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Financial Crisis: Stochastic Volatility and State Space Models

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Abstract

With the rapid spread of the coronavirus disease 2019 and the Russian invasion of Ukraine, the volatility in financial markets worldwide increased considerably. Therefore, in this study, we adopt regime switching models where regression coefficients change in each regime to investigate the relationship between equity returns and factor risk. Fund managers need to insulate their investment portfolios from these tail risk and to understand the relationship between factor risks and equity returns during these highly volatile periods. We apply regime switching models where regression coefficients are updated during each regime to.

We check whether the ESG index outperforms the benchmark such as the S&P 500 as ESG investment is a hotly debated issue in the current investment scenario. We also apply the Markov switching and state space models with the Kalman filter technique to corroborate our findings.

Keywords: *financial crisis, Markov switching model, state space model*

1. INTRODUCTION

We confirm this by employing the daily dataset for the above-mentioned indices and also validating whether the ESG index outperforms the benchmark such as the S&P 500 because ESG investment is a hotly debated issue in the current investment scenario. We use the Markov switching and the state space models with the Kalman filter technique to corroborate our results. Nonlinear models are sometimes suitable, especially when analyzing macroeconomic relationships that are subject to regime changes. Some previous studies verify the relationship between equity return and liquidity risk by using simple regression analyses in which coefficients are constant over time. However, actual financial market environments change according to economic situations. Therefore, equity return and liquidity risk regression models with constant regression coefficients over time may not be appropriate. Thus, we need flexible regression models in which regression coefficients differ in each regime. In this study, we adopt regime switching models where regression coefficients change in each regime to investigate the relationship between equity returns and factor risk. For example, Watanabe and Watanabe (2008) verified the preciseness of the two-stage regime switching model in regression coefficients.

In addition, adopting a dynamic system in state space form has two merits. First, the state space allows unobserved variables, known as the state variables, to be incorporated into the model. Second, a state space model can be analyzed using a powerful recursive algorithm known as the Kalman filter.

In the finance literature, the study by Bos and Newbold (1984) is among the first to allow the possibility of a stochastic beta, estimating the one-factor model of mean reversion of beta using maximum likelihood. Berglund and Knif (1999) demonstrate that an estimated stochastic beta employing the Kalman filter is more precise than fixed beta in the forecast. They also illustrate that a significant positive relationship between returns and the beta forecast is obtained when the proposed approach is applied to data from the Helsinki Stock Exchange. Choudhry and Wu (2009) investigate the forecasting ability of three different GARCH models and the Kalman filter method, concluding that measures of forecast errors overwhelmingly support the Kalman filter approach. Monarcha (2009) develops a dynamic style analysis model to identify hedge fund risk structures and demonstrate its superior explanatory power when applied at the individual fund level compared to asset-based style factor models proposed in previous studies.

2. DATA

Our sample data of monthly returns are collected from the MSCI. MSCI provides the database of MSCI ESG related Indexes. In the analyses, the returns are based on U.S. dollar and historical record periods are from October 1, 2007 to March 31, 2022 except for U.S.A.

The historical record period in U.S.A. is from September 1, 2010 to March 31, 2022.

3. METHODOLOGY

We suppose that the random variable of return, y_t, follows a process that depends on the value of an unobserved discrete state variable, S_t. We also assume M possible regimes such that in the state or regime m in period t, S_t=m, for m=1,..,M. The switching model assumes that a different regression model is associated with each regime. Given regressors X_t and Z_t, the conditional mean of y_t in regime m is assumed to be the linear specification:

$$\mu_t(m) = X_t'\beta_m + Z_t'\gamma \tag{1}$$

where β_m and γ are k_x and k_z vectors of coefficients. Note that the β_m coefficients of X_t are indexed by the regime and that the γ coefficients associated with Z_t are regime invariant. Therefore, we assume that the regression errors are normally distributed with the variance that may depend on the regime. Then, we have the following model:

$$y_t = \mu_t(m) + \sigma(m)\varepsilon_t \tag{2}$$

when S_t=m, where ε_t is *iid* standard normal. Note that the standard deviation, σ, may be regime-dependent, that is, $\sigma(m)$=σ_m. In equation (2), $\mu_t(m)$ and $\sigma(m)$ differ in each regime and the excess return is zero, given the efficient market hypothesis. A linear state space representation of the dynamics of the $n\times1$ vector, y_t, is given by the following system of equations:

$$y_t = c_t + Z_t\alpha_t + \varepsilon_t \tag{3}$$

$$\alpha_{t+1} = d_t + T_t\alpha_t + v_t \tag{4}$$

where α_t is an $m\times1$ vector of possibly unobserved state variables, c_t, Z_t, d_t, and T_t are conformable vectors and matrices, and ε_t and v_t are Gaussian disturbance vectors with mean zero. Notably, the unobserved state vector is assumed to move over time as a first-order vector autoregression.

We refer to the first set of equations as the signal or observation equations and the second set as the state or transition equations. The disturbance vectors, ε_t and v_t, are assumed to be serially independent with contemporaneous variance structure.

$$\Omega_t = \mathrm{var}\begin{bmatrix}\varepsilon_t \\ v_t\end{bmatrix} = \begin{bmatrix}H_t G_t \\ G_t' Q_t\end{bmatrix} \tag{5}$$

where H_t is an $n\times n$ symmetric variance, Q_t is an $m\times m$ symmetric variance matrix, and G_t is an $n\times m$ matrix of covariances.

4. EMPIRICAL RESULTS

4.1. SV Model

As the returns are highly regime-specific, we apply regime switching analysis in this case. In addition, P(S(t))=1 and 3 are normal periods, whereas P(S(t))=2 implies a financial crisis period. We use the example of the factor model that CalPERS

Table 1: ACWIESG Leaders (Oct. 2007–Mar. 2022: USD)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
Risk-Free Rate	0.314460	0.000732	429.7163	0.0000
Inflation	-0.044431	0.000741	-59.97931	0.0000
Growth	1.013272	0.000279	3634.115	0.0000
LOG(SIGMA)	-5.788915	0.469278	-12.33580	0.0000
Regime 2				
Risk-Free Rate	0.358794	0.144380	2.485074	0.0130
Inflation	-0.731850	0.195866	-3.736480	0.0002
Growth	0.968084	0.043346	22.33387	0.0000
LOG(SIGMA)	0.366180	0.112028	3.268657	0.0011
Regime 3				
Risk-Free Rate	0.063661	0.053750	1.184386	0.2363
Inflation	-0.083240	0.065119	-1.278283	0.2011
Growth	0.934906	0.016723	55.90453	0.0000
LOG(SIGMA)	-0.459871	0.076314	-6.026081	0.0000
Transition Matrix Parameters				
P11-C	-5.908004	11.75228	-0.502712	0.6152
P12-C	0.078873	1.479387	0.053315	0.9575
P21-C	0.877841	1.099943	0.798079	0.4248
P22-C	3.156798	0.980908	3.218242	0.0013
P31-C	-4.612753	1.717016	-2.686493	0.0072
P32-C	-3.396763	0.814993	-4.167842	0.0000

Mean dependent var	0.643888	S.D. dependent var	4.681502
S.E. of regression	1.175267	Sum squared resid	223.7628
Durbin-Watson stat	1.781560	Log likelihood	-216.6079
Akaike info criterion	2.696643	Schwarz criterion	3.023442
Hannan-Quinn criter.	2.829213		

Table 2

Constant transition probabilities:

P(i, k) = P(s(t) = k | s(t-1) = i)

(row = i / column = k)

	1	2	3
1	0.001304	0.519031	0.479666
2	0.089428	0.873398	0.037173
3	0.009512	0.032089	0.958400

Constant expected durations:

	1	2	3
	1.001305	7.898795	24.03832

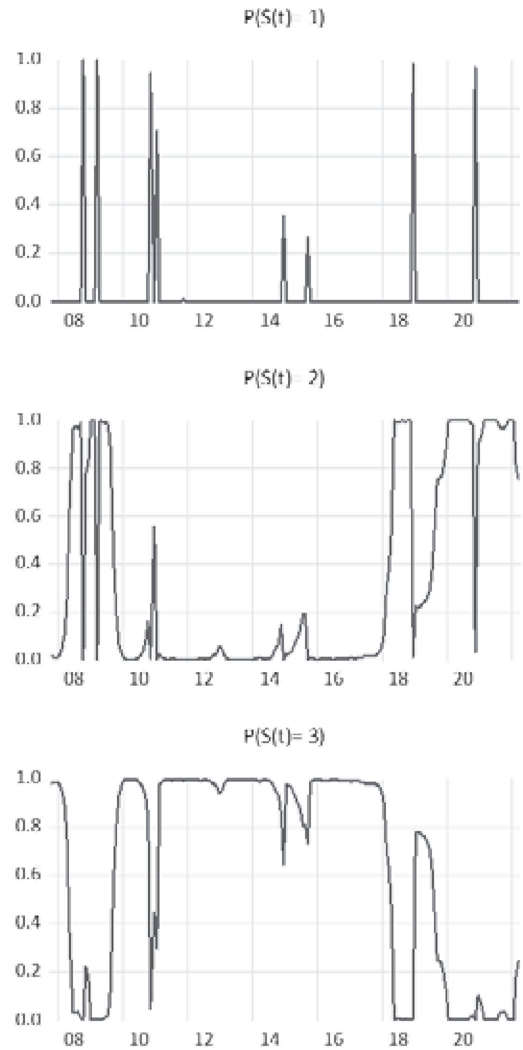


Figure 1: Markov Switching Smoothed Regime Probabilities

Table 3: ACWI (Oct. 2007–Mar. 2022: USD)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Regime 1				
Risk-Free Rate	0.193501	0.405027	0.477750	0.6328
Inflation	0.865540	0.402630	2.149719	0.0316
Growth	-0.268882	0.214334	-1.254497	0.2097
LOG(SIGMA)	1.702966	0.078579	21.67211	0.0000
Regime 2				
Risk-Free Rate	0.628978	0.000557	1128.803	0.0000
Inflation	0.629630	0.000657	957.9339	0.0000
Growth	0.080395	0.000220	364.8632	0.0000
LOG(SIGMA)	-6.968748	0.387376	-17.98963	0.0000
Regime 3				
Risk-Free Rate	1.071535	0.244491	4.382713	0.0000
Inflation	-1.067248	0.473894	-2.252080	0.0243
Growth	0.675759	0.097546	6.927626	0.0000
LOG(SIGMA)	0.437091	0.165875	2.635059	0.0084
Transition Matrix Parameters				
P11-C	1.905060	0.569404	3.345708	0.0008
P12-C	-4.906663	9.611362	-0.510507	0.6097
P21-C	0.855277	1.803898	0.474127	0.6354
P22-C	-0.148238	1.728122	-0.085780	0.9316
P31-C	-1.541467	0.526812	-2.926026	0.0034
P32-C	-2.587203	0.626602	-4.128939	0.0000

Mean dependent var	0.431092	S.D. dependent var	4.784088
S.E. of regression	4.712807	Sum squared resid	3598.109
Durbin-Watson stat	1.812641	Log likelihood	-468.4098
Akaike info criterion	5.590917	Schwarz criterion	5.917715
Hannan-Quinn criter.	5.723486		

Table 4

Constant transition probabilities:

P(i, k) = P(s(t) = k | s(t-1) = i)

(row = i / column = k)

	1	2	3
1	0.869630	0.000957	0.129413
2	0.558112	0.204598	0.237290
3	0.166034	0.058350	0.775616

Constant expected durations:

	1	2	3
	7.670470	1.257225	4.456655

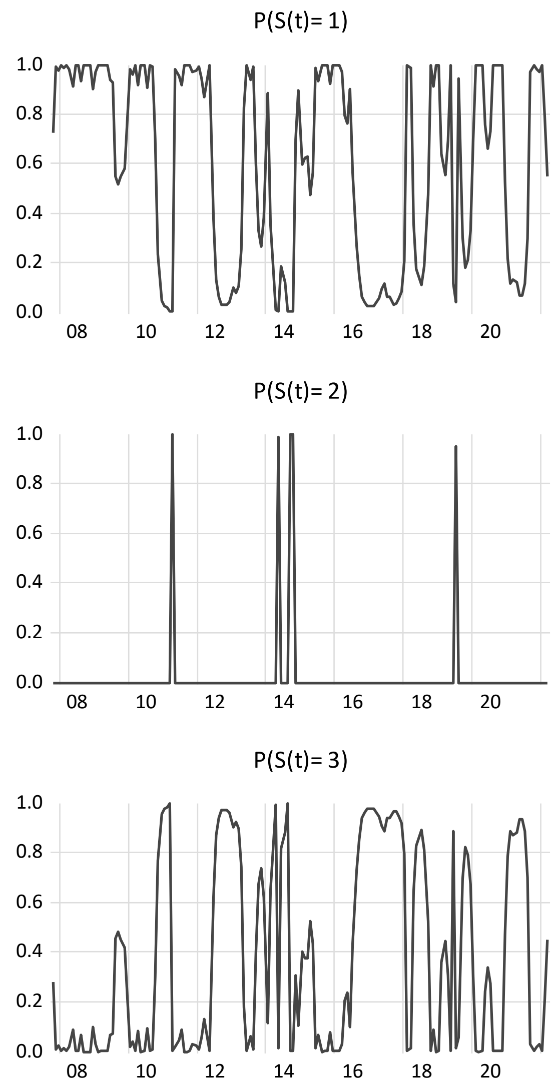


Figure 2: Markov Switching Smoothed Regime Probabilities

adopted. In this factor model, equity returns are decomposed into three factors, risk-free rate, inflation, and growth[1)]. We use MSCI indices for these analyses (Leaders). Judging from Table 1, Table 2, and Figure 1, MSCI all country world (ACW) ESG Leaders index also clearly indicates that ESG investments became a world trend around 2018. We can surmise that ESG-oriented companies have growth potential.

In this case, the CalPERS model, which divides the factors into three categories, holds.

The MSCI ACWI indicates that we cannot determine any relevance judging from Table 3 and Figure 2. Therefore, we surmise that the transition probability from regime one to regime two is extremely low, rendering the estimation difficult from Table 4.

4.2. Kalman filter—State Space Model

The estimation of beta using regression analysis assumes a constant beta during the sample period. In other words, systematic risk (=beta) is unchangeable during this period. To confirm this hypothesis, we consider a simple state space model.

$$\text{Observation equation: } \tilde{R}_t = \alpha + \tilde{\beta}_t \, r_{Index.t} + \tilde{e}_t \quad (6)$$

In equation (6), we suppose that the beta changes stochastically with time. Here, we can consider the S&P 500, TOPIX, ACWI, Kokusai, and Emerging Markets (EM) Asia indices. In equation (7), we can observe that the stochastic beta follows a random walk.

$$\text{State equation: } \tilde{\beta}_t = \tilde{\beta}_{t-1} + \tilde{\varepsilon}_t \quad (7)$$

The state variables have three types of estimated values, one-step-ahead predicted states, filtered state estimates, and smoothed state estimates. For example, one-step-ahead predicted states predict the mean and variance of the state variables at time t using the information at time t–1. Filtered state estimates calculate the mean and variance of state variables in time t by using the information at time t. Smoothed state estimates also calculate the mean and variance of state variables in time t by using the information at time T. More precisely, one-step-ahead is an initial next-period prediction, and the filtered state filters the one-step-ahead prediction.

The predicted states at this moment and the smoothed state trace back all the periods from the final period. Thus, for practical convenience, we mainly refer to the movements of a smoothed state. We consider C(1) as a constant term of the observation equation. And C(1) corresponds to the constant term α in Equation (6). C(2) and C(3) are estimation values of the maximum likelihood for the standard error of the error term. And C(2) corresponds to the error term $\tilde{e}_t$ in Equation (6), and C(3) corresponds to the error term $\tilde{\varepsilon}_t$ in Equation (7).

In Table 5, the constant term is not significant, that is C(1) is zero, implying that the excess return measured by the stochastic beta is zero. By contrast, C(2) of the error is significant and C(3) of the error term is not significant. We can show the graphs of three types of estimated values for the state variables. Here, we only compare the difference between filtered state estimates and smoothed state estimates because the movements of one-step-ahead predicted states and filtered state estimates are similar.

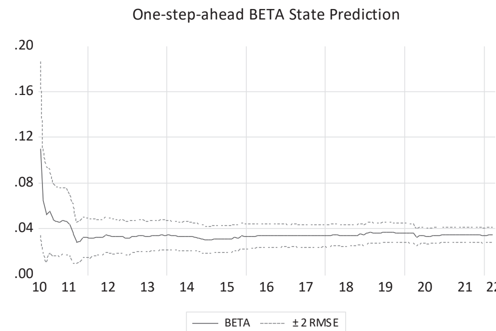
In Figure 3, we use MSCI USA ESG Leaders Index and the S&P 500 for comparison. The value of filtered state beta fluctuates sharply around 2010 following the European debt crisis, and the value of smoothed state shows constant movement by using past historical data. The means of state variables such as beta can be depicted by the time series graphs of the ±2×Root MSE. The value of beta is 0.034875, small enough, and significant.

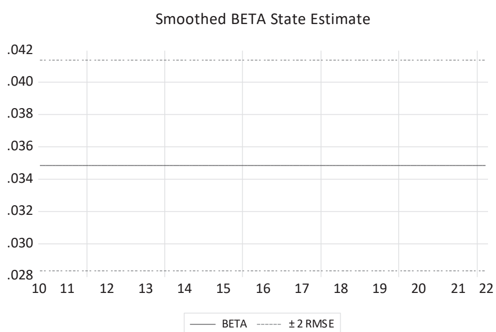
In Table 6, the MSCI EM Asia ESG Leaders and MSCI EM Asia indices are used. The values of C(1), C(2), and C(3) are significant and that of beta is 1.086082 with significance. Although the movement of beta in Figure 4 is affected by the Lehman shock and European debt crisis, the beta continues to move in the upward direction with time. Thus, we can surmise that the EM Asia ESG Leaders index stays strong.

In Table 7, MSCI ACWI ESG Leaders and MSCI Kokusai indices are used. The value of C(1) is not significant, whereas those of C(2) and C(3) are significant. The value of beta is 0.925249 with significance. Although the movement of beta in Figure 5 is influenced by the Lehman shock and European debt crisis, it continues to move in the upward direction from around 2020. Thus, we can

Table 5: ESG USA, S&P 500

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.015031	0.011583	1.297739	0.1944
C(2)	-4.075778	0.098945	-41.19238	0.0000
C(3)	-27.82664	2448204.	-1.14E-05	1.0000
	Final State	**Root MSE**	**z-Statistic**	**Prob.**
BETA	0.034875	0.003265	10.68103	0.0000
Log likelihood	73.89629	Akaike info criterion		-1.020091
Parameters	3	Schwarz criterion		-0.956757
Diffuse priors	1	Hannan-Quinn criter.		-0.994353





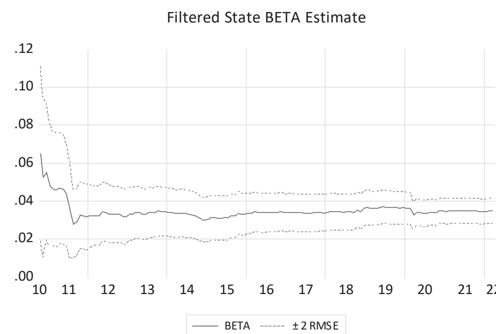
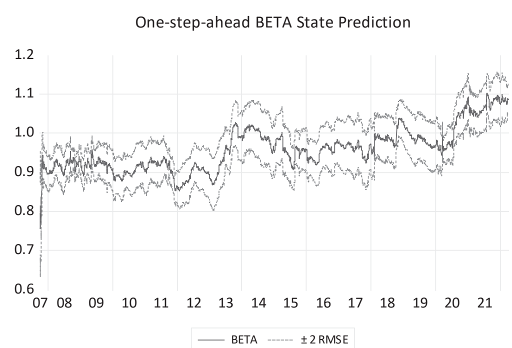
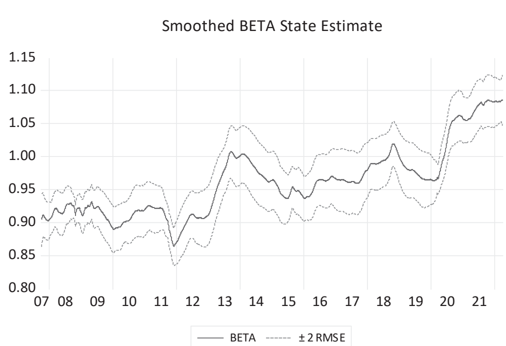


Figure 3

Table 6: EM ESG Leaders EM Asia Index

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.000113	3.36E-05	3.352625	0.0008
C(2)	-12.38066	0.015239	-812.4006	0.0000
C(3)	-11.33956	0.249646	-45.42246	0.0000
	Final State	**Root MSE**	**z-Statistic**	**Prob.**
BETA	1.086082	0.019798	54.85742	0.0000
Log likelihood	18003.59	Akaike info criterion		-9.516570
Parameters	3	Schwarz criterion		-9.511623
Diffuse priors	1	Hannan-Quinn criter.		-9.514811





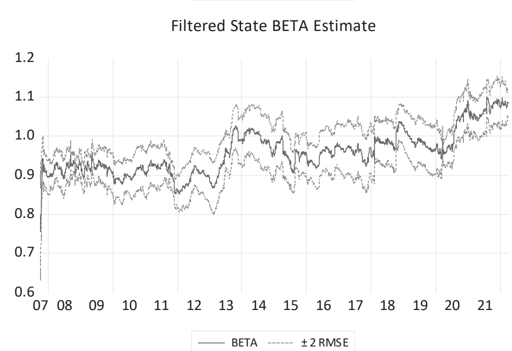
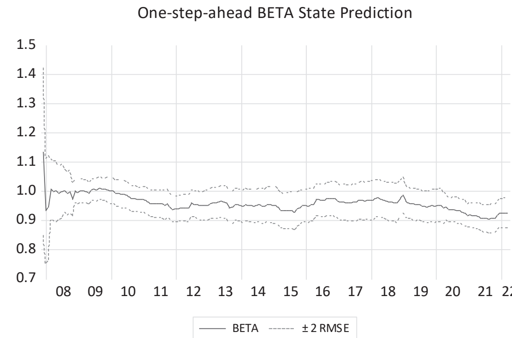
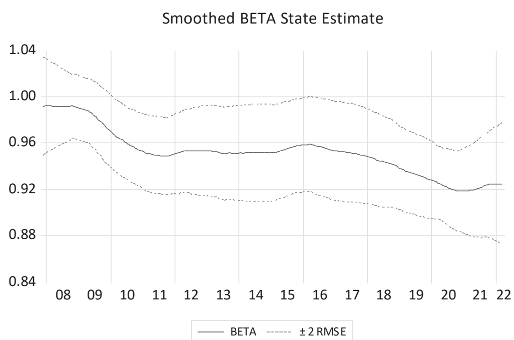


Figure 4

Table 7: ACWIESGL Kokusai

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.017514	0.038876	-0.450499	0.6524
C(2)	-1.393428	0.102902	-13.54127	0.0000
C(3)	-10.35138	1.316784	-7.861106	0.0000
	Final State	Root MSE	z-Statistic	Prob.
BETA	0.925249	0.026830	34.48503	0.0000
Log likelihood	-137.8137	Akaike info criterion		1.646944
Parameters	3	Schwarz criterion		1.702061
Diffuse priors	1	Hannan-Quinn criter.		1.669308





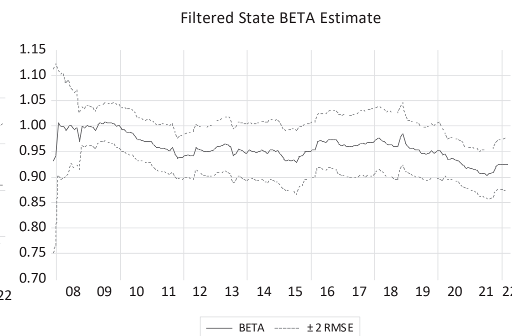
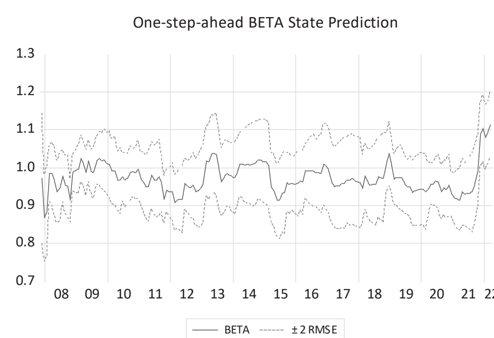
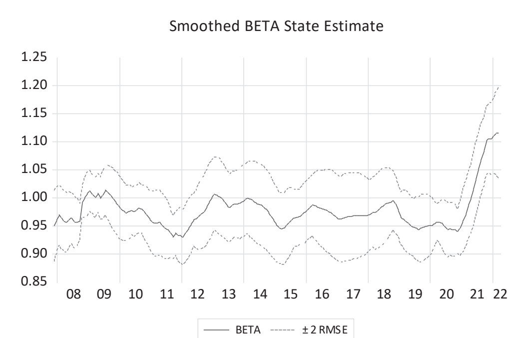


Figure 5

Table 8: ACWIESGL ACWI

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.222599	0.028841	7.718241	0.0000
C(2)	-2.287693	0.110198	-20.75992	0.0000
C(3)	-7.934041	0.365497	-21.70753	0.0000
	Final State	Root MSE	z-Statistic	Prob.
BETA	1.115712	0.045518	24.51118	0.0000
Log likelihood	-78.69863	Akaike info criterion		0.939065
Parameters	3	Schwarz criterion		0.993531
Diffuse priors	1	Hannan-Quinn criter.		0.961160





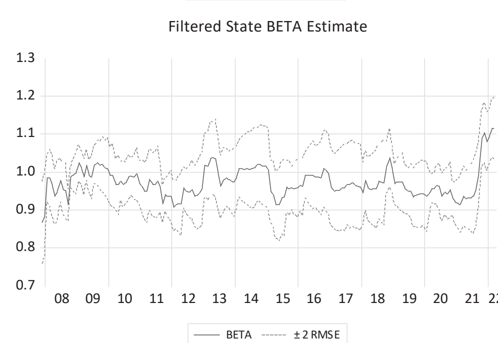
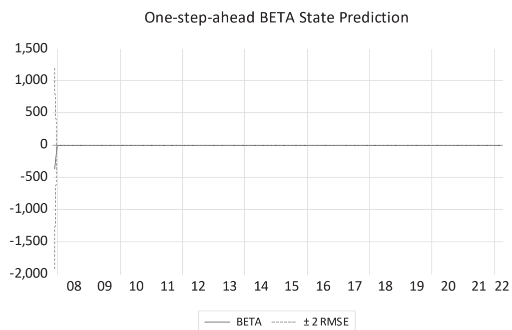


Figure 6

Table 9: ESG JAPANL TOPIX

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.015681	0.050961	0.307716	0.7583
C(2)	-0.949848	0.084314	-11.26565	0.0000
C(3)	-10.29961	1.331230	-7.736912	0.0000
	Final State	Root MSE	z-Statistic	Prob.
BETA	1.030647	0.032233	31.97492	0.0000
Log likelihood	-177.2258	Akaike info criterion		2.071561
Parameters	3	Schwarz criterion		2.126027
Diffuse priors	1	Hannan-Quinn criter.		2.093856



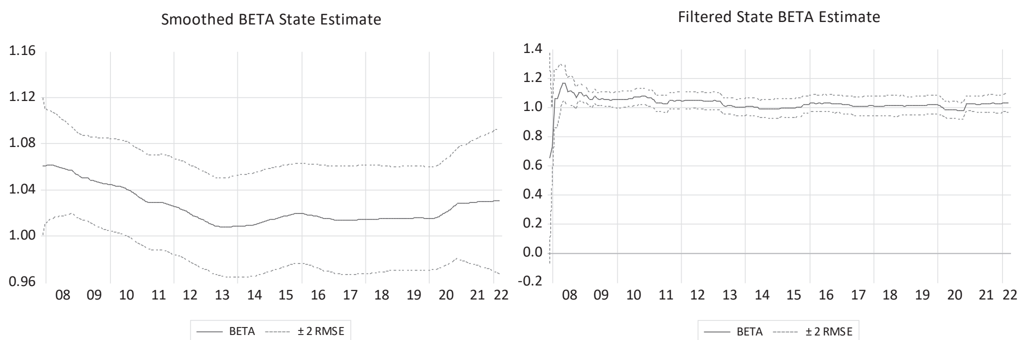


Figure 7

infer that the MSCI Japan ESG Leaders index stays strong relative to the MSCI Kokusai index.

In Table 8, the MSCI ACW ESG Leaders and MSCI ACW indices are used. The values of C(1), C(2), and C(3) are significant and the value of beta is 1.115712 with significance. Although the movement of beta in Figure 6 is impacted by the Lehman shock and European debt crisis, it moves sharply in the upward direction around 2021. Thus, we can conclude that the MSCI ACW ESG Leaders index stays strong and demonstrates the importance of ESG investment.

In Table 9, the MSCI Japan ESG Leaders and TOPIX indices are used. The value of C(1) is not significant, whereas those of C(2) and C(3) are significant. The value of beta is 1.030647 with significance. Although the Lehman shock and European debt crisis affect the movement of beta in Figure 7, the beta movement remains in the upward direction from around 2020. Thus, we can surmise that the MSCI Japan ESG Leaders index stays strong relative to TOPIX.

In Table 10, the MSCI Japan ESG Leaders and MSCI Kokusai indices are used. The value of C(1) is not significant, whereas those of C(2) and C(3) are significant. The value of beta is 0.484922 with significance. Although the Lehman shock and European debt crisis affect the movement of beta in Figure 8, it moves in the downward direction with time till around 2016. Thus, we can infer that the MSCI Japan ESG Leaders index is affected by the sluggish Japanese economy.

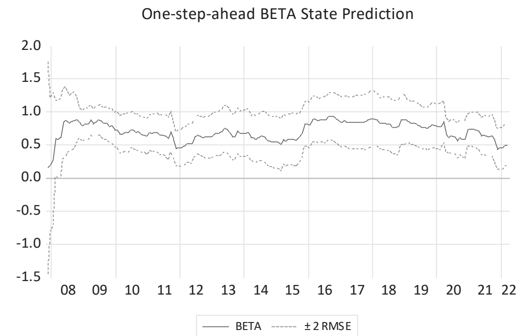
In Table 11, the MSCI Japan ESG Leaders and MSCI ACW indices are used. The value of C(1) is not significant, whereas those of C(2) and C(3) are significant. The value of beta is 0.597077 with significance. Although the Lehman shock and European debt crisis affect the movement of beta in Figure 9, after around 2016, the beta moves in a downward direction with time. Thus, we can deduce that the MSCI Japan ESG Leaders index is affected by the sluggish Japanese economy.

5. CONCLUSION

In particular, we employed the Markov switching and state space models with the Kalman filter technique. For example, the MSCI ACW ESG Leaders

Table 10: ESG JAPANL Kokusai

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	-0.090895	0.215434	-0.421918	0.6731
C(2)	2.043467	0.128071	15.95579	0.0000
C(3)	-6.493164	0.884704	-7.339362	0.0000
	Final State	Root MSE	z-Statistic	Prob.
BETA	0.484922	0.161546	3.001753	0.0027
Log likelihood	-439.7520	Akaike info criterion		5.089103
Parameters	3	Schwarz criterion		5.143570
Diffuse priors	1	Hannan-Quinn criter.		5.111196



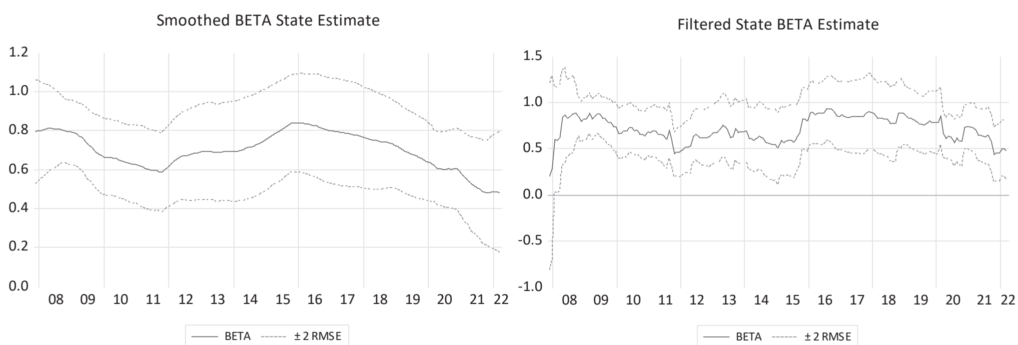
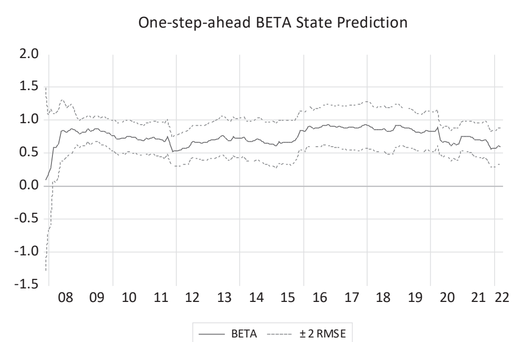


Figure 8

Table 11: ESG JAPANL World

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.070085	0.201727	0.347426	0.7283
C(2)	1.931698	0.124029	15.57456	0.0000
C(3)	-7.000619	0.993503	-7.046396	0.0000
	Final State	Root MSE	z-Statistic	Prob.
BETA	0.597077	0.141927	4.206931	0.0000
Log likelihood	-429.0447	Akaike info criterion		4.966032
Parameters	3	Schwarz criterion		5.020498
Diffuse priors	1	Hannan-Quinn criter.		4.988126



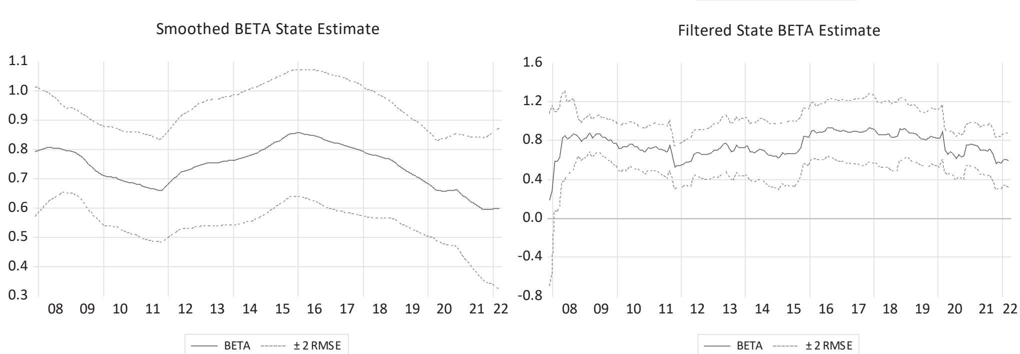


Figure 9

index clearly indicated that ESG investments became a global trend around 2018 in the Markov switching model. We concluded that ESG-oriented companies have growth potential. For the combination of MSCI EM Asia ESG Leaders and MSCI EM Asia indices, we inferred that the EM Asia ESG Leaders index stayed strong. We also enumerated the examples of three analyses in the state space model with the Kalman filter technique. For the combination of the MSCI ACW ESG Leaders and MSCI ACW indices, we deduced that the MSCI ACW ESG Leaders index stayed strong and illustrated the importance of ESG investments. For the MSCI Japan ESG Leaders and TOPIX indices, we concluded that the MSCI Japan ESG Leaders index stayed strong relative to TOPIX. For the combination of MSCI Japan ESG Leaders and MSCI ACW indices, we surmised that the MSCI Japan ESG Leaders index was affected by the sluggish Japanese economy. While, during financial crises, the performance of ESG investments tend to be better compared to other investments. ESG investments are believed to promote sustainable economic growth for companies, which in turn, enhances long-term returns for investors. Furthermore, recent changes in consumer values also play a role in supporting ESG investments.

We propose to conduct further empirical analyses by using statistical methods based on the fact that stocks included in the ESG index represent a relatively small range of stock price declines caused by financial crises.

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NOTE

1) Risk-free rate is the time-value of money in real terms; Inflation is the preservation of purchasing power; Growth is the equity risk premium.

REFERENCES

Ang, A., 2014. *Asset Management*. Princeton University Press.

Albulescu, C. T., 2021. COVID-19 and the United States financial markets' volatility. *Fin. Res. Lett*. 38, article 101699.

Ali, M., et al., 2020. Coronavirus (Covid-19) —An epidemic or pandemic for financial markets. *J. Behav. Exp. Fin*. 27, September Article 100341.

Asl, F. M., Etula, E., 2012. Advancing strategic asset allocation in a multi-factor world. *J. Portfol. Manag*. 39(1), 59–66.

Berglund, T., Knif, J., 1999. Accounting for the accuracy of beta estimates in CAPM tests on assets with time-varying risks. *Eur. Financial. Manag*. 5, 29–42.

Binder, J. J., 1998. The event study methodology since 1969. *Rev. Quant. Fin. Acc*. 11(2), 111–137.

Bos, T., Newbold, P., 1984. An empirical investigation of the possibility of stochastic systematic risk in the market model. *J. Bus*. 57(1), 35–41.

Caballero, R. J., Simsek, A., 2020. A model of asset price spirals and aggregate demand amplification of A "COVID-19" shock. Working Paper 27044, *National Bureau of Economic Research*, 1–39. http://www.nber.org/papers/w27044.

Choudhry, T., Wu, H., 2009. Forecasting the weekly time-varying beta of UK firms: GARCH models vs. Kalman filter method. *Eur. J. Fin*. 15, 437–444.

Cochrane, J. H., 2001. Asset Pricing. 68. Princeton University Press, Davidson, James. (2004) "Forecasting Markov-switching Dynamic, Conditionally Heteroscedastic Processes," *Statistics & Probability Letters*, 137–147.

Deb, P., 1997. Finite sample properties of the ARCH class of models with stochastic volatility. *Econ. Lett*. 55, 27–34.

Diebold, F. X., Lee, J.-H., Weinbach, G. C., 1994. Regime switching with time-varying transition probabilities, in: Hargreaves, C. P. (Ed.), *Nonstationary Time Series Analysis and Cointegration*. Oxford University Press, Oxford, 283–302.

Duffie, D., 2001. *Dynamic Asset Pricing Theory*. Princeton University Press.

Filardo, A. J., 1994. Business-cycle phases and their transitional dynamics. *J. Bus. Econ. Stat*. 12,

299–308.
Frühwirth-Schnatter, S., 2006. *Finite Mixture and Markov Switching Models*. Springer Science +Business Media LLC, New York.
Goldfeld, S. M., Quandt, R. E., 1973. A Markov model for switching regressions. *J. Econ*, 1, 3–15.
Groenewold, N., Fraser, P., 1999. Time-varying estimates of CAPM betas. *Math. Comput. Simul*. 48, 531–539.
Hamilton, J. D., 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*. 57, 357–384.
Hamilton, J. D., 1990. Analysis of time series subject to changes in regime. *J. Econ*. 45, 39–70.
Hamilton, J. D., 1994. *Time Series Analysis*, Chapter 22. Princeton University Press, Princeton.
Hamilton, J. D., 1996. Specification testing in Markov-switching time-series models. *J. Econ*. 70, 127–157.
Hansen, B. E., 1992. The likelihood ratio test under nonstandard conditions: Testing the Markov switching model of GNP. *J. Appl. Econ*. 7, S61–S82.
Kim, C.-J., 1994. Dynamic linear models with Markov-switching. *J. Econ*. 60, 1–22.
Kim, C.-J., Nelson, C. R., 1999. *State-Space Models with Regime Switching*. The MIT Press, Cambridge.
Kim, S., Shepherd, N., Chib, S., 1998. Stochastic volatility: likelihood inference and comparison with ARCH models. *Rev. Econ. Studies*. 65, 361–393.
Krolzig, H.-M., 1997. *Markov-Switching Vector Autoregressions: Modelling, Statistical Inference, and Application to Business Cycle Analysis*. Springer-Verlag, Berlin.
Le, T. H., et al., 2021. Covid-19 pandemic and tail-dependency networks of financial assets. *Fin. Res. Lett*. 38, article 101800.
Leaders, M. A. E. S. G. NR USD and MSCI ACWI GR USD.
Mackinlay, A. C., 1997. Event studies in economics and finance. *J. Econ. Lit*. 35, 13–39.
Maddala, G. S., 1986, Chapter 28. 'Disequilibrium, Self-Selection, and Switching Models,' handbook of econometrics, in: Griliches, Z., Intriligator, M. D. (Eds.), *Handbook of Econometrics*, Volume 3. North-Holland, Amsterdam.
Maheu, J. M., McCurdy, T. H., 2000. Identifying bull and bear markets in stock returns. *J. Bus. Econ. Stat*. 18(1), 100–112.
Marsh, T., Pfleiderer, P., 2012. "Black Swans" and the financial crisis. Rev. Pac. Basin Financ. *Markets Pol*. 15(2) (June 2012), 125008–125001 to 125008-12.
Marsh, T., Pfleiderer, P., 2013. Flight to quality and asset allocation in a financial crisis. *Financ. Anal. J*. 69(4), 43–57.
Mazur, M., et al., 2021. COVID-19 and March 2020 stock market crash. Evidence from S&P 1500. *Fin. Res. Lett*. 38, article 101600.
Monarcha, G., 2009. A dynamic style analysis model for hedge funds, SSRN Scholarly Paper, December 4.
Rodriguez-Nieto, J. A., Mollick, A. V., 2021. The US financial crisis, market volatility, credit risk and stock returns in the Americas. *Financ. Markets Portfol. Manag*. 35(2), 225–254.
Smith, D. R., 2008. Evaluating specification tests for Markov-switching time-series models. *J. Time S. Analysis*. 29, 629–652.
Watanabe, A., Watanabe, M., 2008. Time-Varying Liquidity Risk and the Cross Section of Stock Returns. *The Review of Financial Studies*, Vol. 21, Issue 6, 2449–2486.

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