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Investigating the Intertemporal Risk-Return Relation in International Stock Markets with the Component GARCH Model

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Abstract

We revisit the risk-return relation using the component GARCH model and international daily MSCI stock market data. In contrast with the previous evidence obtained from weekly and monthly data, daily data show that the relation is positive in almost all markets and often statistically significant. Likelihood ratio tests reject the standard GARCH model in favor of the component GARCH model, which strengthens the evidence for a positive risk-return tradeoff. Consistent with U.S. evidence, the long-run component of volatility is a more important determinant of the conditional equity premium than the short-run component for most international markets.

Keywords: GARCH-in-mean, Component GARCH, Risk-return relation, International stock market returns.

JEF number: G10, G12.

I. Introduction

Standard finance theory, e.g., Merton's (1973) intertemporal capital asset pricing model (ICAPM), stipulates a positive relation between the expected excess stock market return and variance. This relation is intuitively appealing and Ghysels, Santa-Clara, and Valkanov (2005) even describe it as the "first fundamental law of finance (p. 510)." However, while French, Schwert, and Stambaugh (1987) estimate the relation to be positive, many other authors, e.g., Campbell (1987), Glosten, Jagannathan, and Runkle (1993), Whitelaw (1994), and Brandt and Kang (2004), find a negative relation in the U.S. data.

Few authors (e.g., Theodossiou and Lee (1995) and Li et al. (2005)) have investigated the risk-return relation in international stock markets, although such a study could help resolve the puzzling results obtained from U.S. data. This paper fills that gap by comprehensively analyzing the risk-return relation using MSCI (Morgan Stanley Capital International) data for 19 major international stock markets, including the world market.

Our approach differs from previous studies along three important dimensions. First, Theodossiou and Lee (1995) and Li. et al. (2005) use *weekly* MSCI data over a sample of about 20 years or less; in contrast, we use *daily* MSCI data over the period January 1974 to August 2003, the longest sample available to us at the time when we first wrote the paper. This difference is potentially important because recent authors argue that greater statistical power is needed to precisely identify the risk-return relation and we might also obtain a better measure of volatility in daily data than weekly data. In particular, Lundblad (2005) and Bali and Peng (2006) uncover a positive and significant relation by using two centuries of monthly data and two decades of 5-minute intraday data, respectively. Second, Ghysels, Santa-Clara, and Valkanov (2005) and Guo and Whitelaw (2006), among others, have emphasized the importance of using better models of conditional volatility. To model the persistence in volatility, we use Engle and Lee's (1999) component GARCH (CGARCH) model because it describes the volatility dynamics better than the standard GARCH model (e.g., Christoffersen et al. (2004)). Third, as in Engle and Lee (1999) and Adrian and Rosenberg (2005), we also distinguish the effects of the long-run and the short-run volatility components on stock prices in the CGARCH model. This extension improves our understanding of the importance of various risks.

Our main results can be summarized as follows. First, in contrast with previous evidence, we document a positive risk-return relation in international stock markets. In particular, the relation is found to be positive in 16 of 19 stock markets using daily data and the CGARCH model; the positive relation is statistically significant at the ten percent level in six countries. Second, using daily data—rather than weekly—accounts for most of the difference with previous results. For example, the risk-return relation is positive in only 10 of 19 stock markets with weekly data. Statistical tests strongly support the more elaborate CGARCH model, which provides modestly more support than the standard GARCH model for a positive risk-return relation. Third, consistent with Engle and Lee (1999) and Adrian and Rosenberg (2005), the long-run volatility component appears to significantly determine the international conditional equity premium while the short-run component does not.[1]

Our international evidence supports Bali and Peng's (2006) finding that one is more likely to uncover a positive risk-return relation by using higher-frequency data. Presumably, the daily data provide better estimates of conditional volatility than the weekly data, enabling more precise estimates of daily volatility (Andersen and Bollerslev (1998)), less error in the explanatory variable and thus better estimates of the risk-return relation. Or these results might

[1] To our knowledge, this feature of the CGARCH model hasn't been explored in the context of international stock markets, as we do in this paper.

also reflect the fact that the hedge demand for time-varying investment opportunities is also an important determinant of the conditional equity premium, as stressed by Merton (1973). In particular, Scruggs (1998) and Guo and Whitelaw (2006) show that ignoring the hedge demand might introduce a downward bias in the estimated risk-return relation because the volatility and the hedge demand could be negatively correlated with each other. However, these authors also find that investment opportunities change slowly at the business cycle frequency. Therefore, their effects on the conditional stock return are likely to be relatively constant at higher—e.g., daily—frequencies, which allow us to precisely identify the risk-return relation.[2] Our results are also consistent with Pastor, Sinha, and Swaminathan (2005), who use the cost of capital as a proxy for the expected stock return and find that it is positively correlated with stock market volatility in G-7 countries.

Engle and Lee (1999) and Christoffersen et al. (2004) find a positive risk-return relation in the U.S. data by excluding the constant term from the excess stock return equation. Our international evidence confirms that one is more likely to uncover a positive risk-return relation by excluding the constant term than including it in the estimation. Lanne and Saikkonen (2005) show that properly excluding the constant improves the power properties of tests of the risk-return relation. However, the simulation results indicate that improperly excluding the constant leads to too many rejections of the null hypothesis. Therefore, choosing the specification requires tradeoffs.

[2] Consistent with this interpretation, the constant term in the return equation might be statistically significant in many international markets because it captures the effect of some omitted risk factors on the expected excess return.

II. Data

We use the MSCI data to construct daily total stock market returns for 18 international markets as well as the world market over the period January 7, 1974 to August 29, 2003. The number of daily observations is about 7600.

The fact that the MSCI daily price index excludes dividends complicates our analysis because one must include dividends to properly estimate the risk-return relation implied by Merton's ICAPM. Fortunately, however, the MSCI also provides two monthly total return indices: (1) the gross total return index and (2) the net total return index. The former approximates the maximum possible dividend reinvestment; the amount reinvested is the dividend distributed to individuals resident in the country of the company and does not include tax credits. The latter approximates the minimum possible dividend reinvestment; the dividend is reinvested after deduction of withholding tax by applying the rate to non-resident individuals who do not benefit from double taxation treaties. For brevity, we only report the results using the gross total return index.

We construct daily gross returns by combining the daily price index with the monthly total return indices that include dividends. Specifically, we calculate the monthly dividend payment by subtracting the capital gain from the total return. Assuming that the dividend is constant within a month, the daily dividend equals the monthly dividend divided by the number of business days in a month. This assumption is unlikely to affect our results in any qualitative manner because the aggregate dividend payment is quite smooth in the data. We then calculate the daily total return using the daily price index and the daily dividend in the usual way.

The risk-free rate is available only at the monthly frequency; the Appendix describes these data. We construct the daily risk-free rate by assuming that it is constant within a month.

The daily excess stock market return is the difference between the daily total stock return and the daily risk-free rate.

For comparison, we also construct the weekly stock returns and risk-free rate using compounded daily data. The weekly excess stock market return is the difference between the two variables. Each market has 1547 weekly observations over January 1974 to August 2003.

Table 1 provides summary statistics of the daily MSCI excess stock market returns. For comparison, we also report the results for the U.S. excess stock market return obtained from CRSP (the Center for Research in Security Prices), which are very similar to those from MSCI. The two return measures are also highly correlated, for example, the correlation coefficient between the two measures is greater than 98% in weekly data. Moreover, as shown below, we find qualitatively similar patterns in the estimation using the U.S. CRSP and MSCI data. These results indicate that the MSCI stock market data are reliable. Consistent with previous studies, stock market returns exhibit excess kurtosis (e.g., Baillie and DeGennaro (1990)). Likelihood ratio (LR) tests—omitted for brevity—clearly indicate that the t-distribution describes the return data much better than the normal distribution. For brevity, we only report t-distribution results, although the normal-distribution results are similar.

III. Empirical Specifications

The GARCH-in-mean model proposed by Engle, Lilien, and Robins (1987) has been widely used in the risk-return relation literature (see, e.g., Bollerslev, Chou, and Kroner (1992) for a comprehensive survey). This paper uses a relatively new variant, the asymmetric Component GARCH or CGARCH model proposed by Engle and Lee (1999). To compare with the extant literature, we also estimate the standard asymmetric GARCH-in-mean model used by Glosten, Jagannathan, and Runkle (1993). The GARCH-in-mean model structure is as follows:

$$
(1) \qquad \begin{aligned} r_{t+1} &= c + \lambda h_{t+1} + \varepsilon_{t+1} \\ \varepsilon_{t+1} &= h_{t+1} z_{t+1} \\ h_{t+1} &= \omega + \alpha\left(\varepsilon_t^2 - \omega\right) + \delta\left(D_t \varepsilon_t^2 - .5\omega\right) + \beta\left(h_t - \omega\right) \end{aligned} .
$$

where r_{t+1} is the excess stock market return, h_{t+1} is conditional variance and z_t is assumed to have t distribution. Finance theory, e.g., Merton's (1973) ICAPM, suggests that the conditional excess stock market return is proportional to its conditional variance, where the factor of proportion is λ, the coefficient of relative risk aversion. Our main testable hypothesis is that λ is positive.

As in many previous studies, we also consider a constant term (c) in the return equation. In Merton's ICAPM, c equals zero. The dummy variable D_t equals one if ε_t is negative and zero otherwise; the term $\delta\left(D_t \varepsilon_t^2 - .5\omega\right)$ captures the fact that negative shocks have larger effects on volatility than positive shocks. In estimating the degrees of freedom along with c, λ, α, δ, and β in equation (1), we restrict $\hat{\omega} = E\left[h_t\right]$, $\hat{\alpha} > 0$, $\hat{\beta} > 0$ and assume that the shock z_{t+1} is i.i.d. t-distributed.

The CGARCH model permits both a long-run component of conditional variance, q_t, which is slowly mean reverting and a short-run component, $h_t – q_t$, that is more volatile. We use Engle and Lee's (1999) specification for the CGARCH model:

$$
(2) \qquad \begin{aligned} r_{t+1} &= c + \lambda h_{t+1} + \varepsilon_{t+1} \\ \varepsilon_{t+1} &= h_{t+1} z_{t+1} \\ h_{t+1} &= q_{t+1} + \alpha\left(\varepsilon_t^2 - q_t\right) + \delta_2\left(D_t \varepsilon_t^2 - .5 q_t\right) + \beta\left(h_t - q_t\right) \\ q_{t+1} &= \omega + \rho q_t + \phi\left(\varepsilon_t^2 - h_t\right) + \delta_1\left(D_t \varepsilon_t^2 - .5 h_t\right) \end{aligned} .
$$

In estimating (2), we restrict $\hat{\omega} = E\left[h_t\right]\left(1 - \hat{\rho}\right)$, $0 < \hat{\rho} < 1$, $\hat{\alpha} > 0$ and $\hat{\beta} > 0$.

Christoffersen et al. (2004) show that distinguishing short- and long-run components enables the CGARCH model to describe volatility dynamics better than the standard GARCH model.[3] Ghysels, Santa-Clara, and Valkanov (2005) and Guo and Whitelaw (2006) stress that better measures of conditional volatility might produce more precise estimates of the risk-return relation.

Equation (2) restricts the prices of risk for long- and short-run components of volatility to be equal. This restriction is arbitrary, however. Engle and Lee (1999) find that the long-run component is a more important determinant of the conditional equity premium than the short-run component. One explanation is that investors require a higher risk price for cash-flow shocks to stock returns than discount-rate shocks (see, e.g., Campbell and Vuolteenaho (2004)). Similarly, Adrian and Rosenberg (2005) develop an ICAPM in which both the short-run and long-run volatility components are priced risk factors. To address this issue, we consider a more flexible specification, in which the long- and short-run volatility components potentially have different coefficients (λ_2 and λ_1) in the return equation:

$$
\begin{aligned}
&r_{t+1} = c + \lambda_1 (h_{t+1} - q_{t+1}) + \lambda_2 q_{t+1} + \varepsilon_{t+1} \\
&\varepsilon_{t+1} = h_{t+1} z_{t+1} \\
&h_{t+1} = q_{t+1} + \alpha\left(\varepsilon_t^2 - q_t\right) + \delta_2\left(D_t \varepsilon_t^2 - .5 q_t\right) + \beta\left(h_t - q_t\right) \\
&q_{t+1} = \omega + \rho q_t + \phi\left(\varepsilon_t^2 - h_t\right) + \delta_1\left(D_t \varepsilon_t^2 - .5 h_t\right)
\end{aligned}
\tag{3}
$$

We will denote the CGARCH model with 2 lambdas as CGARCH2L.

[3] To obtain an exact solution for option prices, Christoffersen et al. (2004) use asymmetry specifications that are slightly different from those in equations (1) and (2). We find very similar results using their specifications. These results are omitted for brevity.

IV. Empirical Results

1. Model Selection

We begin by evaluating the statistical evidence for our 3 candidate models: CGARCH2L, CGARCH and GARCH, with and without a constant term in the return equation. Table 2 shows the p-values from likelihood ratio (LR) tests of various restrictions to the models.

Columns 1-3 of Table 2 report p-values from the test of the null that the constant in the return equation should be restricted to equal zero. The alternative is that the constant is free. The GARCH, CGARCH and CGARCH2L generate 10, 9 and 9 rejections of the restriction, respectively, at the 5 percent level. So many rejections of the null that the constant should be restricted seems to indicate that we should reject that hypothesis. Simulations calibrated to U.S. daily data, however, indicate that one should expect the constant to be significant 17 percent of the time for this sample size, under the null that the constant equals zero. (Full results are omitted for brevity.) In other words, the test is significantly oversized, making 9 or 10 rejections seem less persuasive against the null that the constant equals zero. The evidence on whether the constant should be restricted is mixed. We will report results with and without the constant.

Columns 4-7 of Table 2 manifest that the data reject the parsimonious GARCH model in favor of the CGARCH model with either 1 or 2 lambdas, with or without a constant, for all markets.

Finally, columns 8 and 9 of Table 2 show that the data reject 1 lambdas in favor of the alternative of 2 lambdas 10 of 20 times without a constant and 8 of 20 times with no constant. Again, simulated data calibrated to match the U.S. daily data with 2 lambdas shows that the extra lambda is significant only 20 percent of the time. (Full results omitted for brevity.) That is, if the data are generated by a 2-lambda model—with similar lambdas—one usually fails to reject the restriction to 1 lambda. This suggests that the evidence against CGARCH2L is mixed, at best, and one should consider risk-return evidence from both the 1-lambda and 2-lambda models.

2. *The Component GARCH Model with one Lambda*

Panel A of Table 3 presents the CGARCH return-equation coefficients from equation (2) using a *t* distribution and daily data. The results for the other parameters are very similar to those reported by previous authors (e.g., Engle and Lee (1999)) and so are omitted for brevity. The point estimate of λ is scaled by 100 because we use percentage return in the estimation.

We first discuss the specification with the constant term, which has been commonly used in the existing literature. The estimated coefficient $\hat{\lambda}$ is positive in 16 of 19 markets, including the world market; it is negative in only Australia, Norway, and Sweden. Moreover, the positive risk-return relation is statistically significant or marginally significant in six countries: Austria, Denmark, Germany, Italy, Spain, and the United States.[4] The negative coefficients are always insignificant. Therefore, in contrast with previous evidence, e.g., Theodossiou and Lee (1995) and Li et al. (2005), our results support a positive risk-return relation in international markets.

As mentioned in the introduction, our approach differs from previous studies along two important dimensions: We use (1) higher-frequency (daily) data and (2) variants of the component GARCH model. Below, we investigate the relative contribution of these two factors in accounting for the difference between our results and those reported by previous authors. First, Panel A of Table 4 reports the CGARCH model using weekly data. In sharp contrast with Table 3, weekly data provide much less support for a positive risk-return relation: $\hat{\lambda}$ is positive in only 10 of 19 stock markets and significantly positive in only two countries. Consistent with previous work, weekly data provide mixed evidence on the international evidence of risk-return relation, although we use a much longer sample as well.

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[4] An LR test determines the significance level.

Stronger results for daily data are consistent with some simulation evidence that was omitted for brevity. To investigate whether daily or weekly data provide better test properties, we simulated 100 data sets of daily data from a data generating process (DGP) calibrated to U.S. estimates of GARCH-in-mean models. We then aggregate that data by summing every 5 observations to get corresponding weekly data. To briefly summarize the results, the daily data had somewhat better properties than weekly data. Tests (correctly) find λ to be significant 60 percent of the time for daily data and only 49 percent of the time for weekly data.

For comparison with CGARCH results, Panel B of Table 3 reports these results from the standard GARCH model described by (1) with daily data. As expected, the GARCH model offers weaker evidence of a positive risk-return relation than does the CGARCH model. First, $\hat{\lambda}$ is noticeably smaller in panel B than in panel A for most countries. Second, $\hat{\lambda}$ is positive in 15 countries in the GARCH model (panel B), compared with 16 countries with the CGARCH model (panel A). In particular, for the world market, $\hat{\lambda}$ is negative for the GARCH model but positive for the CGARCH model, although both estimates are insignificant. Third, $\hat{\lambda}$ is significant at the 10% level in one more country for the CGARCH model than the GARCH model. While both daily data and the CGARCH model strengthen the case for a positive risk-return relation, the former contributes much more.

3. *The Constant Term in the Return Equation*

Engle and Lee (1999) and Christoffersen et al. (2004) estimate a variant of equation (2) with no constant term in the return equation. Panel A of Table 3 supports their findings by showing that excluding the constant strengthens support for a positive risk-return relation. When the constant is restricted to equal zero, $\hat{\lambda}$ is significantly positive at the 10% level in 12 countries, compared with only 6 countries when the constant is free. We find very similar patterns for the GARCH model, as reported in panel B of Table 3.

Lanne and Saikkonen (2005) argue that restricting the constant term to equal zero raises the power of the test under the null. Our Monte Carlo simulations confirm that, if the expected stock return is only determined by its conditional variance, as suggested by Merton's ICAPM, one is more likely to uncover a positive risk-return relation by excluding the constant term. That is, correct exclusions increase the power of the test.

However, there is an important caveat. If one excludes the constant when it does belong, one estimates a misspecified model and tests of λ's significance will tend to reject the (correct) null that λ equals zero. We also conduct simulations by assuming that the expected stock return is constant. For the sample size used in this paper, if we (falsely) restrict the constant term to zero, the coefficient $\hat{\lambda}$ is significant in over 50% of the simulated samples. This result should not be too surprising: Because mean returns and volatility are positive, a positive $\hat{\lambda}$ is needed to set the expected error to zero.

To summarize, one is more likely to find a positive risk-return relation by imposing the restriction of no constant term in the return equation. While this restriction improves the power of the test if it is correct, it might also lead to too many rejections of the null hypothesis of no risk-return relation. Because we do not know the true data generating process, these simulation results suggest that long samples are very helpful in reliably inferring the risk-return relation, as stressed by Lundblad (2005) and Bali and Peng (2006).

4. The Component GARCH Model with two Lambdas

This subsection briefly discusses the component GARCH model with two lambdas, as defined in (3). Panel C of Table 3 displays the estimation results obtained from daily data and a CGARCH model with different prices of long- and short-run risk. For the specification with the constant term, the absolute values of the point estimates for $\hat{\lambda}_1$ and $\hat{\lambda}_2$ are substantially more variable than those reported in the single $\hat{\lambda}$ cases (panels A and B). Examination of the correlation matrix of the parameter estimates shows that the parameter on long-run volatility ($\hat{\lambda}_2$) is very often highly correlated with the constant in the return equation, making it difficult to precisely estimate these parameters.

To obtain more precise estimates, we follow Engle and Lee (1999) by restricting the constant term to equal zero. Consistent with Engle and Lee's study of U.S. data, the relation between the expected return and the long-run component of volatility is positive and statistically significant while the short-run component has an insignificant effect on stock returns in international stock markets. In particular, $\hat{\lambda}_2$ is positive in 17 of 19 markets and also statistically significant in 11 countries. This specification provides the strongest support that we have found for a positive risk-return tradeoff. In contrast, $\hat{\lambda}_1$ is statistically insignificant in most markets and has mixed signs. Therefore, the long-run component of volatility appears to determine international expected stock returns much more than the short-run component, as in U.S. data.

V. Conclusion

This paper comprehensively investigates the risk-return relation in major international stock markets using the CGARCH model. In contrast with previous evidence from weekly data, our daily results support a positive risk-return relation. Statistical tests strongly prefer the more elaborate CGARCH model over the standard GARCH model and the CGARCH model offers marginally more support for a positive risk-return relation. While the data are often unable to reject a single price of risk, the evidence is mixed and using two prices of risk for the long- and short-run components indicates that the long-run component is consistently positively priced.

We argue that daily data produces better estimates of the conditional volatility process and enables us to more precisely identify the risk-return relation. Our results might also reflect the fact that the hedge demand for changes in investment opportunities determines expected returns. In particular, because investment opportunities change slowly at the business cycle frequency, their effects on stock returns are likely to be almost constant in daily, data, which allow us to precisely identify the risk-return relation.

Although the risk-return relation is positive in most markets, it is often statistically insignificant. We can extend our analysis along two dimensions to improve its power. First, if the data frequency does matter for the reasons mentioned above, we might find stronger support for a positive risk-return relation in international markets by using intraday data, as in Bali and Peng (2006), than daily data. Second, we might further distinguish the alternative explanations for our results by investigating the relative importance of the hedge demand for changes in investment opportunities. In particular, we can use the value premium as a proxy for it, as advocated by Fama and French (1996) and Campbell and Vuolteenaho (2004).[5] Interestingly, consistent with these authors' conjecture, Guo et al. (2005) uncover a positive risk-return relation after controlling for the conditional covariance between stock market returns and the value premium in the stock return equation. It will be interesting to investigate whether we can replicate the results by Guo et al. by using international stock market return data.

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[5] The value premium is the return on a portfolio that is long in stocks with high book-to-market value ratio and short in stocks with low book-to-market value ratio.

Appendix: Description of the Risk-Free Rate Data

We use the yield on 3-month Treasury bills for the U.S., which is also used for Hong Kong because we cannot find the risk-free rate of its own 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-3.5%) before August 1975 and money market rate thereafter.
UK	Treasury bill yield.
US	Treasury bill yield.

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Table 1: Summary Statistics for Daily Excess Stock Market Returns

Country	Mean	Standard Deviation	Skewness	Kurtosis
Australia	0.013	0.010	-1.526	40.520
Austria	0.002	0.009	-0.200	15.052
Belgium	0.012	0.009	0.011	14.228
Canada	0.006	0.009	-0.456	12.563
Denmark	0.005	0.009	-0.282	8.306
France	0.016	0.012	-0.252	8.040
Germany	0.015	0.012	-0.440	11.249
Hong Kong	0.043	0.018	-0.898	24.964
Italy	0.002	0.014	-0.220	6.757
Japan	0.007	0.011	0.072	15.511
Netherlands	0.027	0.011	-0.127	9.987
Norway	-0.004	0.014	-0.337	15.005
Singapore	0.020	0.013	-0.723	27.910
Spain	0.000	0.012	0.023	8.679
Sweden	0.031	0.013	0.173	8.681
Switzerland	0.024	0.010	-0.689	14.336
UK	0.018	0.011	-0.103	9.391
US	0.017	0.010	-1.059	28.762
US(CRSP)	0.023	0.010	-0.888	21.695
World	0.010	0.007	-0.439	15.867

Notes: The mean is scaled by 100.

Table 2: Model Selection Tests in Daily Data with t-Distributions

	H0: No constant			H0: GARCH		H0: GARCH		H0: CGARCH	
	H1: Constant free			H1: CGARCH		H1: CGARCH with 2 lambda		H1: CGARCH with 2 lambdas	
	GARCH	CGARCH	CGARCH2L	no constant	constant	no constant	constant	no constant	constant
Australia	0.037	0.082	0.015	0.000	0.000	0.000	0.000	0.355	0.053
Austria	0.000	0.001	0.008	0.000	0.000	0.000	0.000	0.000	0.000
Belgium	0.292	0.445	0.000	0.000	0.000	0.000	0.000	0.321	0.000
Canada	0.267	0.144	0.244	0.000	0.000	0.000	0.000	0.000	0.000
Denmark	0.009	0.012	0.289	0.000	0.000	0.000	0.000	0.019	0.648
France	0.181	0.160	0.025	0.000	0.000	0.000	0.000	0.403	0.052
Germany	0.295	0.615	0.486	0.000	0.000	0.000	0.000	0.512	0.416
Hong Kong	0.008	0.017	0.754	0.000	0.000	0.000	0.000	0.016	0.730
Italy	0.100	0.137	0.004	0.000	0.000	0.000	0.000	0.039	0.001
Japan	0.873	0.563	0.008	0.000	0.000	0.000	0.000	0.897	0.010
Netherlands	0.004	0.029	0.918	0.000	0.000	0.000	0.000	0.027	0.687
Norway	0.420	0.744	0.014	0.000	0.000	0.000	0.000	0.200	0.006
Singapore	0.095	0.334	0.289	0.000	0.000	0.000	0.000	0.498	0.421
Spain	0.000	0.000	0.105	0.000	0.000	0.000	0.000	0.000	0.486
Sweden	0.018	0.010	0.000	0.000	0.000	0.000	0.000	0.074	0.000
Switzerland	0.000	0.001	0.537	0.000	0.000	0.000	0.000	0.001	0.794
United Kingdom	0.114	0.133	0.799	0.000	0.000	0.000	0.001	0.138	0.915
United States	0.192	0.610	0.340	0.000	0.000	0.000	0.000	0.459	0.273
World	0.004	0.005	0.000	0.000	0.000	0.000	0.000	0.033	0.003
CRSPVW	0.000	0.000	0.105	0.000	0.000	0.000	0.000	0.001	0.389
PV < 0.05	10	9	9	20	20	20	20	10	8

Notes: The table displays p-values from LR tests of null hypotheses. The columns 1-3 test the null that the constant in the return equation should be restricted to equal zero in the GARCH, CGARCH and CGARCH2L models, respectively. Columns 4 and 5 test the null that GARCH model restrictions over the CGARCH are appropriate, without and with a constant. Columns 6 and 7 test the null that CGARCH model is preferred over the CGARCH with 2 lambdas, without and with a constant. Columns 8 and 9 test the null that GARCH model is preferred over the CGARCH with 2 lambdas, without and with a constant. The last row displays the number of times (out of 20) that the null is rejected.

Table 3: Risk-Return Relation in Daily Data: t-Distributions

Country	Panel A: CGARCH with 1 Lambda			Panel B: GARCH			Panel C: CGARCH with 2 Lambdas				
	With Constant		No Constant	With Constant		No Constant	With Constant			No Constant	
	$\hat{\lambda}$	$\hat{c}$	$\hat{\lambda}$	$\hat{\lambda}$	$\hat{c}$	$\hat{\lambda}$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{c}$	$\hat{\lambda}_1$	$\hat{\lambda}_2$
Australia	-0.479	0.032*	2.435**	-1.421	0.036**	1.775*	8.907*	-5.614*	0.131**	-0.493	1.853
Austria	3.749**	-0.018***	1.541	3.415***	-0.017***	1.382	20.996***	10.883***	-0.012***	21.868***	10.717***
Belgium	2.560	0.008	3.452***	2.285	0.011	3.551***	9.756***	543.271***	-4.501***	2.283	3.517***
Canada	0.763	0.016	2.623**	1.132	0.012	2.467**	-62.093***	6.644***	0.014	-60.573***	8.583***
Denmark	3.823***	-0.025**	1.305	4.497***	-0.026***	1.652	3.581**	5.825	-0.043	3.949***	1.186
France	0.304	0.026	2.084**	0.294	0.024	1.950**	7.233*	-5.286	0.162**	0.330	1.687*
Germany	2.756***	0.006	3.195***	1.979*	0.012	2.792***	0.699	4.928*	-0.041	2.290	2.986***
Hong Kong	0.278	0.048**	1.595***	0.193	0.053***	1.583***	-0.338	0.673	0.023	-0.821	1.060*
Italy	2.510*	-0.035	0.635	2.795*	-0.039	0.729	13.686***	-13.825***	0.386***	4.547**	1.296
Japan	1.433	-0.006	1.014	0.948	0.002	1.079	-4.462*	5.322***	-0.094***	0.838	0.977
Netherlands	1.208	0.032**	3.602***	0.213	0.041***	3.127***	-0.397	2.066	0.007	-0.778	2.302*
Norway	-0.582	0.007	-0.232	-1.236	0.018	-0.289	-4.540**	6.686**	-0.149**	-2.304	-0.379
Singapore	0.494	0.012	1.115	-0.075	0.022*	1.067	2.111	-0.572	0.045	0.301	0.970
Spain	3.517***	-0.055***	-0.084	3.522***	-0.050***	-0.033	3.310**	6.409	-0.092	4.188***	-0.237
Sweden	-0.108	0.043***	2.340***	0.116	0.039**	2.351***	9.179***	-13.867***	0.381***	-0.014	1.938**
Switzerland	1.863	0.033***	4.909***	1.257	0.038***	4.523***	1.067	2.415	0.023	-0.531	3.796***
UK	0.459	0.025	2.344**	0.038	0.026	1.946**	0.093	0.870	0.016	-0.584	1.686
US	2.544*	0.007	3.124***	1.084	0.017	2.512***	-2.136	5.159*	-0.053	1.572	2.712**
World	0.499	0.026***	4.697***	-1.148	0.027***	3.175**	21.771***	-12.152**	0.170***	-1.529	3.109*
CRSP(VW)	1.288	0.042***	5.470***	0.593	0.043***	4.530***	5.010	-1.242	0.089	-1.308	3.719***

Table 4: Risk-Return Relation in Weekly Data: t-Distributions

Country	Panel A: CGARCH with 1 Lambda			Panel B: GARCH			Panel C: CGARCH with 2 Lambdas				
	With Constant		No Constant	With Constant		No Constant	With Constant			No Constant	
	$\hat{\lambda}$	$\hat{c}$	$\hat{\lambda}$	$\hat{\lambda}$	$\hat{c}$	$\hat{\lambda}$	$\hat{\lambda}_1$	$\hat{\lambda}_2$	$\hat{c}$	$\hat{\lambda}_1$	$\hat{\lambda}_2$
Australia	-2.110	0.225**	1.654	-1.366	0.188*	1.598*	-6.330*	6.545	-0.020	-6.230**	5.989***
Austria	3.046***	-0.129**	0.895	2.574**	-0.111***	0.437	3.765**	3.662***	-0.126***	3.997**	3.434**
Belgium	3.685**	-0.082	2.124**	3.688**	-0.079	2.167**	2.956	5.951	-0.145	3.775	1.276
Canada	0.688	0.038	1.414	1.095	0.017	1.405	-2.112	7.270	-0.080	-1.638	3.778
Denmark	3.773	-0.151	0.877	5.472**	-0.219**	1.189	-19.868**	14.950***	-0.368***	-20.187	5.374
France	-1.350	0.229	1.654*	-0.545	0.165	1.542*	-0.427	-14.319**	0.689***	0.330	2.844
Germany	0.927	0.062	1.864*	1.113	0.061	1.968**	-5.228	7.719	-0.040	-4.585	6.161**
Hong Kong	-1.075	0.468***	1.582**	-0.494	0.389**	1.695***	0.769	-4.406*	1.101***	-1.682	1.011
Italy	1.225	-0.107	0.254	0.929	-0.091	0.085	-6.019	1.914	-0.139	-6.110	0.582
Japan	0.469	0.031	0.986	1.010	0.014	1.251	2.936	-1.900	0.086	2.064	0.488
Netherlands	-0.711	0.232***	3.098***	-0.533	0.224***	2.925***	-2.288	1.672	0.192	-3.566	8.280***
Norway	-4.820*	0.463**	-0.013	-3.083	0.302	-0.010	-8.704***	1.896	0.002	-8.718**	1.917
Singapore	-0.297	0.148*	0.999	0.281	0.103	1.240*	-6.973***	2.257	0.049	-7.171***	2.866***
Spain	1.449	-0.113	0.273	1.413	-0.110	0.083	-48.330***	3.281**	-0.177	-47.525***	1.338
Sweden	-0.453	0.243*	2.080***	-0.290	0.227*	2.075***	-19.513***	6.911***	-0.026	-19.503***	6.517***
Switzerland	-0.260	0.202***	3.378***	-0.396	0.195***	2.939***	-2.205	2.376	0.154	-3.036	7.831***
UK	0.714	0.082	1.873**	0.603	0.079	1.636*	0.616	1.216	0.071	0.648	3.525
US	2.367	0.059	3.495***	1.496	0.076	2.875***	4.251	-0.287	0.114	3.489	3.498*
World	-0.149	0.125*	3.459***	-0.630	0.126**	2.799**	-2.923	10.725	0.004	-2.974	11.005***
CRSP(VW)	0.774	0.162*	4.028***	0.922	0.132*	3.378***	0.460	1.326	0.152	-0.424	6.816***