF - LLF)$, is calculated to test the restriction that the transformation parameter *L* equals 1.0, i.e., the functional form is linear. Under the null hypothesis of a linear functional form, *CHIL* has an asymptotic *chi-square* distribution with 1 degree of freedom.
5. Using two-sided 10%-significance level, we then test if the null hypothesis of linear functional form can be rejected. If so, we conclude that the functional form is not linear.
6. A likelihood ratio test statistic, $CHIZ = 2(MLLF - ZLLF)$, is calculated to test the restriction that the transformation parameter *L* equals 0.0, i.e., the functional form is loglinear. Under the null hypothesis of a loglinear functional form, *CHIZ* has an asymptotic *chi-square* distribution with 1 degree of freedom.
7. Using two-sided 10%-significance level, we then test if the null hypothesis of loglinear functional form can be rejected. If so, we conclude that the functional form is not loglinear.

Note that McDonald (1983) used a similar likelihood ratio test procedure. A slightly different procedure was used by Lee (1976). While these studies compare the test results for different functional forms of a given model, we additionally compare the test results across different models and different national markets.

B.2. Factor Structure

Our objective here is to determine if an equally-weighted or a value-weighted global index needs to be included in the empirical return model in addition to the national or domestic market index. We judge the need for inclusion or omission of the global index on the basis of whether the coefficient of the global index is significant in a two-sided *t*-test at 1% significance level. We also look at adjusted R^2 to evaluate the explanatory power of model specifications inclusive and exclusive of a global index.

OLS estimation of *TFEWM* and *TFVWM* leads to coefficient estimate and *t*-ratio for the equally-weighted and the value-weighted global index respectively. *MLE* estimation of *GTFEWM* and *GTFVWM* provides alternative pairs of coefficient estimates and *t*-ratios. We wish to see if:

- A. The coefficient of the global index is significant, and
- B. More importantly, the choice of functional form (here, linear vs. generalized) matters with respect to the significance of a global index.

Additionally, we investigate if these results are materially affected by the use of an equally-weighted vs. a value-weighted global index. One potential area of concern in this regard is the well-known *error-in-variables* problem in regression.⁶ This is because in the models *TFVWM* and *GTFVWM*, we use a value-weighted global index while the national index is equally-weighted. For large stocks, it is possible that security-specific disturbances or measurement errors would materially affect the variation of the value-weighted global index (but not the equally-weighted national index) and would thus tend to inflate the systematic marginal (net of the national effect) impact of the global index on these stocks. However, we do not believe this *error-in-variables* problem to be significant in our study. Our global indexes (both value-weighted and equally-weighted) are constructed from 25 national markets, not just the 10 markets which are represented in our sample of individual stocks. Therefore, even the largest of stocks in our sample would have a minimal impact on the value-weighted global index that we use. Any impact is further minimized due to the fact that the value-weighted global index is constructed by value-weighting the equally-weighted rather than value-weighted national indexes.

B.3. Price Adjustment Pattern

If stock prices adjust fully to domestic and/or global index variations in the same period (month in our study), a static model—linear, loglinear or nonlinear, will be deemed well-specified. We determine the desirability of a static vs. dynamic model through a *t*-test on the coefficient estimate (H_t , b) of the lagged dependent variable at non-sided 10%-significance level. Additionally, explanatory power of a static vs. dynamic specification is evaluated using adjusted R^2 .

Once again, a pertinent question is whether the functional form choice (here, linear vs. generalized) affects the choice between a static vs. dynamic model.

B.4. Best Overall Model

While a separate treatment of the various specification issues are useful in identifying probable sources of misspecification, it is of great practical relevance to identify the best overall empirical model. There is a substantial body of econometric literature dealing with this issue. In this paper, we use the Akaike Information Criterion (AIC) to choose the best model:

$$AIC \text{ for a model} = -2\log\text{likelihood} - 2K/T$$

where K is the number of parameters in a model and T is the number of observations used in its estimation. The AIC rewards a model with greater likelihood. But the likelihood, similar to the R^2 , increases with the number of parameters in a model. To achieve parsimony, the AIC penalizes a model that has more parameters. Thus, similar to the adjusted R^2 in least squares estimation, the AIC serves as an indicator of the explanatory power adjusted for the degrees of freedom in the context of maximum likelihood estimation of both linear and nonlinear models. We use the AIC since it is a more appropriate measure than the adjusted R^2 in selecting the best model from among the 12 linear and generalized specifications entertained in this paper.⁷ The best model for a stock is the one with the highest AIC value. Notice that while the generalized dynamic two-factor models (*GDTFEWM* and *GDTFWWM*) have the most parameters, 5, they are also penalized the most on this account according to the AIC measure.⁸

We also select the best linear model from among *MM*, *DMM*, *TFEWM*, *DTEWM*, *TFVWM*, and *DTFVWM* and the best generalized model from among *GMM*, *GDMM*, *GTFEWM*, *GDTFEWM*, *GTVWM*, and *GDTFWWM*. The linear and generalized model choices are then compared to evaluate the impact of functional form on overall model selection. This produces further evidence regarding the effect of functional form on the relevance of a global index in the empirical return model as well as the choice between a static vs. dynamic specification.

IV. EMPIRICAL RESULTS

A. Functional Form

A.1. Descriptive Statistics

Descriptive statistics on transformation parameter (L) estimates from the six generalized models (*GMM*, *GDMM*, *GTFEWM*, *GDTFEWM*, *GTVWM*, *GDTFWWM*) are presented in Panel A of Table 1.

Table 1. Descriptive Statistics and Test Results for the Functional Form Parameter L A. Descriptive statistics for L

	Stocks		Model and Equation Number					
			GMM 1a	GDMM 2a	GTFEW 3a	GDTFEWM 4a	GTFVWM 5a	GDTFVWM 6a
All	425	Mean	-0.430	-0.489	-0.837	-0.931	-0.620	-0.680
		Median	-0.470	-0.450	-0.880	-1.070	-0.650	-0.680
		Std.dev.	1.831	1.835	1.822	1.820	1.899	1.906
		Minimum	-4.900	-4.000	-4.000	-4.000	-4.000	-4.000
		Maximum	4.250	4.450	4.080	4.300	4.650	4.530
Japan	139	Mean	-1.567	-1.574	-1.962	-2.015	-1.969	-2.019
		Median	-1.550	-1.610	-2.100	-2.210	-2.090	-2.230
		Std.dev.	1.472	1.475	1.366	1.352	1.351	1.337
		Minimum	-4.000	-4.000	-4.000	-4.000	-4.000	-4.000
		Maximum	2.490	2.510	1.650	1.850	1.480	1.510
Australia	7	Mean	0.489	0.375	0.333	0.194	0.391	0.247
		Median	0.620	0.120	-0.110	-0.190	0.290	-0.050
		Std.dev.	1.577	1.626	1.668	1.671	1.692	1.692
		Minimum	-1.880	-2.020	-1.780	-1.860	-1.810	-1.900
		Maximum	2.800	2.480	2.810	2.450	2.810	2.510
France	11	Mean	-0.891	-0.956	-1.325	-1.470	-1.105	-1.170
		Median	-0.860	-0.890	-1.330	-1.420	-1.050	-1.110
		Std.dev.	1.259	1.370	1.154	1.256	1.178	1.243
		Minimum	-5.120	-3.900	-5.110	-3.950	-2.770	-5.670
		Maximum	0.950	0.920	0.640	0.710	0.650	0.720
W. Germany	20	Mean	-0.152	-0.279	-0.412	-0.550	-0.511	-0.459
		Median	-0.305	-0.360	-0.545	-0.630	-0.550	-0.345
		Std.dev.	1.132	1.175	1.338	1.301	1.230	1.306
		Minimum	-2.070	-2.040	-2.960	-2.740	-2.060	-2.120
		Maximum	2.700	2.490	2.490	2.140	2.460	2.110

Italy	8	Mean	-2.036	-1.957	-2.544	-2.457	-2.291	-2.191
		Median	-2.620	-2.620	-2.850	-2.935	-2.700	-2.775
		Std.dev.	1.672	1.761	1.349	1.429	1.423	1.518
		Minimum	-5.930	-5.890	-4.000	-4.000	-4.000	-4.000
		Maximum	0.650	1.010	-0.810	-0.620	-0.280	0.220
Netherlands	7	Mean	0.000	0.004	-0.210	-0.193	0.056	0.064
		Median	-0.510	-0.190	-0.510	-0.330	-0.070	0.040
		Std.dev.	1.153	0.860	1.200	0.847	1.150	0.879
		Minimum	-1.740	-1.530	-1.930	-1.560	-1.770	-1.560
		Maximum	1.600	0.950	1.610	0.950	1.660	0.980
Switzerland	7	Mean	1.474	1.159	1.030	0.329	1.279	0.923
		Median	1.440	0.860	1.140	0.400	1.250	0.800
		Std.dev.	0.874	1.116	0.649	1.342	0.686	0.958
		Minimum	0.350	-0.170	0.040	-2.720	0.260	-0.360
		Maximum	2.950	2.950	2.120	2.340	2.180	2.430
U.K.	36	Mean	0.191	0.103	-0.079	-0.204	0.141	0.034
		Median	0.450	0.135	0.045	-0.395	0.255	-0.085
		Std.dev.	1.540	1.548	1.678	1.685	1.547	1.551
		Minimum	-5.350	-4.000	-5.540	-4.000	-3.320	-4.000
		Maximum	5.090	2.980	5.080	2.980	5.160	5.030
U.S.A.	180	Mean	0.239	0.192	-0.205	-0.322	0.215	0.150
		Median	0.355	0.315	-0.050	-0.210	0.375	0.340
		Std.dev.	1.830	1.863	1.850	1.892	1.871	1.918
		Minimum	-4.000	-4.900	-4.000	-4.000	-4.000	-4.000
		Maximum	4.950	4.450	4.050	4.300	4.650	4.530
Canada	10	Mean	-0.787	-0.664	-0.808	-0.616	-0.851	-0.653
		Median	-0.710	-0.415	-1.035	-0.720	-1.015	-0.990
		Std.dev.	1.427	1.437	1.359	1.566	1.551	1.518
		Minimum	-5.210	-5.310	-2.670	-2.770	-3.040	-3.070
		Maximum	0.930	1.460	0.970	1.540	1.190	1.950

(continued)

Table I. Continued

B. Number of Stocks for which a Linear or Loglinear Functional Form is Rejected in a Likelihood Ratio Test at 10 Percent Significance Level

Stock	Generalized Model and Equation Number					
	GMM	GDMM	GTFEW	GDTFEW	GTFFWM	GDTFWWM
	1a	2a	3a	4a	5a	6a
All	425	220	214	254	235	226
Japan	139	106	105	114	115	114
Australia	7	2	2	5	4	3
France	11	6	6	7	7	6
W. Germany	20	8	8	8	8	9
Italy	8	6	6	8	7	6
Netherlands	7	1	1	1	1	1
Switzerland	7	0	0	0	0	0
U.K.	56	10	10	10	10	10
U.S.A.	180	76	75	79	75	75
Canada	10	5	5	4	4	4
Null hypothesis: Functional Form is loglinear ($L = 0$)						
All	425	151	148	159	155	162
Japan	139	75	73	86	88	90
Australia	7	3	3	3	3	3
France	11	4	4	4	4	4
W. Germany	20	2	2	3	1	2
Italy	8	5	5	6	6	5
Netherlands	7	1	0	1	0	1
Switzerland	7	2	2	1	1	1
U.K.	36	9	8	12	9	10
U.S.A.	180	49	51	42	45	47
Canada	10	1	0	1	0	1

Like McDonald (1983), we find the transformation parameter L to be negative on average. The average L for all 425 stocks in GMM is -0.45 which is fairly close to McDonald's average of -0.46 (in his Table 2). The absolute magnitude of L seems a bit higher in all dynamic models compared to their static counterparts. Further, the four two-factor (national and global) models are characterized by a larger absolute L than the two domestic ones. Another noticeable feature is the dispersion of L across the stocks in our sample. The standard deviation of L values is in the neighborhood of 1.82 to 1.90 , and the minimum and maximum L values range from -4.00 to 4.95 . These dispersion measures are rather large relative to the mean and median L values. This indicates the stock-specific nature of the transformation parameter and raises question about the conventional use of the same transformation parameter (usually 1.0 for linear and 0.0 for loglinear specifications) for all stocks in a study.

Looking at the distribution of L by country, we find that the Italian stocks, followed by the Japanese and the French stocks, have the highest average L in terms of magnitude. The average L is consistently negative in all six models for Japan, France, Germany, Italy, and Canada. On the other hand, Australia and Switzerland have a positive average L in all 6 models. The Netherlands, U.K., and U.S.A. samples are also characterized by a positive average L , except for the two models involving the equally-weighted global index. In all cases of a negative (positive) average L , the absolute magnitude is higher (lower) for the dynamic version. Further, considering the signed magnitude of the average L , the transformation parameter decreases with the presence of a global index in all ten countries. Thus, not only do we observe substantial differences in the functional form across and within the national boundaries, there also appears to be a correlation between the functional form specification (captured by L) and the two other specification issues, viz., the static vs. dynamic and the domestic vs. global nature of the stock returns generation model.

To see if the country differences are statistically significant, we did an ANOVA test on the transformation parameter in each model by country. In all cases, the F statistic is highly significant. The functional form differences across our sample countries are thus substantive irrespective of whether a global index is included or not, and whether a static or dynamic model is chosen. It is also interesting to note that the countries within a region (Pacific, Europe, or North America) do not necessarily share a similar functional form.

A.2. Likelihood Ratio Test Results

In Panel B of Table 1, we report the likelihoodtest results for the linear and loglinear functional forms.

Irrespective of which generalized model we compare to, for more than one-third of our sample a loglinear functional form is rejected and for more than half of our sample a linear functional form is rejected. The majority of these stocks are, however, from Japan where the loglinear form is rejected for more

than 52% of the 139 stocks and the linear form is rejected for 75% or more stocks. These rejection rates are equally high in Italy which has a much smaller sample. The linear functional form is also rejected for a majority of the French stocks. By comparison, the loglinear (linear) form is rejected for no more than 33 (28%) of the British stocks and for no more than 28 (44%) of the American stocks. The Dutch and the Swiss stocks show some of the lowest incidence of a significant departure from the linear or loglinear functional form.

Along with the U.S. evidence of Lee (1979), McDonald (1983), and Bubsys and Lee (1989) among others, our results suggest that a nonlinear functional form is appropriate for a non-negligible number of stocks in many countries and a substantial number stocks in some countries (Japan, Italy, and France). Between the linear and loglinear forms, the latter seems less likely to result in functional form misspecification.

The weight of evidence against a linear functional form in our international sample indicates that the true investment horizon is likely different from one month. For many stocks, specially those in Japan and Italy, the true investment horizon is not instantaneous either. Since the loglinear form is rejected for a smaller number of stocks than the linear form and since values of the functional form parameter in excess of 1.0 are not common, the true investment horizon for the Japanese and the Italian stocks is perhaps significantly less than a month although not instantaneous. An instantaneous horizon or nearly continuous time trading seems to be a more workable assumption, although far from a universal one, in other developed markets including the U.K. and the U.S. One possible reason for the observed cross-country and within-the-country differences in the true investment horizon is the heterogeneity of investment horizon across investors as noted by Lee et al. (1990).

A potential problem with the investment horizon interpretation of our functional form results is the preponderance of negative values for the transformation parameter. For example, in *MM*, out of the 151 stocks where the loglinear form is rejected, 110 stocks have a negative L ; out of the 220 stocks where the linear form is rejected, only 41 have L in excess of 1.0 and all the rest have a negative L . Lee and Bubsys (1989) also observed similar results for the U.S. electric firms. However, Lee and Wei (1988) have shown that the estimated L will be negative instead of positive if security return and market return had a bivariate lognormal distribution. Hence the above functional form results are consistent with most of the stocks in our international sample having lognormally distributed returns.

With regards to the sign of the transformation parameter, L , it is important to note that a positive value of L may be implied by, but does not necessarily imply, the nonsynchrony of the investment horizon and the return observation interval. Similarly, a negative value of L may be implied by, but does not necessarily imply, that the market return and the stock return have a bivariate lognormal distribution.

B. Factor Structure

B.1. National Index

Panel A of Table 2 presents the average national beta estimated from the linear and generalized static models (*MM*, *GMM*, *TFEWM*, *GTFEWM*, *TFVWM*, and *GTFVWM*) as well as the number of stocks for which national beta is significant.

As expected, only a small number of stocks show a lack of significant sensitivity to the domestic market index. Almost all of these stocks are from Japan alone in the domestic models (*MM* and *GMM*), and from Japan and the U.S. in the two-factor models (*TFEWM*, *GTFEWM*, *TFVWM*, and *GTFVWM*). The greatest incidence of a lack of sensitivity to the domestic market index takes place in *TFEWM*.

Except *GTFVWM*, the number of significant national beta stocks is somewhat higher in the generalized models than in their linear counterparts. For all models, however, the difference between linear national beta and generalized national beta is rather small and there does not appear to be any systematic pattern other than the difference being slightly greater in magnitude for the Japanese and Australian stocks. Therefore, as in earlier studies (Lee (1976), McDonald (1983)), the functional form choice does not seem to affect the domestic market beta estimate in a significant way.

B.2. Global Index

The averages and significance results for the pure global beta in the static models (*TFEWM*, *GTFEWM*, *TFVWM*, *GTFVWM*) are reported in Panel B of Table 2. For the sake of brevity, we shall henceforth refer to the pure global beta as just the global beta.

Across all 425 stocks, the average global beta is negative in the linear models (*TFEWM*: -0.010, *TFVWM*: -0.011) and positive in the generalized models (*GTFEWM*: 0.012, *GTFVWM*: 0.007). The global beta estimates exhibit wide variations across the 10 countries. Both linear and generalized global beta are on average positive (negative) in all 4 two-factor static models for the stocks from Japan, Australia, Germany, and the Netherlands (France, Switzerland, U.K. and U.S.A.). In absolute terms, global market variations appear to exert a greater impact on the Japanese, the Australian, the French, and the British stocks on a net (of any impact via the national market) basis. The use of an equally-weighted vs. a value-weighted global index does not seem to affect the global beta in a noticeable or systematic manner.

Looking at the significance results, the effect of functional form is quite noticeable. Beta with respect to the equally-weighted index is significant for a total of 83 stocks (20% of the sample) in the linear model (*TFEWM*) and a total of 148 stocks (35% of the sample) in the generalized model (*GTFEWM*). When

Table 2. Coefficient (Beta) of National, Equally-Weighted (EW) and Value-Weighted Global (VW) Index Estimated from Linear and Generalized Static Models

A. Mean coefficient (*MEANN*) of the national index and the number of stocks (*T*) for which the coefficient is significant in a two-sided *t*-test at 10% significance level

Stocks		Model, Equation Number and Parameter						
		MM	GMM	TFEWM	GTTEWM	TFVWM	GTEVWM	
		1 <i>B</i>	1a <i>b</i>	3 <i>M</i> ^E	3a <i>m</i> ^E	5 <i>M</i> ^V	5a <i>m</i> ^V	
All	425	<i>MEANN</i>	0.975	0.967	0.986	0.973	0.980	0.970
		<i>T</i>	392	403	342	371	370	350
Japan	139	<i>MEANN</i>	0.885	0.855	0.829	0.835	0.865	0.794
		<i>T</i>	106	117	89	101	100	96
Australia	7	<i>MEANN</i>	1.045	1.008	1.008	0.897	0.908	0.986
		<i>T</i>	7	7	7	6	6	7
France	11	<i>MEANN</i>	1.005	0.977	1.050	1.029	1.042	1.033
		<i>T</i>	11	11	11	11	11	11
W. Germany	20	<i>MEANN</i>	0.988	0.999	0.973	0.968	0.958	0.982
		<i>T</i>	20	20	20	19	19	20
Italy	8	<i>MEANN</i>	1.115	1.105	1.128	1.078	1.113	1.098
		<i>T</i>	8	8	8	8	8	8
Netherlands	7	<i>MEANN</i>	1.122	1.135	1.105	1.067	1.050	1.124
		<i>T</i>	7	7	7	7	7	7
Switzerland	7	<i>MEANN</i>	0.982	0.986	0.994	1.017	1.012	0.990
		<i>T</i>	7	7	7	7	7	7
U.K.	36	<i>MEANN</i>	1.039	1.052	1.095	1.120	1.140	1.098
		<i>T</i>	36	36	56	35	35	36
U.S.A.	180	<i>MEANN</i>	1.009	1.014	1.068	1.053	1.042	1.056
		<i>T</i>	180	180	148	168	168	149
Canada	10	<i>MEANN</i>	1.084	1.084	1.051	1.119	1.100	1.074
		<i>T</i>	10	10	9	9	9	9

B. Mean coefficient (MEANG) of global index, the number of stocks (*T*) for which the coefficient is significant in a two-sided *t*-test at 10 percent significance level, and mean adjusted R-Square in percent (ARSQ)

		Model, Equation Number, and Parameter						
		Stocks	MM 1	GMM In	TFEWWM 3 n ^E	GTFEWWM 3a n ^E	TFVWM 5 n ^V	GTFVWM 5a n ^V
All	425	MEANG			-0.010	0.012	-0.011	0.007
		<i>T</i>			83	148	96	115
		ARSQ	57.66	42.98	88.37	46.04	38.85	44.93
Japan	139	MEANG			0.094	0.073	0.049	0.113
		<i>T</i>			41	71	45	70
		ARSQ	21.76	25.95	23.80	32.22	24.21	31.73
Australia	7	MEANG			0.120	0.305	0.286	0.105
		<i>T</i>			1	2	3	1
		ARSQ	41.97	50.55	42.23	55.34	43.04	52.99
France	11	MEANG			-0.107	-0.075	-0.085	-0.111
		<i>T</i>			3	5	5	2
		ARSQ	53.60	58.05	55.85	60.94	54.32	50.62
W. Germany	20	MEANG			0.040	0.037	0.064	0.041
		<i>T</i>			4	5	4	5
		ARSQ	51.95	56.11	51.96	58.17	52.21	57.51
Italy	8	MEANG			-0.047	0.074	0.008	0.037
		<i>T</i>			2	3	1	3
		ARSQ	66.99	73.14	66.54	75.19	66.26	74.33
Netherlands	7	MEANG			0.028	0.103	0.104	0.024
		<i>T</i>			2	1	1	2
		ARSQ	59.14	63.41	59.24	64.66	58.90	64.37
Switzerland	7	MEANG	-0.024	-0.056	-0.047	-0.029		
		<i>T</i>			1	2	2	1
		ARSQ	63.11	63.31	62.94	64.70	63.50	63.77
U.K.	36	MEANG			-0.096	-0.110	-0.155	-0.082
		<i>T</i>			3	8	4	3
		ARSQ	46.13	51.78	46.03	53.03	46.40	52.67
U.S.A.	180	MEANG			-0.081	-0.022	-0.046	-0.059
		<i>T</i>			22	48	35	24
		ARSQ	42.47	47.10	42.52	49.83	43.15	48.15
Canada	10	MEANG			0.045	-0.053	-0.020	0.002
		<i>T</i>			4	3	3	4
		ARSQ	56.79	43.15	37.44	44.95	37.59	45.11

the value-weighted index is used, these numbers are 96 stocks (23% of the sample) in the linear model (*TFWM*) and 115 stocks (27% of the sample) in the generalized model (*GTFWM*). In any case, Japan accounts for 50% or more of the stocks for which the global beta is significant. The increase in significance of the equally-weighted global beta with the use of a generalized functional form is shared by all countries other than the Netherlands and Canada. The significance of the value-weighted global beta in fact goes down for many countries including U.S.A. when the generalized functional form is used. In Japan, however, the significance results do not depend on the choice of the global index.

The average adjusted R^2 figures for the static models are also reported in Panel B of Table 2. In the linear models, the inclusion of the global index adds about one percent in explanatory power. In the generalized models, however, inclusion of the global index leads to about 3 to 4% increase in explanatory power. While in almost all countries the global index adds more explanatory power when a generalized functional form is used, this effect is most noticeable for Japan.

Between the two global indexes, the value-weighted index fares a bit better in the linear models while the equally-weighted index adds relatively more explanatory power in the generalized models. These results are largely shared by the various countries as well.

Overall, considering both significance and explanatory power, the choice of functional form does seem to affect the relevance of a global index in a stock return model. The choice between an equally-weighted and a value-weighted global index does not seem to be as crucial. The enhanced role of the global index in a generalized functional form for the stock return model has important implications for international asset pricing. If a researcher using a static model does not find the global market variations to be a significant determinant of individual stock returns, our results indicate that the misspecification of the functional form may be the reason. This would be specially so for a Japanese sample or a sample containing many Japanese stocks. While our results apply not just to the Japanese stocks, the importance of Japanese stocks in the international capital market can hardly be overemphasized.

In this paper, we do not directly test whether the international capital market is integrated or segmented. However, the results that we have reported so far do not support the prevalent practice of using a linear two-factor stock return model in such tests. If insignificant pure global betas from a misspecified stock return model are used to test whether the pure global risk is priced, the test may be biased towards the segmentation hypothesis. Misspecification of the functional form is also likely to induce dependence in errors which unless properly addressed in estimation may influence the significance results of a test of integration vs. segmentation.

C. Price Adjustment Patterns

The averages and significance results for the coefficient of the lagged dependent variable in dynamic models (*DMM*, *GDMM*, *DTEWM*, *GDTFEWM*, *DTFVWM*, *GDTFVWM*) are reported in Table 3.

On average, the coefficient (\bar{H}_t) of the lagged dependent variable is negative in the total sample as well as in all countries other than Australia and Italy. This means that the Australian and the Italian stocks are in general sluggish in adjusting to the domestic and global market changes. Stocks in the world's major financial centers (Japan, U.K., and U.S.A.), on the other hand, have a tendency to overreact to these changes. Considering that the stocks in our sample are in general large and the most liquid in their respective countries, market inefficiency is not a likely explanation for such contemporaneous under- or over-adjustment. A time-zone effect is ruled out as an explanation since we consider monthly returns. Perhaps market frictions such as legal barriers to cross-country capital flow induce this type of incomplete price adjustment.

Considering the total sample, the absolute magnitude of the lagged dependent variable's coefficient (\bar{H}_t) is a bit higher in the generalized models than in the linear models. However, on a country basis, this pattern is shared by Japan, the Netherlands, and Switzerland only. The Japanese stocks exhibit the largest differences going from the linear to the generalized functional forms. The results are similar whether a global index is used or not, and whether it is equally-weighted or value-weighted.

The British stocks show the highest incidence (25-28%) of a statistically significant lagged dependent variable, while the magnitude of the lagged dependent variable's coefficient is the largest (0.12-0.14) for the Australian stocks. The statistical significance of the lagged dependent variable improves somewhat going from the linear to the generalized models. In the generalized (linear) models, the lagged dependent variable is significant for about 23(20%) of the total sample. Japan shows the most noticeable increase in significance (from about 14% to about 20%) going from the linear to the generalized models. In most other countries, the significance results do not change very much. A comparison of the average adjusted R^2 figures in Tables 2 (Panel B) and 3 reveals that the additional explanatory power of a dynamic version is negligible in the linear specifications, and is about 2% in the generalized specifications.

A dynamic stock return model is necessary when security prices either respond in a sluggish fashion or overreact to domestic and global market variations. In our sample, while a lack of complete contemporaneous price adjustment is not pervasive in statistical tests, it is not inconsequential either. There is also some evidence that a dynamic specification is more relevant once a generalized functional form is entertained.

It is interesting to note that one out of five stocks in the highly developed capital markets of the world is characterized by a statistically significant incomplete (too little or too much) price response to domestic and global market

Table 3. Mean coefficient (*MEANH*) of Lagged Dependent Variable Estimated from Linear and Generalized Dynamic Models, the Number of Stocks (*T*) for which the Coefficient is Significant in a Two-sided t-test at 10 Percent Significance Level, and Mean Adjusted R-Square in Percent (*ARSQ*)

	Stocks		Model, Equation Number, and Parameter					
			DMM 2 H	GDMM 2a h	DTFEWM 4 H ^E	GDTFEWM 4 h ^E	DTFVWM 6 H ^V	GDTFVWM 6a h ^V
All	425	MEANH	-0.049	-0.053	-0.049	-0.056	-0.049	-0.057
		T	85	97	85	95	86	94
		ARSQ	38.01	43.88	38.03	47.89	39.18	46.55
Japan	139	MEANH	-0.043	-0.065	-0.047	-0.077	-0.047	-0.079
		T	18	26	20	29	21	29
		ARSQ	22.28	27.87	24.12	34.35	24.65	33.72
Australia	7	MEANH	0.158	0.121	0.137	0.117	0.135	0.121
		T	2	5	2	2	2	3
		ARSQ	44.80	55.84	45.14	60.00	46.57	58.24
France	11	MEANH	-0.068	-0.056	-0.064	-0.056	-0.070	-0.052
		T	5	5	5	3	2	2
		ARSQ	53.76	59.11	53.90	62.56	54.37	60.66
W. Germany	20	MEANH	-0.055	-0.052	-0.032	-0.031	-0.036	-0.030
		T	5	4	5	3	5	5
		ARSQ	52.40	57.45	52.52	59.50	52.60	58.74
Italy	8	MEANH	0.056	0.037	0.058	0.027	0.056	0.035
		T	1	0	1	0	1	0
		ARSQ	66.47	73.49	66.96	75.20	66.64	74.50
Netherlands	7	MEANH	-0.010	0.002	-0.004	0.000	-0.009	0.009
		T	1	1	1	1	1	1
		ARSQ	59.04	64.01	59.21	65.19	58.77	64.99
Switzerland	7	MEANH	-0.032	-0.036	-0.034	-0.035	-0.033	-0.039
		T	2	2	2	2	2	2
		ARSQ	63.74	65.66	63.54	68.89	64.16	66.21
U.K.	36	MEANH	-0.067	-0.059	-0.065	-0.056	-0.065	-0.056
		T	10	10	9	10	9	9
		ARSQ	47.03	54.07	46.96	56.46	47.31	55.11
U.S.A.	180	MEANH	-0.063	-0.058	-0.061	-0.055	-0.060	-0.056
		T	42	47	40	44	41	44
		ARSQ	42.58	48.40	42.56	51.51	43.26	49.46
Canada	10	MEANH	-0.080	-0.068	-0.089	-0.075	-0.088	-0.075
		T	1	1	2	1	2	1
		ARSQ	35.78	42.92	36.57	44.20	36.39	44.70

changes. From an investment perspective, an incomplete price response implies predictable variation in the returns of these stocks. Further research is necessary to identify the source of the incomplete price response phenomenon and to evaluate the economic significance of the implied predictable variation in stock returns.

D. Best Overall Model

Panel A of Table 4 present the overall model selection results based upon the Akaike Information Criterion (*AIC*). Figures in Panel A indicate the number of stocks for which a particular model has the best explanatory power (highest *AIC* value) among all 12 (linear and generalized) models considered in this paper. To further ascertain the importance of the main specification issues, the linear, generalized, and overall model selection results are organized according to the specification issues in Panel B of Table 4.

According to Panel A, the top 3 model choices are the GMM (75 stocks), the MM (65 stocks), and the *GTFEWFM* (48 stocks). However, there is noticeable cross-country variation in the model selection results. A majority of the stocks (35 of 65) for which the MM is the best model are from U.S.A. Japan dominates the cases where the GMM (35 of 75) or the *GTFEWFM* (27 of 48) is the best model. On the other hand, the *DMM* is the best model for 1 of 4 British stocks. Not only the most suitable model is different for different countries, there is also considerable heterogeneity in model choice among stocks from a given country as shown by the samples from U.K., Japan and U.S.A.

The results in Panel B of Table 4 shed light on the importance of the specification issues addressed in this paper.

First: The best stock return model is a generalized one for 234 (55%) of our total sample of 425 stocks. This confirms an earlier observation in Section A.2 that a linear model is a poor choice for a large majority of stocks in our sample. Except for the Netherlands and Switzerland, a generalized functional form is appropriate for a large portion of stocks in the other 8 countries including U.K. and U.S.A. Consistent with the likelihood ratio test results in Table 1 (Panel B), a nonlinear functional form is almost a necessity for the Japanese and the Italian stocks.

Second: A dynamic specification is called for more than one-third (37% or 156) of the stocks in our sample when we consider the best model among all 12 linear and generalized models. While these stocks cover all 10 countries, relatively speaking a dynamic specification seems more important for stocks from U.K. (18 of 36), U.S.A. (75 of 180), the Netherlands (3 of 7), France (4 of 11), and Japan (42 of 139).

Third: The inclusion of a global index is necessary to best fit the return process of nearly half (209 of 425) of the stocks in our sample. Consistent with results presented earlier in Section B.2, the relevance of the global index is the highest (88 of 139) in Japan. A large proportion of stocks from U.K. (15 of 56),

Table 4. The Number of Stocks for which a Given Model (Linear or Generalized) has the Best Fit Among All The 12 Linear and Generalized Models and the Number of Stocks for which the Model With Best Fit Includes A given Specification Type, viz., Linear or Generalized, Static or Dynamic, and One-Factor (National Index Only) or Two-Factor (National Index and a Global Index)

A. Model selection among all the 12 linear and generalized models

Stocks	Model and Equation Number												
	MM 1	DMM 2	TF- EWM 3	DTF- EWM 4	TF- VWM 5	DTF- VWM 6	GMM 1a	GDMM 2a	GTF- EWM 3a	GDTF- EWM 4a	GTF- VWM 5a	GDTF- VWM 6a	
All	425	63	42	34	22	23	7	75	36	48	27	26	22
Japan	139	5	0	6	5	4	1	35	11	27	8	20	17
Australia	7	1	0	1	0	0	0	0	1	3	0	0	1
France	11	1	1	1	0	0	0	2	2	3	1	0	0
W. Germany	20	6	2	1	0	2	0	2	2	3	1	1	0
Italy	8	0	0	0	0	0	0	4	1	2	0	1	0
Netherlands	7	3	1	0	0	1	1	0	1	0	0	0	0
Switzerland	7	3	1	2	1	0	0	0	0	0	0	0	0
U.K.	36	6	9	3	3	4	1	3	5	2	2	0	0
U.S.A.	180	35	28	20	12	11	4	27	14	8	14	4	5
Canada	10	3	0	0	1	1	0	2	1	0	1	0	1

B. Model Selection Results by Model Specification Issues

Stocks	Linear/ Generalized		Static/Dynamic			Absence/Presence of Global Factor		
	Among All 12 Models	Among 6 Linear Models	Among 6 Generalized Models	Among All 12 Models	Among 6 Linear Models	Among 6 Generalized Models	Among All 12 Models	
All	425	191/254	285/140	273/152	269/156	242/183	209/216	216/209
Japan	139	21/118	108/ 51	96/ 43	97/ 49	66/ 73	50/ 89	51/ 88
Australia	7	2/ 5	5/ 2	5/ 2	5/ 2	2/ 5	2/ 5	2/ 5
France	11	3/ 8	7/ 4	7/ 4	7/ 4	7/ 4	6/ 5	6/ 5
W. Germany	20	11/ 9	14/ 6	15/ 5	15/ 5	15/ 7	11/ 9	12/ 8
Italy	8	0/ 8	7/ 1	7/ 1	7/ 1	5/ 3	5/ 3	5/ 3
Netherlands	7	6/ 1	4/ 3	5/ 2	4/ 3	5/ 2	5/ 2	5/ 2
Switzerland	7	7/ 0	5/ 2	5/ 2	5/ 2	4/ 3	3/ 4	4/ 3
U.K.	36	26/ 10	19/ 17	18/ 18	18/ 18	24/ 12	21/ 15	21/ 15
U.S.A.	180	110/ 70	110/ 70	108/ 72	105/ 75	110/ 70	100/ 80	104/ 76
Canada	10	5/ 5	6/ 4	7/ 3	6/ 4	6/ 4	6/ 4	6/ 4

U.S.A. (76 of 180), France (5 of 11), Germany (8 of 20), and Australia (5 of 7) also need a two-factor international model to best capture their return behavior.

It can be seen from Panel A of Table 4 that the equally-weighted global index is more suitable than the value-weighted global index as a proxy for the world market portfolio. Of the 209 stocks for which a two-factor model is the best model, the equally-weighted index is present in 65% (131) of the cases.

Fifth: A comparison of the results about the best model among the 6 linear models and the best model among the 6 generalized models may reveal if a functional form misspecification leads to misspecification in another dimension (price adjustment pattern or factor structure). The results in Panel B of Table 4 indicate that the effect of functional form on the relevance of a dynamic specification is modest. The number of stocks for which a dynamic specification is suitable increases by 12 (from 140 to 152) when a generalized rather than a linear functional form is used. This increase is mostly accounted for by some Japanese stocks.

However, a functional form misspecification does seem to have a noticeable impact on the inclusion of a global index in the best model. A global index is present in the best of the 6 linear models for 43% (183 of 425) of the stocks. This proportion increases to 51% (216 of 425) when we consider the best of the 6 generalized models. While this increase is wide spread among the sample countries, relatively speaking it is most visible in Japan. This finding raises the possibility that the extent of international capital market integration would perhaps be better captured by a nonlinear risk-return relationship. The extant evidence in this regard is largely based upon linear models.

Overall, the model selection results in this section show that a *generalized functional form should be the rule rather than an exception* for empirical stock return models. A two-factor model which includes a global index, preferably an equally-weighted one, should be used for almost every other stock, especially those in Japan. Further, to capture incomplete price adjustment, a dynamic specification should be considered, especially for the British stocks.

V. CONCLUSION

In this paper, we have studied three specification issues of an empirical stock return model using a sample of 425 stocks from Japan (139), Australia (7), France (11), Germany (20), Italy (8), the Netherlands (7), Switzerland (7), U.K. (36), U.S.A. (180), and Canada (10). With regards to functional form, our results suggest that the frequently used linear and loglinear specifications may not be appropriate for many stocks. Thus the use of a generalized functional form should be the rule rather than an exception. What is a suitable functional form varies across countries and stocks within the same country.

The weight of evidence against a linear functional form in our international sample indicates that the true investment horizon is likely different from one

month. For many stocks, specially those in Japan and Italy, the true investment horizon is not instantaneous either as the loglinear form is rejected for them. One possible reason for the observed cross-country and within-the-country differences in the true investment horizon is the heterogeneity of investment horizon across investors as noted by Lee, Wu, and Wei (1990).

Similar to MacDonald (1983) and Bubens and Lee (1989), we encounter a preponderance of negative estimates for the horizon parameter in our sample. However, Lee and Wei (1988) have shown that the estimated Z will be negative instead of positive if security return and market return had a bivariate lognormal distribution. Hence the above functional form results are consistent with most of the stocks in our international sample having lognormally distributed returns. It is worthwhile to mention that, in the context of a functional form other than a linear or loglinear one, the beta with respect to untransformed market returns would be a function of the level of untransformed market returns. This may lead to instability of linear or loglinear beta and elasticity estimates over different phases of a market cycle (Fabozzi, Francis and Lee (1980)). Researchers and practitioners should thus exercise caution when using linear or loglinear models to measure risk-adjusted performance over bull and bear market periods. Given the importance of the issue, we show in the Appendix how the generalized functional form captures a wider range of relationships between stock return and market return than the traditional (linear and loglinear) models.

As to other specification issues, our evidence suggests that a two-factor model which includes a global index, preferably an equally-weighted one, should be entertained to best capture the return behavior of nearly every other stock. Considering both statistical significance and explanatory power, we find that the relevance of a global index in a stock return model is enhanced when a generalized functional form used instead of a linear one. This has important implications for international asset pricing. If a global index in a linear model is an insignificant determinant of stock returns, it may be because of the misspecified functional form of the model. The commonly cited dominance of the national index may not after all be as dominant. And perhaps the extent of international capital market integration will be better captured in a generalized functional form framework.

Our results concerning the functional form parameter and the global beta show the need for a theoretical international asset pricing model along the lines of Lee et al. (1990). If a homogenous investment horizon assumption is tenuous in the context of domestic asset pricing, it would be more so in the context of international asset pricing. From a more practical point of view, practitioners who rely upon linear index models for management of international stock portfolios or country portfolios are advised to include a global index in a generalized model, and specially so for Japanese stock portfolios.

Lastly, we find that one out of five stocks in our sample responds either too little or too much to domestic and global market changes. The use of a dynamic stock return model is desirable for this type of situation. Further research is nec-

essary to identify the source of the incomplete price response phenomenon and to evaluate the economic significance of the implied predictable variations in stock returns.

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APPENDIX: GENERALIZED FUNCTIONAL FORMS FOR SLOPE AND ELASTICITY

This appendix illustrates how the generalized functional form captures a wider range of relationships between the stock return and the market return than the traditional linear or loglinear models. For this purpose, let us consider the linear market model (*MM*) in Equation 1 and the generalized market model (*GMM*) in Equation 1a. In the context of these models, it can be shown that:

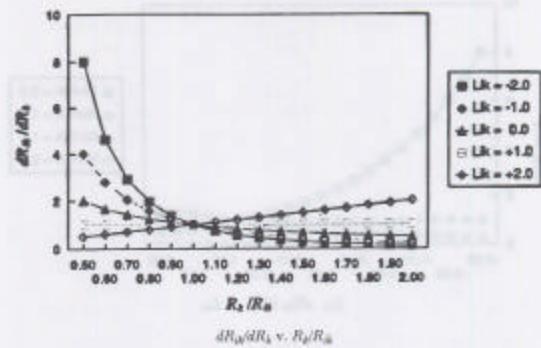
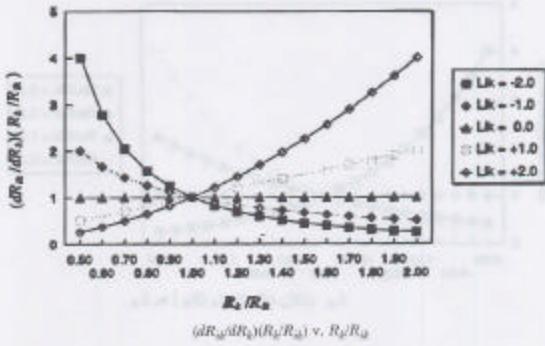
$$\frac{dR_{ik}}{dR_k} = b_{ik}(R_k/R_M)^{1/b_k - 1} \quad (A)$$

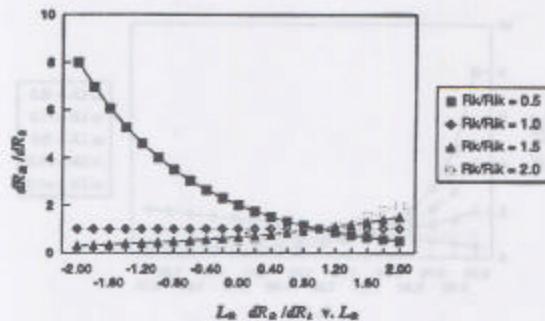
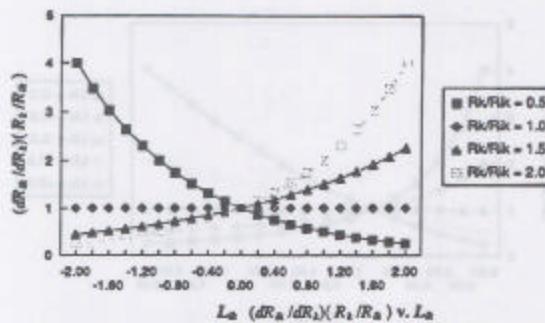
$$(dR_{ik}/dR_k)(R_k/R_M) = b_{ik}(R_k/R_M)^{1/b_k} \quad (B)$$

Expression A is the generalized form of the slope or the marginal impact of the market return on the stock return. Expression B is the generalized form of the elasticity of the stock return with respect to the market return and measures percentage change in the stock return for unit percentage change in the market return. If $b_{ik} = 1.0$, from Expression A, we obtain the traditional constant slope or linear market model. As shown by Expression B, the elasticity is, however, nonconstant and increases linearly with the ratio of market return to stock return. If $b_{ik} = 0.0$, we obtain the loglinear or constant elasticity model with the elasticity being equal to b_{ik} . As shown by Expression A, the slope is, however, nonconstant and decreases with the ratio of market return to stock return in a nonlinear fashion.

To further demonstrate the generality of the return behavior captured by the generalized functional form, we plot in Figures 1 and 2 the slope and the elasticity respectively as a function of the ratio of market return to stock return for alternative values of the transformation parameter, t . Figures 3 and 4, on the other hand, show the slope and the elasticity respectively as a function of the transformation parameter, t_{ik} , for alternative values of the ratio of market return to stock return. In all cases, we assume $b_{ik} = 1.0$ for simplicity.

Figures 1, 2, 3, and 4 clearly indicate that the use of a linear or loglinear functional form may lead to quite erroneous conclusion about market sensitivity (slope or elasticity) of stocks when the transformation parameter, t_{ik} , is not close to 0.0 (linear) or 1.0 (loglinear).

Figure 1. Generalized Market Model with $b_M = 1.0$ Figure 2. Generalized Market Model with $b_A = 1.0$

Figure 3. Generalized Market Model with $b_{ik} = 1.0$ Figure 4. Generalized Market Model with $b_{ik} = 1.0$

NOTES

*Direct all correspondence to: M.M. Chaudhury, University of Saskatchewan, College of Commerce, 25 Campus Drive, Saskatoon, SK, Canada S7N5A7.

1. In the context of a continuous time CAPM implicitly derived by Cox, Ingersoll, and Ross (1985), Longstaff (1989) has shown that the equilibrium unconditional expected return of a security measured over a discrete interval is a complicated nonlinear function of three unconditional moments. One of these moments is the security's covariance with the market. The other two moments are the variance and the autocovariance of the security.

2. While we do not report them here, quite a few national indexes including Italy and U.K. exhibited nontrivial level of serial correlation during our sample period.

3. Carriwright and Lee (1987) refers to the full beta as the long-run multiplier.

4. The terminology of Errunza and Losq is in fact somewhat different. In their theory part, securities are classified into two groups—eligible and ineligible. The ineligible securities are those in which foreign ownership is not allowed and as such have to be owned wholly by the domestic (unrestricted) investors. In market equilibrium, these investors are additionally compensated for the systematic risk with respect to the market portfolio of ineligible securities given the prices of eligible securities. If all of the securities of a country are ineligible and all of the securities of the other country are eligible, the market portfolio of eligible or ineligible securities are just respective national portfolios. Thus the conditional market risk of Errunza and Losq could be proxied for by the purely national index variations.

5. Although incomplete price adjustment can be treated as a specification problem in factor structure as lagged market returns become relevant regressors, we chose to entertain it as a separate specification issue for clarity of exposition.

6. We thank an anonymous referee for cautioning us about this problem.

7. Given our assumption of normally distributed i.i.d. errors, the choice of the best model among the 6 linear specifications is not affected by whether the AIC or the adjusted R^2 is used as the measure of best fit.

8. According to the AIC measure, the dynamic models are at a disadvantage compared to the static models since the former models are estimated with 1 less observation than the latter models.

9. For example, Errunza et al. (1992) test the segmentation hypothesis by using whether the pure global risk is priced or not.

REFERENCES

- Bohm, E.L. and C.F. Lee. 1989. "Linear and Generalized Functional Form Market Models for Electric Utility Firms," *Journal of Economics and Business*, 41: 213-225.
 Carriwright, Phillip A. and Cheng F. Lee. 1987. "Time Aggregation and the Estimation of the Market Model: Empirical Evidence," *Journal of Business and Economic Statistics*, 5: 131-145.

- Cheng, P.L. and M.K. Deets. 1973. "Systematic Risk and the Horizon Problem," *Journal of Financial and Quantitative Analysis*, 8: 299-316.
- Cox, J.C., J.E. Ingersoll, Jr. and S.A. Ross. 1985. "A Theory of the Term Structure of Interest Rates," *Econometrica*, 53: 363-384.
- Erturk, Vihang and Etienne Losq. 1985. "International Asset Pricing under Mild Segmentation: Theory and Test," *Journal of Finance*, 40: 103-124.
- _____. 1989. "Capital Flow Controls, International Asset Pricing, and Investors' Welfare: A Multi-Country Framework," *Journal of Finance*, 44: 1025-1037.
- Erturk, Vihang, Etienne Losq and Prasad Padmanabhan. 1992. "Tests of Integration, Mild Segmentation and Segmentation Hypotheses," *Journal of Banking and Finance*, 16: 949-972.
- Fabozzi, F., J. Francis and C.F. Lee. 1980. "Generalized Functional Form for Mutual Fund Returns," *Journal of Financial and Quantitative Analysis*, 15: 1107-1119.
- Fama, Eugene and Kenneth French. 1992. "The Cross-Section of Expected Stock Returns," *Journal of Finance*, 47: 427-465.
- Gilster, J. 1979. "Autocorrelation, Investment Horizon and Efficient Frontier Composition," *Financial Review*, 14: 25-39.
- Jensen, M.C. 1969. "Risk, the Pricing of Capital Assets, and the Evaluation of Investment Portfolios," *Journal of Business*, 42: 167-247.
- Jorion, Philippe and Edwards Schwartz. 1986. "Integration vs. Segmentation in the Canadian Stock Market," *Journal of Finance*, 41: 603-613.
- Lee, C.F. 1976. "Investment Horizon and the Functional Form of the Capital Asset Pricing Model," *Review of Economics and Statistics*, 58: 356-363.
- _____. 1977. "Functional Form, Skewness Effect, and the Risk Return Relationship," *Journal of Financial and Quantitative Analysis*, 12: 35-72.
- Lee, C.F. and J.K.C. Wei. 1988. *Impact of Rates of Return Distributions on the Functional Form of CAPM*. Unpublished manuscript.
- Lee, C.F., C. Wu and K.C.J. Wei. 1990. "The Heterogenous Investment Horizon and the Capital Asset Pricing Model: Theory and Implications," *Journal of Financial and Quantitative Analysis*, 25: 361-376.
- Lessard, Donald R. 1974. "World, National, and Industry Factors in Equity Returns," *Journal of Finance*, 29: 579-591.
- Levhari, D. and H. Levy. 1977. "The Capital Asset Pricing Model and the Investment Horizon," *Review of Economics and Statistics*, 59: 92-104.
- Levy, H. 1972. Portfolio Performance and the Investment Horizon," *Management Science*, 18: B645-B653.
- Levy, H. and P. Samuelson. 1992. "The Capital Asset Pricing Model with Diverse Holding Periods," *Management Science*, 38: 1529-1542.
- Longstaff, F. 1989. "Temporal Aggregation and the Continuous-Time Capital Asset Pricing Model," *Journal of Finance*, 44: 871-897.
- McDonald, B. 1985. "Functional Forms and the Capital Asset Pricing Model," *Journal of Financial and Quantitative Analysis*, 18: 319-329.
- Roll, R. 1992. "Industrial Structure and the Comparative Behavior of International Stock Market Indices," *Journal of Finance*, 47: 3-41.
- Sharpe, W.F. 1963. "A Simplified Model for Portfolio Analysis," *Management Science*, 9: 277-293.
- Solnik, Bruno. 1974a. "An Equilibrium Model of International Capital Market," *Journal of Economic Theory*, 36: 500-524.

- 1974b. "An International Market Model of Security Price Behavior," *Journal of Financial and Quantitative Analysis*, 10: 557-564.
- 1974c. "The International Pricing of Risk: An Empirical Investigation of the World Capital Market Structure," *Journal of Finance*, 29: 365-377.

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