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The Financial Review 41 (2006) 565–587

The
Financial
Review

The Risk-Return Relation in International Stock Markets

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Abstract

We investigate the risk-return relation in international stock markets using realized variance constructed from MSCI (Morgan Stanley Capital International) daily stock price indices. In contrast with the capital asset pricing model, realized variance by itself provides negligible information about future excess stock market returns; however, we uncover a positive and significant risk-return tradeoff in many countries after controlling for the (U.S.) consumption-wealth ratio. U.S. realized variance is also significantly related to future international stock market returns; more importantly, it always subsumes the information content of its local counterparts. Our results indicate that stock market variance is an important determinant of the equity premium.

Keywords: capital market integration, stock return predictability, out-of-sample forecasts

JEL Classification: G1

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This paper formerly circulated under the titles "On the Out-of-Sample Stock Return Predictability: The International Evidence" and "Does Stock Market Volatility Forecast Returns: The International Evidence." I especially thank an anonymous referee for many insightful and constructive comments. I also thank conference participants of the 2004 FMA meeting for helpful suggestion. Bill Bock and Jason Higbee provided excellent research assistance. The views expressed in this paper are those of the author and do not necessarily reflect the official positions of the Federal Reserve Bank of St. Louis or the Federal Reserve System. Morgan Stanley Capital International, Inc. (MSCI), its affiliates, and information providers make no warranties with respect to data used in this article. The MSCI data used in this article may not be used, distributed, or disseminated without the written consent of MSCI.

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1. Introduction

The capital asset pricing model (CAPM) stipulates a positive relation between conditional stock market returns and variance. However, the empirical results, which are obtained mainly for the U.S. data, are mixed: While some authors (e.g., French, Schwert, and Stambaugh, 1987) report a positive risk-return tradeoff, others (e.g., Campbell, 1987) report a negative one. Guo (2004) attempts to reconcile the conflicting evidence by arguing that, in addition to a risk premium, as in CAPM, investors also require a liquidity premium because of limited stock market participation. Since the two components of the equity premium can be negatively related in his model, Guo suggests that early authors fail to uncover a positive risk-return relation because they do not explicitly take into account the liquidity premium. This interpretation is also consistent with Merton's (1973) intertemporal CAPM (ICAPM), in which a hedge for time-varying investment opportunities is also an important determinant of the equity premium, in addition to the risk premium. Scruggs (1998) and Guo and Whitelaw (2006), among others, provide empirical support for Merton's ICAPM.

Consistent with Guo's (2004) conjecture, Guo (2006) finds that realized stock market variance is indeed positively and significantly related to future returns after controlling for the consumption-wealth ratio (*cay*) as a proxy for the liquidity premium. Lettau and Ludvigson (2001) construct the *cay* variable as the residual from the cointegration relation among consumption, wealth, and labor income. It is negatively related to shareholders' liquidity conditions because the higher stock prices are or the lower *cay* is, the less likely that shareholders are borrowing constrained, and the lower the liquidity premium is. The predictive power of *cay* is also consistent with Campbell and Cochrane's (1999) habit-formation model.

In this paper, we investigate whether the omitted variables problem accounts for the puzzling negative risk-return relation in international stock markets (see, e.g., Li, Yang, Hsiao, and Chang, 2005). Our analysis of international data should also provide an out-of-sample test on whether Guo's (2006) results reflect data mining, as cautioned by Lo and MacKinlay (1990) and many others.

This paper uses quarterly data for two reasons. First, *cay* is reliably available only on a quarterly basis. Second, Ghysels, Santa-Clara, and Valkanov (2005) show that realized variance is a function of long distributed lags of daily stock returns; therefore, realized variance is better measured in quarterly data than monthly data. Quarterly realized variance is constructed using Morgan Stanley Capital International (MSCI) daily price indices for 18 individual stock markets (including the United States) as well as the world stock market over the period 1974:Q1–2002:Q4. However, we use *cay* obtained from the U.S. data to capture the predictable variation in international stock returns that is not explained by stock market variance. Although this specification reflects the fact that we do not have sufficient data to construct country-specific *cay*, we believe that it is appropriate for the purposes of this paper. In particular, Lettau and Ludvigson (2001) argue that *cay* forecasts asset wealth; therefore, to the extent that U.S. households own international equities, *cay* might also forecast their returns. Moreover, many authors (e.g., Campbell and Hamao, 1992; Harvey, 1991) find that

U.S. predictive variables forecast international stock market returns and often drive out their local counterparts. These results have been interpreted as evidence of capital market integration; for example, Harvey suggests that “expected returns in individual countries appear to be generated by common world factors” (p. 147). Therefore, the U.S. *cay* variable might be influenced by worldwide liquidity shocks, which also affect international stock market returns. In this paper, we find that it is indeed a strong predictor of international stock returns.

Consistent with the early literature, we find that stock market variance is positively autocorrelated, indicating that realized variance contains important information about future variance. In contrast with CAPM, realized variance is significantly correlated with future excess stock returns at the 10% level in only four stock markets; however, we uncover a positive and significant risk-return relation in nine stock markets after controlling for *cay* in the regression. Therefore, the early evidence of a negative risk-return tradeoff in international stock markets might reflect the omitted variables problem and thus should be interpreted with caution.

U.S. stock market variance appears to be a more important determinant of international stock market returns than their own variance: When combined with *cay*, U.S. variance is significant at the 10% level in 16 stock markets, and it almost always subsumes the information content of country-specific variance. We find qualitatively the same results using realized world stock market variance, which is highly correlated with U.S. variance, with a correlation coefficient of 0.92. Therefore, country-specific variance forecasts stock returns mainly because of its comovements with United States or world variance. These results are consistent with the conjecture that, if capital markets are integrated, international stock returns are determined by systematic risk but not country-specific risk.

Brennan and Xia (2005) argue that the predictive ability of *cay* comes mainly from a look-ahead bias introduced by using the full sample to estimate the cointegration parameters. Also, Bossaerts and Hillion (1999) and Goyal and Welch (2003), among others, cast doubt on the in-sample stock return predictability documented by early authors (e.g., Campbell, 1987; Fama and French, 1989) because of the negligible out-of-sample forecasting power. To address these issues, we conduct the out-of-sample forecast for international stock market returns using only information available at the time of the forecast. In particular, we assume that macrovariables are available with a one-quarter delay in the recursive estimation of *cay*. Consistent with the in-sample evidence, we find that the U.S. forecasting variables have significant out-of-sample predictive power for stock returns in many international markets. Therefore, our main results are not driven by the look-ahead bias.

2. Data

We follow Lettau and Ludvigson (2001) in the construction of the *cay* variable, which is the error term from the cointegration relation among consumption, labor income, and net worth. We obtain the consumption and labor income data from the Bureau of Economic Analysis and the net worth data from the Federal Reserve Board.

The net worth data span the period 1952:Q1–2002:Q4, the longest sample available to us when we first wrote the paper. Because it requires a relatively large number of observations to obtain reasonable estimates of the cointegration parameters, unless otherwise indicated, we calculate *cay* using the full sample.

For the United States, we use the S&P 500 index return as a proxy for stock market returns and use the yield on three-month Treasury bills as a proxy for the risk-free rate. To calculate daily excess returns, we assume that the risk-free rate is constant within a month.[1] Thus, daily excess returns are the difference between daily stock market returns and the daily risk-free rate. As in Merton (1980) and Andersen, Bollerslev, Diebold, and Labys (2003), among many others, realized stock market variance in a quarter is the sum of the squared deviation of daily excess stock market returns from their quarterly mean. Following Campbell, Lettau, Malkiel, and Xu (2001), we adjust downward realized stock market variance for 1987:Q4 because the 1987 stock market crash has confounding effects on it.

We also construct realized stock market variance using daily MSCI price indices for 18 individual (including the United States) markets and the world market. The data span the period January 1, 1974 to December 31, 2002. The United States and the world price indices are denominated in U.S. dollars. For each of the other 17 international stock markets, there are two indices: One is denominated in the local currency and the other in U.S. dollars. To be consistent in calculating excess returns, we use the local risk-free rate in the first case and the U.S. risk-free rate in the second case. We obtain monthly risk-free rates from International Financial Statistics and provide some information about the data in Appendix A. Again, we assume that the risk-free rate is constant within a month, and daily excess returns are thus the difference between daily stock returns and the daily risk-free rate. We find that measures of realized stock market variance based on excess returns in the local currency and in U.S. dollars are essentially the same. To conserve space, we use only the former in our analysis. Daily price indices do not include dividend payments; therefore, we use monthly MSCI gross price indices to calculate quarterly excess stock returns. We find qualitatively the same results using returns denominated in U.S. dollars and the local currency; for brevity, we report results only for the former in the paper.

Figure 1 shows realized stock market variance for 18 individual stock markets and the world stock market using the MSCI data. Similar to the U.S. data, realized variance has a large spike during 1987:Q4 in most international stock markets as well as the world stock market. To mitigate the potential outlier effect, we replace the realized variance of 1987:Q4 with the second-largest realized variance if the former is larger than the latter.

In panel A of Table 1, we report the summary statistics of quarterly excess returns denominated in U.S. dollars. Excess returns on the U.S. and the world indices

[1] In particular, we first divide the annualized risk-free rate by 12 to get the monthly risk-free rate and then divide the monthly rate by the number of trading days in a month to obtain the daily risk-free rate.

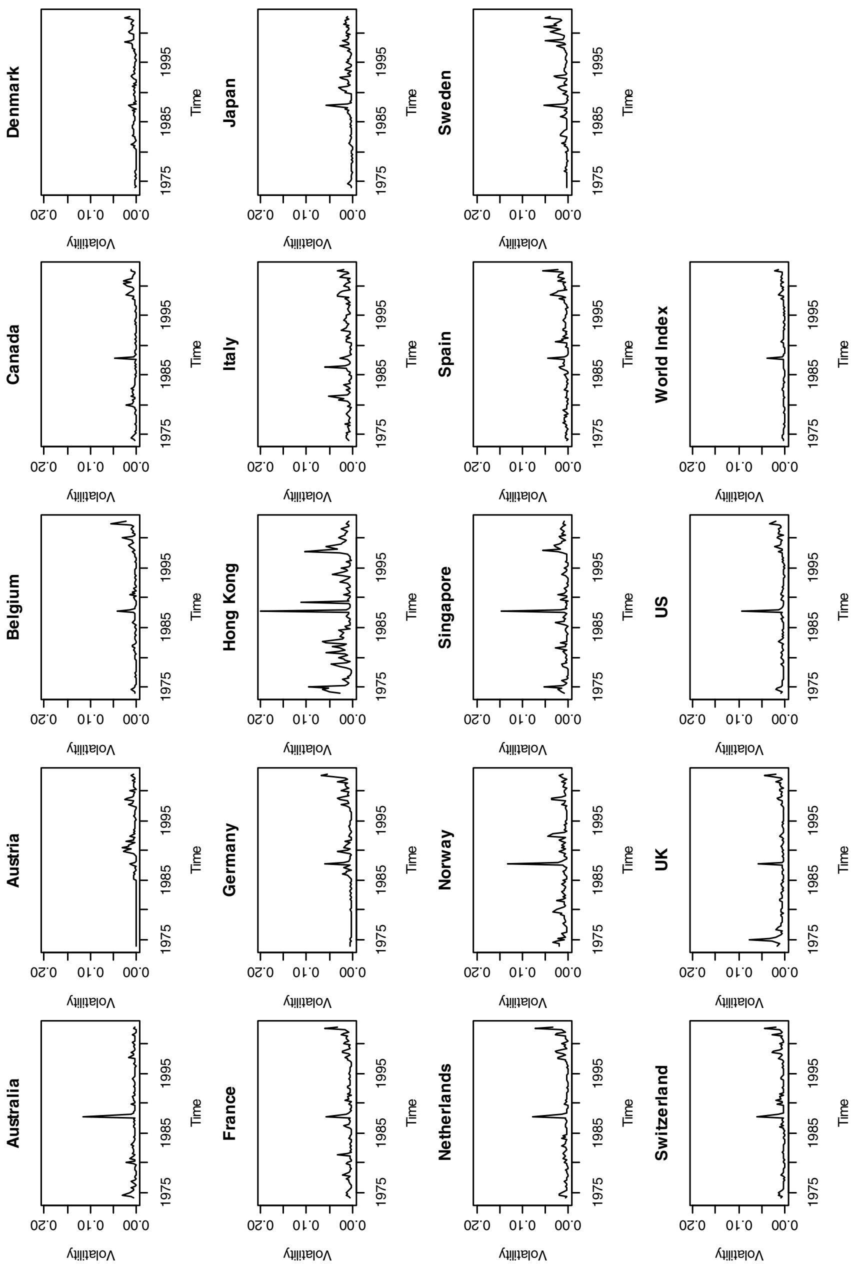

Figure 1

Realized stock market variance

Table 1

Summary statistics of excess returns and realized variance

Country	Mean	SD	Minimum	Maximum	Correlation with World	Correlation with U.S.
Panel A: Excess returns in U.S. dollars						
Australia	0.64	12.81	−55.21	25.00	0.67	0.64
Austria	0.18	11.02	−36.03	43.01	0.37	0.32
Belgium	1.21	10.94	−32.55	28.84	0.68	0.55
Canada	0.31	10.12	−30.50	25.60	0.78	0.78
Denmark	0.92	8.95	−25.26	23.95	0.55	0.51
France	1.06	12.65	−48.65	32.77	0.70	0.62
Germany	0.82	11.39	−45.93	28.83	0.67	0.59
Hong Kong	1.39	18.77	−64.45	47.53	0.58	0.56
Italy	0.11	14.07	−32.39	52.08	0.59	0.45
Japan	0.41	12.45	−40.59	31.85	0.74	0.46
Netherlands	1.80	9.92	−37.50	29.26	0.83	0.75
Norway	−0.07	14.46	−50.92	40.69	0.53	0.50
Singapore	0.17	15.91	−47.65	68.65	0.62	0.58
Spain	0.08	13.12	−44.68	50.93	0.59	0.49
Sweden	1.64	13.16	−36.62	36.84	0.73	0.66
Switzerland	1.27	10.56	−26.80	31.60	0.73	0.64
UK	1.29	11.46	−36.03	58.67	0.72	0.65
US	1.05	8.76	−31.77	19.37	0.90	1.00
World	0.85	8.51	−27.72	21.71	1.00	0.90
Panel B: Realized variance						
Australia	0.61	0.50	0.17	3.19	0.46	0.58
Austria	0.47	0.62	0.01	3.17	0.47	0.32
Belgium	0.53	0.74	0.06	5.50	0.84	0.82
Canada	0.53	0.58	0.09	2.82	0.66	0.72
Denmark	0.57	0.46	0.04	2.63	0.72	0.64
France	0.89	0.89	0.18	6.12	0.80	0.76
Germany	0.87	1.11	0.12	6.82	0.85	0.79
Hong Kong	2.08	2.19	0.26	11.27	0.42	0.44
Italy	1.16	0.94	0.19	6.08	0.39	0.34
Japan	0.72	0.64	0.06	2.87	0.62	0.44
Netherlands	0.84	1.07	0.14	7.34	0.85	0.85
Norway	1.17	0.86	0.26	4.58	0.43	0.46
Singapore	0.97	1.00	0.08	5.64	0.51	0.52
Spain	0.87	0.88	0.09	5.69	0.82	0.72
Sweden	1.08	1.11	0.12	5.32	0.77	0.69
Switzerland	0.60	0.72	0.06	4.41	0.84	0.80
UK	0.82	0.99	0.16	7.59	0.56	0.61
US	0.62	0.54	0.11	3.23	0.92	1.00
World	0.36	0.31	0.07	1.96	1.00	0.92

Note: We use MSCI gross price indices denominated in U.S. dollars to construct excess returns (panel A). We construct quarterly realized variance using MSCI daily price indices denominated in the local currency and the local risk-free rate (panel B).

are substantially less volatile than those on international indices. For example, the standard deviation is about 19% for Hong Kong, compared with less than 9% for the United States. Also, international stock market returns are closely correlated with world stock market returns: The correlation coefficient is between 0.37 for Austria and 0.90 for the United States, and the average is 0.67. International stock market returns are also closely related to U.S. stock market returns, with an average correlation coefficient of 0.60. Panel B reports the summary statistics of quarterly realized stock market variance. Again, international stock market variance is closely related to that of the world and the U.S. stock markets, with an average correlation coefficient of 0.66 and 0.63, respectively.

3. Results

3.1. In-sample regression

In panel A of Table 2, we report the ordinary least-squares (OLS) regression results of realized stock market variance, $\sigma^2_{i,t}$, on its own lag, $\sigma^2_{i,t-1}$, for 18 individual markets and the world market:

$$\sigma^2_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \varepsilon_{i,t}. \tag{1}$$

Consistent with the early literature, stock market variance is positively autocorrelated, with an average R^2 of 20%. Therefore, realized variance contains important information about future stock market variance. In panel B, we present the OLS regression results of excess stock market returns in U.S. dollars, $R_{i,t}$, on lagged country-specific realized variance, $\sigma^2_{i,t-1}$:

$$R_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \varepsilon_{i,t}. \tag{2}$$

In contrast with CAPM, the risk-return relation is negative though insignificant in five markets. Also, the relation is significantly positive at the 5% level in only the Australian and Spanish markets and at the 10% level in only the United States and world markets. Overall, consistent with early authors, we find little support for a positive risk-return relation in international stock markets.

To investigate whether an omitted variables problem prevents finding the predicted positive risk-return tradeoff, we also include the lagged U.S. consumption-wealth ratio, cay_{t-1}, in the regression and report the OLS estimation results in Table 3:

$$R_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \gamma_i cay_{t-1} + \varepsilon_{i,t}. \tag{3}$$

The Wald test of the null hypothesis that *cay* and realized variance are jointly equal to zero is presented in the last column. Consistent with Guo (2006), realized stock market variance becomes highly significant for the U.S. data: The two variables jointly account for over 18% of stock return variations, compared with only 2% in Table 2. The Wald test also indicates that the predictability is statistically significant at the conventional level. Similarly, the risk-return relation in the world stock market is also highly significant after we include *cay* as an additional regressor. Overall,

Table 2

Regression of excess returns (in U.S. dollars) and variance on lagged own variance

	Panel A: Variance		Panel B: Excess returns	
Country	$\sigma^2_{i,t-1}$	R^2	$\sigma^2_{i,t-1}$	R^2
Australia	0.350***	0.123	5.390***	0.044
	(3.670)		(2.755)	
Austria	0.570***	0.325	1.773	0.010
	(7.109)		(0.830)	
Belgium	0.431***	0.176	2.282	0.022
	(5.061)		(1.557)	
Canada	0.548***	0.299	0.955	0.003
	(0.000)		(0.485)	
Denmark	0.588***	0.333	−0.449	0.001
	(5.359)		(−0.237)	
France	0.331***	0.103	0.865	0.003
	(3.599)		(0.791)	
Germany	0.554***	0.264	0.333	0.001
	(5.068)		(0.424)	
Hong Kong	0.305**	0.093	−0.307	0.001
	(2.491)		(−0.381)	
Italy	0.375***	0.140	1.014	0.005
	(2.726)		(0.786)	
Japan	0.536***	0.287	1.940	0.010
	(4.884)		(1.273)	
Netherlands	0.382***	0.138	0.588	0.004
	(3.378)		(0.917)	
Norway	0.432***	0.188	−0.333	0.000
	(5.167)		(−0.193)	
Singapore	0.335***	0.112	−0.710	0.002
	(3.443)		(−0.350)	
Spain	0.422***	0.174	2.944***	0.038
	(4.574)		(2.813)	
Sweden	0.533***	0.270	0.157	0.000
	(4.153)		(0.126)	
Switzerland	0.381***	0.141	−0.113	0.000
	(4.900)		(−0.105)	
UK	0.420***	0.176	0.759	0.004
	(2.932)		(0.689)	
US	0.504***	0.241	2.276*	0.019
	(6.147)		(1.727)	
World	0.471***	0.205	3.859*	0.019
	(3.555)		(1.940)	

Note: The table presents the OLS estimation results of forecasting variance, (panel A) $\sigma^2_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \varepsilon_{i,t}$, and excess stock market returns, (panel B) $R_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \varepsilon_{i,t}$. Heteroskedasticity-consistent t-statistics are in parentheses.

***, **, and * denote the significance level of 1%, 5%, and 10%, respectively.

Table 3

Regression of excess returns (in U.S. dollars) on lagged own variance and *cay*

Country	cay_{t-1}	$\sigma^2_{i,t-1}$	R^2	Wald test $\chi^2(2)$
Australia	1.941**	5.830***	0.083	17.579
	(2.319)	(3.267)		(0.000)
Austria	1.531**	1.922	0.043	4.831
	(2.186)	(0.898)		(0.089)
Belgium	2.027***	3.577**	0.073	10.662
	(2.739)	(2.572)		(0.005)
Canada	2.820***	4.804**	0.086	7.682
	(2.691)	(2.103)		(0.021)
Denmark	1.344**	1.409	0.030	5.571
	(2.355)	(0.733)		(0.062)
France	2.559***	1.984*	0.067	8.699
	(2.780)	(1.698)		(0.013)
Germany	2.197**	1.268*	0.057	8.805
	(2.579)	(1.808)		(0.012)
Hong Kong	1.964*	−0.108	0.020	2.987
	(1.711)	(−0.144)		(0.225)
Italy	2.209**	1.850	0.044	5.992
	(2.304)	(1.380)		(0.050)
Japan	1.134	2.379	0.023	3.618
	(1.388)	(1.541)		(0.164)
Netherlands	2.322***	1.430**	0.089	11.990
	(3.118)	(2.291)		(0.002)
Norway	2.221**	0.154	0.040	5.995
	(2.383)	(0.086)		(0.050)
Singapore	1.085	−0.263	0.009	0.928
	(0.880)	(−0.120)		(0.629)
Spain	2.013***	3.892***	0.074	20.602
	(2.732)	(3.836)		(0.000)
Sweden	2.433**	1.442	0.048	4.635
	(2.026)	(1.294)		(0.099)
Switzerland	2.078***	0.759	0.062	7.351
	(2.700)	(0.644)		(0.025)
UK	2.409***	1.216	0.079	11.139
	(3.184)	(0.910)		(0.004)
US	3.075***	5.710***	0.187	25.883
	(4.768)	(3.557)		(0.000)
World	2.295***	7.628***	0.125	20.115
	(3.697)	(3.601)		(0.000)

Note: The table presents the OLS estimation results of forecasting excess stock market returns, $R_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \gamma_i cay_{t-1} + \varepsilon_{i,t}$. Heteroskedasticity-consistent *t*-statistics are in parentheses.
***, **, and * denote the significance level of 1%, 5%, and 10%, respectively.

realized stock variance is significantly positive at the 10% level in nine markets, compared with only four markets in Table 2. Also, *cay* is statistically significant in most countries. Therefore, as conjectured, we fail to uncover a positive risk-return tradeoff in Table 2 possibly because of the omitted variables problem.

Table 4

Regression of excess returns (in U.S. dollars) on lagged U.S. variance and *cay*

Country	cay_{t-1}	$\sigma^2_{\mathrm{US},t-1}$	R^2	Wald test $\chi^2(2)$
Australia	2.734***	7.291***	0.081	10.712
	(2.786)	(3.031)		(0.005)
Austria	1.935**	3.557*	0.044	6.485
	(2.461)	(1.865)		(0.039)
Belgium	2.302***	5.766***	0.074	10.545
	(2.967)	(2.585)		(0.005)
Canada	2.545***	6.490***	0.108	14.540
	(2.884)	(3.658)		(0.001)
Denmark	2.162***	5.181***	0.095	18.095
	(3.743)	(3.441)		(0.000)
France	3.159***	5.868**	0.089	11.214
	(3.252)	(2.363)		(0.004)
Germany	2.308**	3.508*	0.056	6.667
	(2.494)	(1.715)		(0.036)
Hong Kong	3.467**	6.632*	0.049	6.144
	(2.474)	(1.647)		(0.046)
Italy	2.471**	5.289**	0.047	7.232
	(2.418)	(2.069)		(0.027)
Japan	1.098	1.570	0.011	1.434
	(1.190)	(0.549)		(0.488)
Netherlands	2.831***	4.997**	0.115	12.724
	(3.510)	(2.469)		(0.002)
Norway	3.243***	5.993***	0.072	11.072
	(3.185)	(2.738)		(0.004)
Singapore	2.870*	9.614*	0.075	4.092
	(1.865)	(1.891)		(0.129)
Spain	2.214***	6.543***	0.056	11.611
	(2.816)	(2.832)		(0.003)
Sweden	2.751**	8.821***	0.073	12.927
	(2.312)	(3.349)		(0.002)
Switzerland	2.360***	2.977	0.068	7.603
	(2.753)	(1.308)		(0.022)
UK	3.458***	5.810	0.127	13.923
	(3.177)	(1.616)		(0.001)
US	3.255***	6.872***	0.208	31.313
	(5.297)	(4.065)		(0.000)
World	2.546***	5.455***	0.136	18.281
	(4.036)	(3.237)		(0.000)

Note: The table presents the OLS estimation results of forecasting excess returns, $R_{i,t} = \alpha_i + \beta_i \sigma^2_{\mathrm{US},t-1} + \gamma_i cay_{t-1} + \varepsilon_{i,t}$. Heteroskedasticity-consistent t-statistics are in parentheses.
***, **, and * denote the significance level of 1%, 5%, and 10%, respectively.

The predictive power of the U.S. *cay* variable is consistent with Campbell and Hamao (1992) and Harvey (1991), who find that U.S. predictive variables provide important information about international stock market returns. To further address this issue, we present the regression results of international stock returns on lagged U.S. stock variance, $\sigma^2_{\mathrm{US},t-1}$, and *cay* in Table 4:

$$R_{i,t} = \alpha_i + \beta_i \sigma^2_{\mathrm{US},t-1} + \gamma_i cay_{t-1} + \varepsilon_{i,t}. \quad (4)$$

We find a strong positive relation between U.S. realized stock market variance and international stock market returns. The result for the world market is very similar to that reported in Table 3 because the U.S. variance is highly correlated with the world variance (Table 1).[2] Of 17 international stock markets, U.S. realized variance always has a positive coefficient. Moreover, it is statistically significant at the 5% level in 10 countries and significant at the 10% level in four countries. It is statistically insignificant only in Japan, Switzerland, and the U.K.

Comparing results in Table 4 with those in Table 3, we find that the U.S. realized variance is significantly positive in more countries than the country-specific realized variance. One possible explanation is that, as we explain below, if capital markets are integrated, the country-specific variance forecasts international stock market returns mainly because of its comovements with the U.S. variance. To illustrate this point, we write the excess stock market return of country i, $R_{i,t}$, as a linear function of the U.S. excess stock market return, $R_{US,t}$, and the country-specific risk, $\zeta_{i,t}$:

$$R_{i,t} = b_i R_{\mathrm{US},t} + \zeta_{i,t}. \quad (5)$$

As Table 1 shows, U.S. stock market returns and volatility are highly correlated with those of the world market index. Therefore, we can think of Equation (5) as a variant of the international CAPM, in which U.S. stock market returns serve as a proxy for systematic risk.[3] By definition, $R_{US,t}$ and $\zeta_{i,t}$ are orthogonal to each other. Then it is straightforward to show that realized stock variance of country i, $\sigma^2_{i,t}$, is approximately a linear function of realized U.S. stock variance, $\sigma^2_{\mathrm{US},t}$, and realized variance of the country-specific risk, $\sigma^2_{i,c,t}$:

$$\sigma^2_{i,t} \approx a_i + b_i^2 \sigma^2_{\mathrm{US},t} + \sigma^2_{i,c,t}, \quad (6)$$

where $\sigma^2_{i,c,t}$ is realized variance of the country-specific risk, $\zeta_{i,t}$. Equation (6) suggests that the international stock market volatility is closely correlated with the U.S. stock market volatility (panel B, Table 1) possibly because international stock market returns are closely correlated with U.S. stock market returns (panel A, Table 1).

If capital markets are integrated, investors do not require a risk premium for bearing the country-specific risk, $\zeta_{i,t}$, and its variance ($\sigma^2_{i,c,t}$) should be uncorrelated with future stock returns. In that case, Equation (5) indicates that international stock market returns are predictable only by variables that forecast U.S. stock returns. Therefore, the country-specific volatility forecasts international stock market returns

[2] The results for the United States are slightly different from those reported in Table 3 because we construct realized stock market variance using the S&P 500 index in Table 4 and using the MSCI U.S. price index in Table 3.

[3] Strictly speaking, realized world stock market variance is a more proper measure of systematic risk than realized U.S. stock market variance. However, given that the two variance measures are highly correlated (Table 1), such a distinction is found to be empirically unimportant. To conserve space, we do not report the results obtained using world stock variance but they are available upon request.

mainly because of its comovements with the U.S. volatility. This implication appears to be consistent with the results reported in Tables 3 and 4. To formally investigate the relative importance of the U.S. variance and the country-specific variance, we include both variables in the regression:

$$R_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \gamma_i cay_{t-1} + \delta_i \sigma^2_{\mathrm{US},t-1} + \varepsilon_{i,t}. \tag{7}$$

There is a caveat, however. The specification in Equation (7) is potentially vulnerable to a multicollinearity problem because Table 1 shows that the country-specific volatility is closely related to the U.S. volatility. Nevertheless, the correlation is not perfect, possibly because variance of the country-specific risk is also an important determinant of the country-specific variance in Equation (6). Therefore, the regression might still provide some indications on the relative importance of these two variables. With this caveat in mind, we report the OLS estimation results in Table 5.

Table 5 shows that, of the 17 international stock markets, the country-specific variance is statistically significant only in Spain. In contrast, the U.S. variance is significant in four markets and marginally significant in three markets. Also, while the coefficient is always positive for the U.S. variance, it is negative in many markets for the country-specific variance. Although these results need to be interpreted with caution because of the multicollinearity problem, they nevertheless suggest that, consistent with the hypothesis of capital market integration, the country-specific realized variance provides information about future international stock market returns mainly because of its comovements with the U.S. realized variance.

To partially address the multicollinearity problem, we regress the country-specific variance, $\sigma^2_{i,t}$, on the U.S. variance, $\sigma^2_{\mathrm{US},t}$, and then use the residual in the forecasting regression of stock returns. As shown in Equation (6), the residual is mainly the realized variance of the country-specific risk, $\sigma^2_{i,c,t}$, which should be uncorrelated with future stock market returns if capital markets are integrated. Indeed, we find that the orthogonalized country-specific variance has negligible explanatory power for international stock market returns, even when combined with *cay*. This result provides support for the hypothesis of capital market integration. For comparison, we also orthogonalize the U.S. variance by each country-specific variance and find that the orthogonalized U.S. variance remains significant or marginally significant for many international stock markets when combined with *cay*. Overall, these results are consistent with those reported in Table 5 that the U.S. variance is a more relevant measure of systematic risk than the country-specific variance. For brevity, we do not report these results here but they are available on request.

An alternative explanation for the results reported in Table 5 is that the lagged U.S. variance has better predictive power for the country-specific variance than its own lag. To address this issue, we run the regression of the country-specific variance on its own lag, the lagged U.S. variance, and *cay*[4]:

[4] We include *cay* because Lettau and Ludvigson (2003) find that it is negatively related to future U.S. stock market variance. Nevertheless, excluding it does not affect our results in any qualitative manner.

Table 5

Regression of excess returns (in U.S. dollars) on lagged own variance, U.S. variance, and *cay*

Country	cay_{t-1}	$\sigma^2_{i,t-1}$	$\sigma^2_{\mathrm{US},t-1}$	R^2
Australia	2.760**	3.329	5.115*	0.102
	(2.562)	(1.219)	(1.658)	
Austria	2.040***	1.202	2.977	0.054
	(2.653)	(0.527)	(1.447)	
Belgium	2.328***	1.966	3.471	0.081
	(2.875)	(0.873)	(1.011)	
Canada	2.963***	1.873	5.279**	0.117
	(2.849)	(0.636)	(2.283)	
Denmark	1.848***	−2.050	6.177***	0.092
	(3.177)	(−0.886)	(3.179)	
France	3.218***	−0.058	5.956	0.089
	(3.131)	(−0.033)	(1.626)	
Germany	2.481**	0.325	3.016	0.063
	(2.545)	(0.222)	(0.771)	
Hong Kong	3.199**	−0.718	7.993	0.047
	(2.215)	(−0.842)	(1.643)	
Italy	2.939***	1.338	4.706*	0.063
	(2.772)	(0.986)	(1.780)	
Japan	1.178	2.305	0.285	0.023
	(1.255)	(1.329)	(0.094)	
Netherlands	2.920***	−0.524	5.971	0.115
	(3.302)	(−0.455)	(1.606)	
Norway	3.335***	−1.327	7.119**	0.075
	(3.146)	(−0.688)	(2.487)	
Singapore	2.649*	−2.391	11.783*	0.091
	(1.736)	(−1.214)	(1.908)	
Spain	2.316***	2.944**	2.830	0.079
	(2.924)	(2.259)	(1.049)	
Sweden	3.069**	−0.432	7.482***	0.086
	(2.557)	(−0.423)	(3.739)	
Switzerland	2.653***	−1.478	4.854	0.078
	(2.851)	(−0.814)	(1.389)	
UK	3.312***	−0.169	5.986	0.115
	(2.979)	(−0.186)	(1.598)	

Note: The table presents the OLS estimation results of forecasting excess returns, $R_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \gamma_i cay_{t-1} + \delta_i \sigma^2_{\mathrm{US},t-1} + \varepsilon_{i,t}$. Heteroskedasticity-consistent *t*-statistics are in parentheses. ***, **, and * denote the significance level of 1%, 5%, and 10%, respectively.

$$\sigma^2_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \gamma_i cay_{t-1} + \delta_i \sigma^2_{\mathrm{US},t-1} + \varepsilon_{i,t}. \tag{8}$$

Table 6 shows that the own lag is positive and statistically significant in all countries except Netherlands. In contrast, the lagged U.S. variance is insignificant in all countries except Spain, which has a negative coefficient. These results might reflect a multicollinearity problem because Table 1 shows that the country-specific variance and the U.S. variance are closely correlated to each other. Another plausible

Table 6

Regression of variance on lagged own variance, U.S. variance, and *cay*

Country	cay_{t-1}	$\sigma^2_{i,t-1}$	$\sigma^2_{\text{US},t-1}$	R^2
Australia	−0.058	0.374***	−0.070	0.140
	(−1.476)	(2.971)	(−0.638)	
Austria	−0.026	0.599***	−0.123	0.331
	(−0.554)	(6.495)	(−1.326)	
Belgium	−0.137**	0.356***	−0.024	0.226
	(−2.132)	(3.031)	(−0.146)	
Canada	−0.216***	0.335**	−0.139	0.450
	(−3.996)	(2.516)	(−1.114)	
Denmark	−0.113***	0.540***	−0.160	0.408
	(−3.069)	(4.832)	(−1.495)	
France	−0.165**	0.216**	0.110	0.167
	(−2.419)	(2.330)	(0.808)	
Germany	−0.132*	0.452***	0.132	0.291
	(−1.660)	(3.900)	(0.637)	
Hong Kong	−0.221	0.287**	−0.048	0.108
	(−1.278)	(0.014)	(−0.089)	
Italy	−0.093*	0.360**	−0.117	0.152
	(−1.660)	(2.260)	(−0.644)	
Japan	−0.054	0.511***	0.011	0.299
	(−1.355)	(4.226)	(0.082)	
Netherlands	−0.187**	0.237	0.212	0.200
	(−2.180)	(1.540)	(0.768)	
Norway	−0.099	0.449***	−0.163	0.205
	(−1.538)	(4.960)	(−0.954)	
Singapore	−0.111	0.185**	0.444	0.186
	(−1.276)	(2.516)	(1.188)	
Spain	−0.203***	0.475***	−0.385**	0.247
	(−2.652)	(4.810)	(−2.084)	
Sweden	−0.266***	0.301**	0.309	0.374
	(−3.205)	(2.192)	(1.074)	
Switzerland	−0.095	0.295**	0.092	0.177
	(−1.473)	(2.458)	(0.434)	
UK	−0.044	0.337***	0.288	0.200
	(−0.387)	(3.400)	(0.736)	

Note: The table presents the OLS estimation results of forecasting stock market variance, $\sigma^2_{i,t} = \alpha_i + \beta_i \sigma^2_{i,t-1} + \gamma_i cay_{t-1} + \delta_i \sigma^2_{\text{US},t-1} + \varepsilon_{i,t}$. Heteroskedasticity-consistent t-statistics are in parentheses. ***, **, and * denote the significance level of 1%, 5%, and 10%, respectively.

explanation is that the lagged U.S. variance is unlikely to provide much information about variance of the country-specific risk, $\sigma^2_{i,c,t}$, in Equation (6). Overall, it seems reasonable to conclude that the lagged own variance has better forecasting power for the country-specific variance than the lagged U.S. variance. If capital markets are segmented, this result suggests that the lagged own variance is a more important determinant of individual stock market returns than the lagged U.S. variance. However,

Table 7

Pooled regression of excess returns (in U.S. dollars) on lagged U.S. variance and *cay*

Group	cay_{t-1}	$\sigma^2_{\mathrm{US},t-1}$	p-value of OIR test
All Countries	2.765***	6.425***	0.465
	(10.160)	(9.638)	
G7	2.991***	6.693***	0.204
	(6.126)	(4.773)	
Non-G7	2.251***	5.489***	0.352
	(6.448)	(6.464)	
Japan and World	3.662***	8.309***	0.113
	(4.097)	(4.370)	
Japan and US	3.048***	7.318***	0.057
	(5.335)	(4.330)	

Note: The table presents the pooled OLS estimation results of forecasting excess returns:

$$\begin{aligned} R_{1,t} &= \alpha + \gamma cay_{t-1} + \delta\sigma^2_{\mathrm{US},t-1} + \varepsilon_{1,t} \\ &\vdots \\ R_{18,t} &= \alpha + \gamma cay_{t-1} + \delta\sigma^2_{\mathrm{US},t-1} + \varepsilon_{18,t} \end{aligned}.$$

Heteroskedasticity-consistent t-statistics are in parentheses.
***, **, and * denote the significance level of 1%, 5%, and 10%, respectively.

Table 5 shows that this implication is overwhelmingly rejected by the data. Therefore, the evidence in Table 6 reinforces the argument for capital market integration.

In Table 5, the coefficients on *cay* and the U.S. stock market variance have a relatively small dispersion across countries. These results indicate that expected international stock returns tend to move in the same directions. To address this issue, we pool the forecasting equations of all 18 countries and assume that the intercept and slope parameters are the same:

$$\begin{aligned} R_{1,t} &= \alpha + \gamma cay_{t-1} + \delta\sigma^2_{\mathrm{US},t-1} + \varepsilon_{1,t} \\ &\vdots \\ R_{18,t} &= \alpha + \gamma cay_{t-1} + \delta\sigma^2_{\mathrm{US},t-1} + \varepsilon_{18,t}. \end{aligned} \tag{9}$$

This specification is similar to the integration test in Campbell and Hamao (1992), who assume that coefficients in the Japanese return equation are proportional to those in the U.S. return equation. The equation system is over-identified with 51 degrees of freedom, and we can use the over-identifying restriction (OIR) test to determine the goodness of fit. Table 7 shows that both variables are highly significant in the pooled regression, and the OIR test does not reject the specification at over 40% significance level. Therefore, according to Campbell and Hamao's definition, our evidence indicates that the international stock markets are reasonably integrated. We find very similar results using the returns of the G7 countries as well as the non-G7 countries. However, evidence of integration between the Japanese and the world market and between the Japanese and the U.S. market is noticeably weaker. The latter result should not be a surprise because we have found little predictability in Japanese excess stock market returns.

To summarize, our results are consistent with the hypothesis that international stock markets are integrated, as argued, for example, by Campbell and Hamao (1992) and Harvey (1991). In particular, the U.S. stock market variance is an important determinant of international stock market returns because it is a proxy for systematic risk. In contrast, the country-specific stock market variance forecasts stock returns mainly because of its comovements with the U.S. stock market variance.

3.2. *Alternative specification of* cay

As argued by Lettau and Ludvigson (2001), *cay* does not suffer from a generated regressor problem because the cointegrating parameters are superconsistent and thus can be treated as known in the second-stage regression. To further illustrate this point, we follow Lettau and Ludvigson (2005) and use lagged consumption (c), asset wealth (a), and labor income (y) as independent variables instead of the estimated *cay* variable:

$$R_{i,t} = \alpha_i + \beta_i \sigma^2_{\mathrm{US},t-1} + \gamma_i c_{t-1} + \delta_i a_{t-1} + \lambda_i y_{t-1} + \varepsilon_{i,t}. \tag{10}$$

Under the null hypothesis that c, a, and y have a single cointegration relation, the limiting distributions for β_i, γ_i, δ_i, and λ_i are standard, and the OLS estimation of Equation (10) provides valid $R^2$and t-statistics. To make inference on the parameters, β_i, γ_i, δ_i, and λ_i, we can rewrite Equation (10) so that the hypotheses to be tested are written as a restriction on I(0) variables (e.g., Sims, Stock, and Watson, 1990). For example, Lettau and Ludvigson (2005) show that we can test the hypothesis $\gamma_i = 0$ by rewriting Equation (10) as

$$\begin{aligned} R_{i,t} = \alpha_i + \beta_i \sigma^2_{\mathrm{US},t-1} + \gamma_i cay_{t-1} + [\delta_i + \gamma_i \omega] a_{t-1} \\ + [\lambda_i + \gamma_i (1-\omega)] y_{t-1} + \varepsilon_{i,t}, \end{aligned} \tag{11}$$

where ω is a cointegration parameter: $cay_t = c_t - \omega a_t - (1-\omega) y_t$. The OLS estimate of γ_i has a limiting distribution given by

$$\sqrt{T}(\hat{\gamma}_i - \gamma_i) \\ \to N\left(0, \frac{\sigma^2_\varepsilon \sum_{t=1}^{T} \left(\sigma^2_{\mathrm{US},t-1} - \bar{\sigma}^2_{\mathrm{US},t-1}\right)^2}{T\left\{\sum_{t=1}^{T} \left(\sigma^2_{\mathrm{US},t-1} - \bar{\sigma}^2_{\mathrm{US},t-1}\right)^2 \sum_{t=1}^{T} (cay_{t-1} - \overline{cay}_{t-1})^2 - \left[\sum_{t=1}^{T} \left(\sigma^2_{\mathrm{US},t-1} - \bar{\sigma}^2_{\mathrm{US},t-1}\right)(cay_{t-1} - \overline{cay}_{t-1}\right]^2\right\}}\right),$$

where $\sigma^2_\varepsilon$is the variance of the error term $\varepsilon_{i,t}$ in Equation (10), T is the number of observations, $\bar{\sigma}^2_{\mathrm{US},t-1}$ is the sample mean of $\sigma^2_{\mathrm{US},t-1}$, and $\overline{cay}_{t-1}$ is the sample mean of cay_{t-1}. These may be evaluated using the full-sample estimates of cay. A similar rearrangement can be used to test hypotheses about δ_i and λ_i. Note that the full-sample estimates of the cointegration coefficients are only required for the inference about the regression; they do not affect the regression itself. Finally, the OLS estimate of β_i has a limiting distribution given by

$$\sqrt{T}(\hat{\beta}_i - \beta_i) \\ \to N\left(0, \frac{\sigma_\varepsilon^2 \sum_{t=1}^{T}(cay_{t-1} - \overline{cay}_{t-1})^2}{T\left\{\sum_{t=1}^{T}\left(\sigma_{\mathrm{US},t-1}^2 - \bar{\sigma}_{\mathrm{US},t-1}^2\right)^2 \sum_{t=1}^{T}(cay_{t-1} - \overline{cay}_{t-1})^2 - \left[\sum_{t=1}^{T}\left(\sigma_{\mathrm{US},t-1}^2 - \bar{\sigma}_{\mathrm{US},t-1}^2\right)(cay_{t-1} - \overline{cay}_{t-1})\right]^2\right\}}\right).$$

The estimation results of Equation (10) are reported in Table 8. For the U.S., all the independent variables are highly significant, with R^2 of 21%. Moreover, the point estimate and the t-value of the U.S. variance are almost identical to those reported in Table 4. Similarly, we find qualitatively the same results for world and international stock market returns. Therefore, as dictated by the cointegration theory, cay does not suffer from the generated regressor problem.

3.3. Out-of-sample forecasts

This subsection evaluates the out-of-sample forecasting performance. In particular, to address the look-ahead bias, we estimate recursively the cointegration parameters using macrovariables with a one-quarter lag.

The sample used in the out-of-sample forecast spans the period 1993:Q1–2002:Q4, with a total of 40 observations. That is, for excess returns on each index, we use all the data available up to 1992:Q4 for the in-sample regression and generate a forecast for 1993:Q1. We then expand the in-sample regression to 1993:Q1 and generate a forecast for 1993:Q2, and so forth. Figure 2 shows that the recursively estimated cointegration coefficients of the consumption-wealth ratio are relatively stable over this period.

Table 9 reports the out-of-sample forecast results. We consider three forecasting models: (1) a benchmark of constant returns, (2) a model using cay only, and (3) a model using cay and σ_{US}^2. The root mean-squared forecasting error (RMSE) of the three models is reported in the first three columns. For the last two forecasting models, the RMSE is in bold if it is smaller than that of the benchmark model.

Consistent with Guo (2006), we find that, in the U.S. data, the model of cay and σ_{US}^2 produces an RMSE of 0.0773, which is substantially smaller than 0.0850 for the benchmark model and 0.0835 for the model of cay. This result confirms the in-sample evidence that realized variance provides important information about future stock returns beyond cay. We find the same pattern for world excess returns.

Table 8

Regression of excess returns (in U.S. dollars) on lagged U.S. variance, consumption, labor income, and asset wealth

Country	$\sigma^2_{\text{US},t-1}$	C_{t-1}	A_{t-1}	Y_{t-1}	R^2
Australia	7.401***	2.277**	−0.961***	−0.758	0.102
	(2.872)	(2.399)	(−3.849)	(−1.272)	
Austria	3.466	2.251**	−0.558**	−1.451**	0.051
	(1.196)	(2.110)	(−1.988)	(−2.165)	
Belgium	5.841**	2.050*	−0.674**	−1.047	0.077
	(2.203)	(2.100)	(−2.625)	(−1.708)	
Canada	6.430***	2.618***	−0.735***	−1.538***	0.114
	(2.612)	(2.888)	(−3.085)	(−2.702)	
Denmark	4.915**	3.091***	−0.341*	−2.780***	0.120
	(2.550)	(4.355)	(−1.829)	(−6.238)	
France	5.728*	3.411***	−0.834***	−2.230***	0.090
	(1.896)	(3.066)	(−2.851)	(−3.192)	
Germany	3.589	3.179***	−0.496**	−2.645***	0.077
	(1.398)	(3.364)	(−1.997)	(−4.455)	
Hong Kong	6.955*	2.289*	−0.938***	−0.889	0.046
	(1.920)	(1.717)	(−2.673)	(−1.061)	
Italy	5.061	2.182	−0.931***	−0.634	0.075
	(1.372)	(1.606)	(−2.608)	(−0.744)	
Japan	2.450	0.226	−0.354	0.235	0.038
	(.804)	(0.201)	(−1.201)	(0.334)	
Netherlands	5.134**	3.026***	−0.696***	−2.116***	0.118
	(2.518)	(4.031)	(−3.523)	(−4.488)	
Norway	5.720*	2.921**	−0.989***	−1.364*	0.079
	(1.783)	(2.473)	(−3.182)	(−1.839)	
Singapore	10.336***	1.538	−0.886***	−0.212	0.088
	(3.027)	(1.227)	(−2.687)	(−0.270)	
Spain	5.900*	2.604**	−0.707**	−1.455**	0.079
	(1.905)	(2.283)	(−2.357)	(−2.032)	
Sweden	6.955**	3.446***	−0.741**	−2.486***	0.089
	2.198)	(2.957)	(−2.419)	(−3.397)	
Switzerland	2.812	2.704***	−0.660***	−1.755***	0.076
	(1.249)	(3.261)	(−3.025)	(−3.369)	
UK	5.933***	3.202***	−0.854***	−2.022***	0.116
	(2.811)	(4.120)	(−4.179)	(−4.143)	
US	6.674***	3.740***	−0.793***	−2.668***	0.209
	(3.632)	(5.527)	(−4.453)	(−6.277)	
World	5.573***	2.577***	−0.665***	−1.664***	0.137
	(2.816)	(3.535)	(−3.471)	(−3.636)	

Note: The table presents the OLS estimation results of forecasting excess returns, $R_{i,t} = \alpha_i + \beta_i \sigma^2_{\text{US},t-1} + \gamma_i c_{t-1} + \delta_i a_{t-1} + \lambda_i y_{t-1} + \varepsilon_{i,t}$. Heteroskedasticity-consistent t-statistics are in parentheses. ***, **, and * denote the significance level of 1%, 5%, and 10%, respectively. See subsection 3.2. for more information.

For the 17 international stock markets, the model of *cay* and σ^2_{US} outperforms the benchmark model in eight countries; similarly, the model of *cay* outperforms the benchmark model in seven countries. Our results thus indicate that there is out-of-sample predictability in international stock markets.

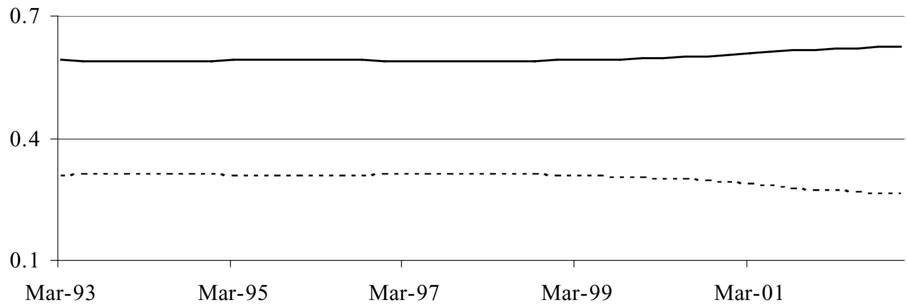

Figure 2

Parameters of labor income (solid line) and net worth (dotted line)

Table 9

Out-of-sample forecasts

		Own forecast		U.S. forecast		World forecast	
Country	Benchmark	cay_{t-2}	$cay_{t-2}+\sigma^2_{\mathrm{US},t-1}$	cay_{t-2}	$cay_{t-2}+\sigma^2_{\mathrm{US},t-1}$	cay_{t-2}	$cay_{t-2}+\sigma^2_{\mathrm{US},t-1}$
Australia	0.084	0.089	0.087	0.084	**0.082**	0.084	**0.081**
Austria	0.082	**0.082**	0.083	0.082	**0.077**	0.082	**0.077**
Belgium	0.102	**0.100**	**0.096**	**0.101**	**0.096**	**0.101**	**0.096**
Canada	0.108	0.110	**0.107**	**0.107**	**0.103**	**0.107**	**0.103**
Denmark	0.080	0.080	**0.079**	**0.079**	**0.079**	**0.078**	**0.077**
France	0.105	0.107	**0.104**	**0.105**	**0.101**	**0.105**	**0.101**
Germany	0.123	**0.121**	**0.121**	**0.120**	0.123	**0.120**	**0.122**
Hong Kong	0.159	0.165	0.165	**0.157**	0.159	**0.157**	**0.158**
Italy	0.115	0.119	0.116	0.115	**0.110**	0.115	**0.110**
Japan	0.122	0.123	0.124	**0.120**	0.124	**0.120**	0.123
Netherlands	0.102	**0.099**	**0.097**	**0.099**	**0.098**	**0.100**	**0.098**
Norway	0.105	**0.105**	**0.104**	**0.102**	**0.103**	**0.102**	**0.102**
Singapore	0.155	0.158	0.157	**0.154**	**0.152**	**0.154**	**0.152**
Spain	0.115	0.117	**0.114**	**0.114**	**0.105**	**0.114**	**0.106**
Sweden	0.152	**0.151**	0.152	**0.148**	**0.149**	**0.149**	**0.148**
Switzerland	0.092	**0.091**	**0.091**	**0.090**	0.092	**0.090**	**0.091**
UK	0.075	0.084	0.078	**0.073**	**0.072**	**0.073**	**0.071**
US	0.085	**0.085**	**0.081**	**0.085**	**0.081**	**0.085**	**0.080**
World	0.080	0.080	**0.077**	**0.080**	**0.078**	0.080	**0.077**

Note: The table reports the RMSE from the out-of-sample forecast of excess returns in U.S. dollars over the period 1993:Q1–2002:Q4. For the benchmark, we assume that excess returns are constant. We consider two forecasting models: (1) *cay* only and (2) *cay* and Under "Own Forecast," we make the out-of-sample forecasts for each stock market. Under "US Forecast" and "World Forecast," we assume that the expected returns of international stock markets are the same as those of the United States and the world stock markets, respectively. To address the look-ahead bias, we assume that macrovariables are available with a one-quarter delay and estimate the cointegration parameters of *cay* recursively.

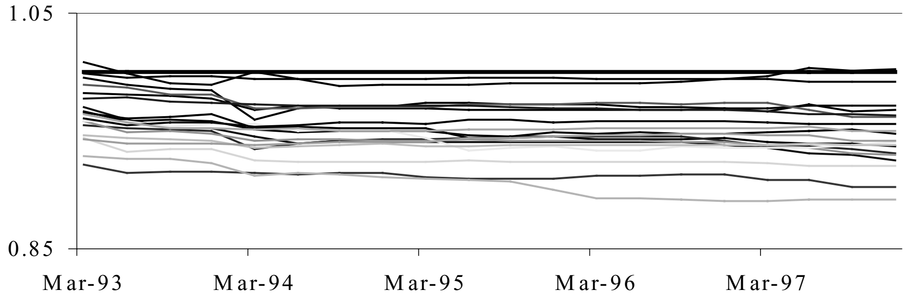

Figure 3

RMSE ratio of forecasting model of *cay* and σ^2_{US} (column 7 in Table 9) versus benchmark model (column 1 in Table 9)

As shown in Table 7, there is some evidence that expected international stock returns tend to move in the same directions. To further explore this issue, we assume that all the countries have the same out-of-sample forecast as the U.S. and report the associated RMSE in columns 4 and 5 under "US Forecast" of Table 9. That is, we first calculate the out-of-sample forecasts for the U.S. excess returns and then use them as the forecasts for excess returns on each country's price index to calculate the RMSE. Interestingly, the out-of-sample forecasts of the U.S. excess returns apparently capture a significant portion of variations of excess returns in most countries. For example, in 13 international markets the model of *cay* and σ^2_{US} outperforms the benchmark model; the model of *cay* outperforms the benchmark model in 14 countries. We also report the RMSE of using the out-of-sample forecasts of world excess returns as the forecasts for each of the 18 countries in columns 6 and 7 under "World Forecast." The model of *cay* and σ^2_{US} outperforms the benchmark (column 1) in all countries except Japan. Similarly, the model of *cay* beats the benchmark model in 14 countries. Moreover, the model of *cay* and σ^2_{US} performs better than the model of *cay* in all countries except Germany, Hong Kong, Japan, Spain, and Switzerland, indicating that realized stock variance provides important information about future international stock returns.

To further check the robustness of our results, Figure 3 plots the recursive RMSE ratio of the model of *cay and* σ^2_{US} (column 7 of Table 9) to the benchmark model (column 1 of Table 9) through time for the 18 countries. The horizontal axis denotes the starting forecast date. For example, the value corresponding to March 1995 is the RMSE ratio over the forecast period 1995:Q1–2002:Q4. We choose the range 1993:Q1–1997:Q4 for the starting forecast date; therefore, the out-of-sample test utilizes at least 21 observations. Figure 3 shows that the ratio is always below 1, which is indicated by the thick solid line, for all countries except Japan. Therefore, the out-of-sample predictability is not influenced by the particular choice of the forecasting sample.

3.4. More robustness checks

We use the *cay* variable constructed from the current vintage data. One concern is that its out-of-sample forecasting power might be substantially attenuated if we take into account the data revision. However, investors might obtain similar information from alternative sources. In particular, Guo and Savickas (2006) show that value-weighted idiosyncratic volatility, which is available in real time, has forecasting abilities very similar to *cay*. We repeat the analysis using the idiosyncratic volatility and find qualitatively the same results. To conserve space, these results are not reported here but are available upon request.

Although the forecasting power of stock market variance and the consumption-wealth ratio for stock market returns are theoretically motivated, it is possible that some other important variables are omitted. To address this issue, we add other commonly used U.S. predictive variables, including the dividend yield, the term premium, the default premium, and the short-term interest rate, to the regression and find qualitatively the same results. Of course, this issue cannot be fully addressed because we do not know the "correct" model. Nevertheless, given the large R^2documented in this paper, e.g., 20% in the U.S. data (Table 4), the omitted variables problem is unlikely to affect our results in any qualitative manner.

4. Conclusion

We find that, when combined with the U.S. *cay* variable, realized stock market variance is significantly and positively related to future returns in many international markets. This result suggests that the puzzling negative risk-return relation documented by early authors reflects an omitted variables problem and should be interpreted with caution.

If capital markets are integrated, international stock market returns should be determined by systematic risk rather than country-specific risk. In this paper, we find that U.S. stock market variance, a proxy for systematic risk, subsumes the information content of its local counterparts in the regression of international stock market returns. Moreover, the U.S. *cay* variable is also significantly related to future stock returns of many international stock markets. The results are consistent with the hypothesis that capital markets are integrated, as argued by Campbell and Hamao (1992) and Harvey (1991), among others.

The international stock return predictability documented in this paper has important implications. For example, CAPM is unlikely to price the cross section of international stock returns because shocks to investment opportunities are also important risk factors (Merton, 1973). Similarly, investors might want to exploit stock return predictability in international asset allocations. A formal investigation of these issues is beyond the scope of this paper, and we leave it for future research.

Appendix A: Description of the risk-free rate data

We use the yield on three-month Treasury bills for the United States, which is also used for Hong Kong because we cannot find its own risk-free rate over the period 1974–2002. We obtain all the data from International Financial Statistics for all the other countries.

Country	Data sources
Australia	Money market rate
Austria	Money market rate
Belgium	Treasury bill yield
Canada	Treasury bill yield
Denmark	Money market rate before March 2001 and Euro interbank rate thereafter
France	Treasury bill yield before September 2002 and Euro interbank rate thereafter
Germany	Money market rate
Hong Kong	US risk-free rate
Italy	Money market rate
Japan	Money market rate
Netherlands	Money market rate
Norway	Money market rate
Singapore	Treasury bill yield
Spain	Money market rate
Sweden	Treasury bill yield before October 2001 and Euro interbank rate thereafter
Switzerland	Long-term government bond yield minus 3.5% before August 1975 and money market rate thereafter
UK	Treasury bill yield
US	Treasury bill yield

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