

# Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence\*

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## Abstract

Recent empirical evidence suggests that the variance risk premium predicts aggregate stock market returns. We demonstrate that statistical finite sample biases cannot “explain” this apparent predictability. Further corroborating the existing evidence of the U.S., we show that country specific regressions for France, Germany, Japan, Switzerland and the U.K. result in quite similar patterns. Defining a “global” variance risk premium, we uncover even stronger predictability and almost identical cross-country patterns through the use of panel regressions. These new findings are broadly consistent with the implications from a two-country general equilibrium model explicitly incorporating the effects of time-varying economic uncertainty.

**JEL classification:** C12, C22, G12, G13.

**Keywords:** Variance risk premium; return predictability; over-lapping return regressions; international stock market returns; global variance risk.

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## **Abstract**

Recent empirical evidence suggests that the variance risk premium predicts aggregate stock market returns. We demonstrate that statistical finite sample biases cannot “explain” this apparent predictability. Further corroborating the existing evidence of the U.S., we show that country specific regressions for France, Germany, Japan, Switzerland and the U.K. result in quite similar patterns. Defining a “global” variance risk premium, we uncover even stronger predictability and almost identical cross-country patterns through the use of panel regressions. These new findings are broadly consistent with the implications from a two-country general equilibrium model explicitly incorporating the effects of time-varying economic uncertainty.

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# 1 Introduction

A number of recent studies have argued that aggregate U.S. stock market return is predictable over horizons ranging up to two quarters based on the difference between options-implied and actual realized variation measures, or the so-called variance risk premium (see, e.g., Bollerslev, Tauchen, and Zhou, 2009; Drechsler and Yaron, 2011; Gabaix, 2012; Kelly, 2011; Zhou, 2010; Zhou and Zhu, 2009, among others). These findings are distinctly different from the longer-run multi-year return predictability patterns that have been studied extensively in the existing literature, in which the predictability is typically associated with more traditional valuation measures such as dividend yields, P/E ratios, or consumption-wealth ratios (see, e.g., Fama and French, 1988; Campbell and Shiller, 1988b; Lettau and Ludvigson, 2001, among others). The present paper builds and further expands on the scope of these striking new empirical findings.

The variance risk premium is formally defined as the difference between the risk-neutral and statistical expectations of the future return variation.<sup>1</sup> It may be interpreted as a measure of both aggregate risk aversion and aggregate economic uncertainty. In our main empirical investigations reported on below, we follow Bollerslev, Tauchen, and Zhou (2009) in approximating the variance risk premium by the difference between one-month forward looking model-free options implied variances and the actual one-month realized variances at the time. This directly observable proxy has the obvious advantage of being simple to implement and completely model-free.

Our investigations are essentially threefold. First, to assess the validity of the previously documented predictability patterns, we report the results from a Monte Carlo simulation study designed to closely mimic the dynamic dependencies inherent in daily U.S. returns and variance risk premia. Our results clearly show that statistical biases can not “explain” the documented return predictability patterns. The results also make clear that the use of finer sampled daily as opposed to monthly data, as employed in the above cited studies, provides limited additional power to detect the predictability inherent in the variance risk

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<sup>1</sup>The variance risk premium is sometimes defined the other way around as the statistical minus risk-neutral expectations. This, of course, is immaterial for all of the results reported on below.

premium.

Second, in a separate effort to corroborate and further expand on the existing empirical evidence based on monthly U.S. data prior to the advent of the financial crises, we extend the same basic return predictability regressions to five five other countries and more recent “out-of-sample” data spanning the financial crisis. We show that the same predictability pattern that exist for the U.S. hold true for most of the other countries, although the magnitudes are generally somewhat attenuated.

Third, motivated by this apparent commonality across countries, we define a “global” variance risk premium. We show that this simple aggregate world-wide variance risk premium results in strong predictability for all of the countries in the sample. We further show that these new empirical findings are broadly consistent with the implications from a stylized theoretical two-country general equilibrium model that explicitly incorporates the effect of time-varying economic uncertainty across countries.

The finite sample properties of overlapping long-horizon return regressions have been studied extensively in the literature. Boudoukh, Richardson, and Whitelaw (2008), for instance, have recently shown that even in the absence of any increase in the true predictability, the values of the  $R^2$ 's in regressions involving highly persistent predictor variables and overlapping returns will by construction increase roughly proportional to the return horizon and the length of the overlap.<sup>2</sup> By contrast, the variance risk premium is not especially persistent at the monthly horizon. Our simulations is based on a bivariate VAR-GARCH-DCC model designed to closely mimic the relevant joint dynamic dependencies in the daily return and variance risk premium. We find that the robust  $t$ -statistics usually employed in the literature are reasonably well behaved, albeit slightly over-sized under the null hypothesis of no predictability. We also find that the quantiles in the finite sample distribution of the  $R^2$ 's from the regressions are spuriously increasing with the return horizon under the null of no predictability, although less so than the  $R^2$ 's actually observed in the U.S. data at the 2-4 months horizons.

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<sup>2</sup>Closely related issues pertaining to the use of persistent predictor variables have also been studied by, e.g., Stambaugh (1999), Ferson, Sarkissian, and Simin (2003), Baker, Taliaferro, and Wurgler (2006), Campbell and Yogo (2006), Ang and Bekaert (2007), and Goyal and Welch (2008), among others.

Guided by the Monte Carlo simulations, we rely on monthly return regressions along with Newey-West based  $t$ -statistics to summarize our new international evidence. Due to data availability and liquidity considerations, we restrict our attention to the six major financial markets of France, Germany, Japan, Switzerland, the U.K., and the U.S. Regressing the individual country returns on the country specific variance risk premia result in similar hump-shaped regression coefficients and  $R^2$ 's for all of the six countries. However, the degree of predictability afforded by the country specific variance risk premia and the statistical significance of the regression coefficients are generally not as strong as the previously reported results for the U.S.

These results naturally raise the question of whether world-wide variance risk, as opposed to the country specific variance risk, is being priced by the market? To investigate this idea, we construct a simple “global” variance risk premium proxy, defined as the market capitalization weighted average of the individual country variance risk premia. Restricting the effect on this “global” variance risk premium to be the same across countries in a panel return regression results in much stronger findings for all of the countries, with a systematic peak in the degree of predictability around the four month horizon. Moreover, the degree of predictability afforded by this “global” variance risk premium easily exceeds that of the implied and realized variation measures when included in isolation. It also clearly dominates that of other traditional predictor variables that have been shown to work well over longer annual horizons, including the P/E ratio.<sup>3</sup>

Our use of the variance difference as a simple proxy for the variance risk premium implicitly assumes that the volatility follows a random walk.<sup>4</sup> To investigate the sensitive of our main international findings to this simplifying assumption, we define a forward looking

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<sup>3</sup>Related evidence has also been reported in a few other recent studies pertaining to other markets. In particular, in concurrent independent work, Londono (2011) finds that the U.S. variance risk premium predicts several foreign stock market returns. In a slightly different context, Mueller, Vedolin, and Zhou (2011) argue that the U.S. variance risk premium predicts bond risk premia, beyond the predictability afforded by forward rates, while Buraschi, Trojani, and Vedolin (2010) and Zhou (2010) show that the variance risk premium also helps predict credit spreads, over and above the typical interest rate predictor variables.

<sup>4</sup>Of course, the variance difference may simply be interpreted as powerful predictor variable in its own right.

“global” variance risk premium from the differences between the individual countries one-month options implied volatilities and the corresponding one-month VAR-based forecasts for the actual volatilities. This alternative definition of the “global” variance risk premium give rise to almost identical international return predictability patterns.

Putting things into perspective, our new empirical findings are clearly related to the large existing literature on international stock return predictability (see, e.g., Harvey, 1991; Bekaert and Hodrick, 1992; Campbell and Hamao, 1992; Ferson and Harvey, 1993, among others). However, the focus of this literature has traditionally been on longer-run multi-year return predictability. By contrast, our results pertaining to the “global” variance risk premium concern much shorter-run within year predictability, and are essentially “orthogonal” to the findings reported in the existing literature.<sup>5</sup>

The rest of the paper is organized as follows. Section 2 presents our simulation-based results pertaining to the statistical inference procedures and robustness of the existing empirical evidence for the U.S. Section 3 details our international data and country specific return regressions. The results based on our new “global” variance risk premium and the combined panel regressions for all of the countries, along with our equilibrium model based calibrations, are discussed in Section 4. Section 5 concludes.

## 2 General Setup and Monte Carlo Simulations

The key empirical findings reported in Bollerslev, Tauchen, and Zhou (2009) (BTZ, henceforth), and the subsequent studies cited above, are based on simple OLS regressions of the returns on the aggregate market portfolio over monthly and longer return horizons on a measure of the one-month variance risk premium.

In particular, let  $r_{t,t+\tau}$  and  $VRP_t$  denote the continuously compounded return from time  $t$  to time  $t + \tau$  and the variance risk premium at time  $t$ , respectively. Defining the unit time interval to be one trading day, the multi-period return regressions in BTZ may then be

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<sup>5</sup>Other recent studies highlighting short-run international predictability include Rapach, Strauss, and Zhou (2010) based on lagged U.S. returns, Ang and Bekaert (2007) and Hjalmarsen (2010) based on short-term interest rates, and Bakshi, Panayotov, and Skoulakis (2011) based on the Baltic Dry Index.

expressed as special cases of,

$$\frac{1}{h} \sum_{j=1}^h r_{t+(j-1)s, t+js} = a_s(h) + b_s(h)VRP_t + u_{t,t+hs} \quad (1)$$

for  $s = 20$  (monthly) and return horizon  $hs$ , where  $t = 1, s + 1, 2s + 1, \dots, T - hs$  refer to the specific observations used in the regression. The use of finer sampling frequencies, say  $s = 5$  (weekly) or  $s = 1$  (daily), may, of course, give rise to more powerful inference, and we will investigate that below.

Meanwhile, it is well known that in the context of overlapping return observations, the regression in (1) can result in spuriously large and highly misleading regression  $R^2$ 's, say  $R_s^2(h)$ , as the horizon  $h$  increases; see, e.g., the discussion and many references in Campbell, Lo, and MacKinlay (1997). Similarly, the standard errors for the OLS estimates designed to take account of the serial correlation in  $u_{t+hs,t}^s$  based on the Bartlett kernel advocated by Newey and West (1987) (NW, henceforth), and the modification proposed by Hodrick (1992) (HD, henceforth), can also both result in  $t$ -statistics for testing hypotheses about  $a_s(h)$  and  $b_s(h)$  that are poorly approximated by a standard normal distribution.

Most of the existing analyses pertaining to these and other related finite sample biases, however, have been calibrated to situations with a highly persistent predictor variable, as traditionally used in long-horizon return regressions. Even though the variance risk premium is fairly persistent at the daily frequency, it is much less so at the monthly level, and as such one might naturally expect the finite sample biases to be less severe in this situation.<sup>6</sup> Our Monte Carlo simulations discussed in the next section confirm this conjecture in an empirically realistic setting designed to closely mimic the joint dependencies in actual daily returns and variance risk premia.

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<sup>6</sup>The first order autocorrelation coefficient for the monthly U.S. variance risk premium analyzed in the empirical section below equals 0.39, and it is even lower for all of the other countries included in our subsequent analysis. By comparison, the first order autocorrelations for monthly dividend yields, P/E ratios, and other valuation ratios typically employed in the long-horizon regression literature, are around 0.95-0.99.

## 2.1 Simulation Design

The model underlying our simulations is based on daily S&P 500 composite index returns (obtained from CRSP). The corresponding daily observations on the variance risk premium are defined as  $VRP_t = IV_t - RV_{t-20,t}$ , where we rely on the square of the new VIX index (obtained from the CBOE) to quantify the implied variation  $IV_t$ , and the summation of current and previous 20 trading days daily realized variances (obtained from the Oxford-Man Institute's Realized Volatility Library) together with the squared overnight returns to quantify the total realized variation over the previous month  $RV_{t-20,t}$ .<sup>7</sup>

The sample period runs from February 1, 1996 to December 31, 2007, for a total of 2,954 daily observations. The end of the sample purposely coincide with that in BTZ. We will later investigate the sensitivity of the empirical results to the inclusion of more recent data involving the financial crisis. The span of the data exactly matches the length of the commonly available sample for the six countries analysis below.

After some experimentation, we arrived at the following bivariate VAR(1)-GARCH(1,1)-DCC model (see Engle, 2002, for additional details on the DCC model) for the two daily time series,

$$\begin{aligned}
r_{t-1,t} &= \underset{(0.001)}{-1.958\text{e-}5} - \underset{(0.016)}{0.009}r_{t-2,t-1} + \underset{(0.010)}{0.025}VRP_{t-1} + \epsilon_{t,r} \\
VRP_t &= \underset{(0.001)}{3.759\text{e-}5} + \underset{(0.017)}{0.033}r_{t-2,t-1} + \underset{(0.010)}{0.972}VRP_{t-1} + \epsilon_{t,vrp} \\
\sigma_{t,r}^2 &= \underset{(1.68\text{e-}6)}{1.280\text{e-}6} + \underset{(0.004)}{0.071}\epsilon_{t-1,r}^2 + \underset{(0.008)}{0.920}\sigma_{t-1,r}^2 \\
\sigma_{t,vrp}^2 &= \underset{(7.59\text{e-}6)}{2.038\text{e-}7} + \underset{(0.004)}{0.133}\epsilon_{t-1,vrp}^2 + \underset{(0.028)}{0.871}\sigma_{t-1,vrp}^2 \\
Q_t &= \begin{pmatrix} \underset{(0.036)}{0.997} & \underset{(0.040)}{-0.754} \\ \underset{(0.040)}{-0.754} & \underset{(0.060)}{1.023} \end{pmatrix} + \underset{(0.002)}{0.011}\eta_{t-1}\eta'_{t-1} + \underset{(0.004)}{0.979}Q_{t-1} \\
R_t &= \text{diag}\{Q_t\}^{-1}Q_t\text{diag}\{Q_t\}^{-1},
\end{aligned}$$

where  $\eta_t \equiv (\frac{\epsilon_{t,r}}{\sigma_{t,r}}, \frac{\epsilon_{t,vrp}}{\sigma_{t,vrp}})'$ , and  $E_{t-1}(\eta_t) = 0$  and  $E_{t-1}(\eta_t\eta'_t) = R_t$  by assumption. The specific

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<sup>7</sup>This directly mirrors the definition of the variance risk premium employed in BTZ. Forward looking measures of  $VRP_t$  that align  $IV_t$  with a measure of the expected volatility  $E_t(RV_{t,t+20})$  have also been used in the literature. However, this requires additional modeling assumptions for calculating  $E_t(RV_{t,t+20})$ , whereas the  $VRP_t$  used here has the obvious advantage of being directly observable at time  $t$ . We will return to this issue in Section 4 below.



parameter values refer to Quasi Maximum Likelihood Estimates (QMLE) obtained under the auxiliary assumption of conditional normality, with robust standard errors following Bollerslev and Wooldridge (1992) in parentheses. With the exception of the lagged daily returns, most of the dynamic coefficients are highly significant at conventional levels.

The model implies a strong negative (on average) correlation between the innovations to the return and VRP equations. This, of course, is consistent with the well documented “leverage” effect; see, e.g., Bollerslev, Sizova, and Tauchen (2012) and the many references therein. At the same time, as is evident from the equation for  $Q_t$ , the conditional correlation clearly varies over time, and as shown in the top panel in Figure 1 reaches a low of close to -0.85 toward the end of the sample. The bottom three panels in Figure 1 indicate that the distribution of the estimated standardized residuals from the model (i.e.,  $\hat{c}\eta_t \equiv \hat{F}_t^{-1}\hat{\eta}_t$ , where  $\hat{F}_t \cdot \hat{F}_t' = \hat{R}_t$ ) are well behaved and centered at zero, with variances close to unity, albeit not normally distributed.<sup>8</sup> Thus, all in all the model provides a reasonably good fit to the joint dynamic dependencies inherent in the two daily series.

As such, we will use this relatively simple-to-implement model as our basic data generating process for the Monte Carlo simulations, and our analysis of the finite sample properties of the NW and HD  $t$ -statistics, and  $R_s^2(h)$ ’s from the overlapping return regressions in equation (1).<sup>9</sup> Our simulated finite sample distributions will be based on a total of 2,000 bootstrapped replications from the model. We will look at sample frequencies of  $s = 1$  (“daily”),  $s = 5$  (“weekly”) and  $s = 20$  (“monthly”), and return horizons  $hs$  ranging up to 240 “days,” or 12 “months.” The number of observations for each of the simulated samples is fixed at  $T = 2,954$  “days” (or 598 “weeks,” or 149 “months”), corresponding to the length of the actual sample used in the estimation of the VAR-GARCH-DCC model above.<sup>10</sup> We begin

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<sup>8</sup>The sample means for  $\hat{c}\eta_{t,1}$  and  $\hat{c}\eta_{t,2}$  equal -0.044 and 0.088, the standard deviations equal 0.999 and 1.007, while the skewness and kurtosis equal -0.469 and 0.894, and 4.913 and 7.860, respectively. Further diagnostic checks also reveal that while the residuals from the return equation appear close to serially uncorrelated, there is some evidence for neglected longer-run serial dependencies in the equation for the variance risk premium.

<sup>9</sup>The bandwidth in the Bartlett kernel employed in our implementation of the NW standard errors is set to  $m = [h + 4 * ((T - hs)/100)^{2/9}]$ , where  $[\cdot]$  refers to the integer value. We also experimented with the reverse regression technique suggested by Hodrick (1992) for testing  $b^s(h) = 0$ . The results, available upon request, were very similar to the ones for the HD  $t$ -statistic reported below.

<sup>10</sup>As previously noted, this also mimics the length of the commonly available sample for the international

with a discussion of the size and power properties of the two  $t$ -statistics.

## 2.2 Size and Power

Our characterization of the distributions under the null hypothesis of no return predictability is based on restricting the coefficients associated with  $r_{t-2,t-1}$  and  $VRP_{t-1}$  in the return equation to be identically equal to zero, leaving all of the other coefficients at their estimated values. Table 1 reports the resulting simulated 95th percentiles of the  $t^{NW}$  and  $t^{HD}$  test statistics, along with the regression  $R^2$ 's. In line with the evidence in the existing literature, both of the  $t$ -statistics exhibit non-trivial size distortions relative to the nominal one-side 95-percent critical value of 1.645. Also, the distortions tend to increase with the return horizon  $h$ . Moreover, consistent with the results reported in Hodrick (1992), the biases for the NW based standard error calculations generally exceed those for the HD standard errors, and markedly more so the longer the return horizon.

To illustrate the results, we plot in the three left panels in Figure 2 the simulated 95-percent critical values for the  $t^{NW}$  (dashed lines) and the  $t^{HD}$  (solid lines) statistics for  $s = 1, 5, 20$ . We also include in the figure the  $t$ -statistics obtained by running these same regressions on the actual daily, weekly and monthly data over the February 1996 through December 2007 sample period used in calibrating the simulated model. As the figure shows, the actual  $t^{NW}$ -statistics systematically exceeds the simulated critical values for return horizons in the range of 2 to 3 months. This is true regardless of whether the regressions are based on daily, weekly, or monthly data. Meanwhile, the  $t^{HD}$ -statistics generally do not exceed the simulated critical values and accordingly do not support the idea of return predictability.

In order to better understand this discrepancy in the conclusions drawn from the two tests, we report in Table 2 the power of the tests to detect predictability implied by the unrestricted VAR-GARCH-DCC model. To facilitate comparisons we only report the size-adjusted power for a 5-percent test. Not surprisingly, the power of both tests decrease with the return horizon. But, the power of the  $t^{NW}$  test systematically exceed that of the  $t^{HD}$  test for return horizons less than a year, and the differences appear most pronounced at the

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data analyzed below.

2-4 month horizons.

These differences are also evident in the three right panels in Figure 2, which plot the relevant power curves. Comparing the simulations across the three different panels also point to fairly small losses in terms of power when decreasing the sampling frequency of the data used in the regressions from  $s = 1$  (“daily”) to  $s = 5$  (“weekly”) to  $s = 20$  (“monthly”).

Guided by these findings, we will follow the standard approach in the literature and base our subsequent empirical investigations on the commonly used monthly return regressions and NW-based standard errors, recognizing that the finite sample distributions of the  $t^{NW}$ -statistics tend to be slightly upward biased under the null of no predictability.

## 2.3 $R^2$

In addition to the  $t$ -statistics associated with the  $b_s(h)$  coefficients, the  $R_s^2(h)$ ’s from the return regressions are also commonly used to assess the strength of the relationship and the effectiveness of the predictor variable across different horizons. Of course, it is well known that the biases exhibited by the  $t$ -statistics in the context of long-horizon return regressions with persistent predictor variable carry over to the  $R_s^2(h)$ ’s, and that these need to be carefully interpreted as well (see, e.g., the aforementioned study by Boudoukh, Richardson, and Whitelaw, 2008, for a recent analysis, along with the many references therein).

The corresponding columns in Table 1 show that, while less dramatic than the biases that exist over multi-year return horizons with highly persistent predictor variables, the  $R_s^2(h)$ ’s can still be quite different from zero under the null of no predictability in the present setting. In particular, the 95th percentiles are around 5-6 percent at the 2-4 months horizon for all of the three sampling frequencies  $s = 1, 5, 20$ .

Further to this effect, we show in the top panel in Figure 3 select quantiles in the simulated distribution of the  $R_1^2(h)$ ’s that obtain in the absence of any predictability. Consistent with the findings in the extant literature pertaining to monthly observations and longer return horizons, all of the quantiles increase monotonically with the return horizon, and this increase is especially marked for the higher percentiles. Intuitively as the horizon increases, the overlapping return regressions become closer to a spurious type regression.

In addition to the simulated quantiles, the figure also shows the  $R_1^2(h)$ 's obtained from the actual return regressions based on the same daily data used in estimating the VAR-GARCH-DCC model. Comparing the actual  $R_1^2(h)$ 's to the simulated percentiles again suggest that the degree of predictability is most significant at the intermediate 2-4 months horizon. This, of course, is directly in line with the inference based on the  $t$ -statistics discussed in the previous section. It also supports the prior empirical evidence reported in BTZ.

The hump-shaped pattern in the actual  $R_1^2(h)$ 's, with an apparent peak in the degree of predictability at the intermediate 2-4 months horizon, also closely mimics the patterns in the simulated quantiles for the estimated VAR-GARCH-DCC model depicted in the bottom panel in Figure 3. Interestingly, this striking similarity arises in spite of the fact that the simulated model involves only first-order dynamics in the equations that describe the daily conditional means.

To appreciate this, consider the VAR(1) corresponding to the conditional mean dependencies in the Monte Carlo simulation design,

$$\begin{aligned} r_{t-1,t} &= a_1 + b_1 r_{t-2,t-1} + c_1 VRP_{t-1} + \epsilon_{r,t} , \\ VRP_t &= a_2 + b_2 r_{t-2,t-1} + c_2 VRP_{t-1} + \epsilon_{vrp,t} . \end{aligned}$$

Following Campbell (2001), it is possible to show that the population regression coefficients and  $R^2$ 's from the overlapping return regressions in (1) may be expressed as,<sup>11</sup>

$$\begin{aligned} b(h) &= \left( c_1 \frac{1 - c_2^h}{1 - c_2} \right) + \left( b_1 + c_1 b_2 \frac{1 - c_2^{h-1}}{1 - c_2} \right) \frac{Cov(r_{t-1,t}, VRP_t)}{Var(VRP_t)} \\ &\quad + b_1 b(h-1) + c_1 b_2 [b(h-2) + c_2 b(h-3) + \dots + c_2^{h-3} b(1)] , \end{aligned}$$

$$R^2(h) = \frac{b(h)^2}{h} \frac{Var(VRP_t)}{[h^{-1} Var(\sum_{j=1}^h r_{t-1+j,t+j})]} .$$

Hence, the strength of the predictability over different horizons  $h$  is primarily determined by the interaction between the short-run predictability, or  $Cov(r_{t-1,t}, VRP_t)$  and  $c_1$ , and the own persistence of the  $VRP_t$  predictor variable and  $c_2$ .

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<sup>11</sup>We have omitted the implicit dependence on the sampling frequency  $s = 1$  for notational simplicity. Further details concerning these derivations are available upon request.

To further illustrate this, the solid lines in each of the four panels in Figure 4 show the  $R^2(h)$ 's implied by the unrestricted VAR(1) coefficient estimates used in the simulations. Indirectly confirming the satisfactory fit of the model, the theoretically implied population  $R^2(h)$ 's are generally close to the  $R^2(h)$ 's actually estimated from the sample regressions depicted by the star-dashed line in the previous Figure 3. Meanwhile, marginally decreasing the value of each of the VAR(1) coefficients,  $b_1$ ,  $c_1$ ,  $b_2$  and  $c_2$ , by ten percent, results in quite different  $R^2(h)$ 's, as shown by the dashed lines in Figure 4. In particular, the proportional decrease in  $c_2$  has by far the largest effect. Moreover, the value of  $c_2$  and the own persistence of  $VRP_t$  is intimately linked to the location of the maximum in the hump shaped predictability pattern.

Taken as a whole, our Monte Carlo simulations and the new regression results based on daily U.S. returns discussed above clearly support the variance risk premium as a powerful predictor at the 2-4 month horizons. At the same time, the overlapping nature of the return regressions tend to attenuate the strength of the predictability somewhat. Hence, in an effort to further corroborate the existing empirical evidence pertaining exclusively to the U.S. market and data prior to the 2008 financial crisis, we next turn to a discussion of our new empirical findings involving more recent data and several other countries.

### 3 International Evidence

Motivated by the Monte Carlo simulation results, we will rely on the common benchmark monthly sampling frequency, along with the traditional NW-based standard errors and  $t^{NW}$ -statistics for characterizing the return predictability internationally, keeping in mind the finite sample biases documented in the simulations. We will restrict our analysis to France, Germany, Japan, Switzerland, the U.K., and the U.S., all of which have highly liquid options markets and readily available model-free implied variances for their respective aggregate market indexes (see Siriopoulos and Fassas, 2009, for a recent summary of the model-free and parametric options implied volatility indexes available for different countries). We begin with a brief discussion of the data.

### 3.1 Data and Summary Statistics

Our monthly aggregate market returns for the different countries are based on daily data for the French CAC 40 (obtained from Euronext), the German DAX 30 (obtained from Deutsche Börse), the Japanese Nikkei 225, the Swiss SMI, and the U.K. FTSE 100 (all obtained from Datastream), and the U.S. S&P 500 (obtained from Standard & Poor's). We use the sum of the daily squared returns over a month to construct end-of-month realized variances  $RV_t^i$  for each of the countries. We obtain the corresponding end-of-month model-free implied volatilities  $(IV_t^i)^{1/2}$  for the S&P 500 (VIX) from the CBOE, the CAC (VCAC) from Euronext, the DAX (VDAX) from Deutsche Börse, while those for the FTSE (VFTSE) and the SMI (VSMI) were both obtained from Datastream. Our data for the Japanese volatility index (VXJ) was obtained directly from the Center for the Study of Finance and Insurance at Osaka University (see Nishina, Maghrebi, and Kim, 2006, for a more detailed discussion of the VXJ index). Finally, the risk-free rates used in the construction of the excess returns were obtained from the Federal Reserve Board and Eurocurrency via Datastream.<sup>12</sup>

The sample period for each of the series extends from January 2000 to December 2011. The beginning of the sample coincides with the back-dated initial date of the NYSE Euronext volatility indices.<sup>13</sup> The use of more recent data through 2011 allows for additional validation of the original empirical evidence for the U.S. based on data prior to the financial crisis.

In accordance with the empirical analysis in the previous section, the proxy for the variance risk premium for each of the individual countries is simply defined by  $VRP_t^i \equiv IV_t^i - RV_{t-20,t}^i$ . As noted above, this proxy has the obvious advantage of being directly observable. The time series plots of  $VRP_t^i$  for each of the six countries in Figure 5 clearly show the dramatic impact of the financial crisis, and the exceptionally large variance risk premia observed in the Fall of 2008. Interestingly, however, the premium for the DAX, and to a lesser extent the SMI, were almost as large and negative in 2001-2002.

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<sup>12</sup>The use of excess returns, as opposed to raw returns, has almost no effect on the results from the return predictability regressions reported below.

<sup>13</sup>The volatility indexes is available prior to January 2000 for some of the countries; VDAX (December 1994), VXJ (January 1998), VSMI (January 1999) and VIX (January 1990). Comparable results to the ones for the country specific regressions discussed below based on the longest possible sample for each of the countries are reported in a Supplementary Appendix available upon request.

The standard set of summary statistics reported in Table 3 also show a remarkable coherence in the distributions of the variance risk premia and monthly excess returns across countries. In particular, looking at Panel A the average excess returns all reflect the often-called “lost decade,” ranging from a high of -2.49 for Switzerland to a low of -8.35 for France. Of course, the corresponding standard deviations all point to considerable variations in the returns around their negative sample means.

The variance risk premia are all positive on average, ranging from a low of 2.75 for France to a high of 12.32 for Japan on a percentage-squared monthly basis. “Selling” volatility has been highly profitable on average over the last decade. Meanwhile, consistent with the visual impressions from Figure 5, all of the premia are significantly negatively skewed and exhibit large excess kurtosis. Even though the implied and realized variances are both strongly serially correlated for all of the countries, the variance risk premia are generally not very persistent, and the maximum first order serial correlation observed for the S&P 500 equals just 0.39. Turning to Panels B and C, the sample cross-country correlations are all fairly high, and with the exceptions of those for the Nikkei, the correlations for the returns all exceed 0.80, while those for the variance risk premia are in excess of 0.70.

The similarities in the summary statistics in Table 3 and the time series plots in Figure 5, naturally suggest that the same predictive relationship documented for the U.S. returns and variance risk premium may hold true for the other countries. The results discussed in the next subsection generally corroborate this conjecture.

### 3.2 Country Specific Regressions

In parallel to the general multi-period return regressions defined in (1), our monthly return regressions for each of the individual countries may be conveniently expressed as,

$$h^{-1}r_{t,t+h}^i = a^i(h) + b^i(h)VRP_t^i + u_{t,t+h}^i, \quad (2)$$

where  $r_{t,t+h}^i$  and  $VRP_t^i$  refer to the  $h = 1, 2, \dots, 12$  month excess return and variance risk premium for country  $i$ , respectively.<sup>14</sup>

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<sup>14</sup>We omit the  $s = 20$  monthly subscript on the regressors and regression coefficients for notational simplicity.

The actual estimates for  $b^i(h)$  and the corresponding  $t^{NW}$ -statistics reported in Table 4 obviously differ somewhat across countries. However, with the exception of France and the U.S., the estimated coefficients all show the same general pattern starting out fairly low and insignificant at the shortest one-month horizon, rising to their largest values at 3-5 months, and then gradually tapering off thereafter for longer return horizons. These similarities are also evident in Figure 6, which displays the regression coefficients along with their two NW standard error bands.<sup>15</sup>

These similarities in the patterns in the estimated  $b^i(h)$  coefficients naturally translate into very similar patterns in the regression  $R^2(h)$ 's as well. In particular, looking at the plots in Figure 7, all of the  $R^2(h)$ 's exhibit an almost identical hump-shaped pattern with the degree of predictability maximized around the 4 months horizon. Of course, the actual values of the  $R^2(h)$ 's vary somewhat across the different country indices, achieving a maximum of only 0.58 percent for the Nikkei 225 compared to 13.02 percent for the S&P 500.<sup>16</sup> Interestingly, this value of  $R^2(3) = 13.02$  for the U.S. exceeds that obtained with monthly data through the end of 2007 previously reported in BTZ and Drechsler and Yaron (2011). It also exceeds the corresponding  $R^2(80)$  for the daily U.S. returns in Figure 3 discussed in Section 2 above.

The qualitative results from the country specific VRP regressions, while not as significant, are generally in line with the existing results for the U.S. Going one step further, the similarities in the patterns observed across the different countries also suggest that even stronger results may be available by pooling the regressions and entertaining the notion of a common “global” variance risk premium. We explore these ideas next.

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<sup>15</sup>Our Monte Carlo simulations discussed above suggest that the two standard error bands are likely somewhat conservative vis-a-vis the usual 95-percent coverage in this setting, and that they and should be interpreted accordingly.

<sup>16</sup>This lack of predictability for Japan is also consistent with the evidence reported in Ubukata and Watanabe (2011).



## 4 Global Variance Risk

Our proxy for the “global” variance risk premium is based on a simple capitalization weighted average of the proxies for country specific variance risk premia,

$$VRP_t^{global} \equiv \sum_{i=1}^6 w_t^i VRP_t^i ,$$

where  $i = 1, 2, \dots, 6$  refer to each of the six countries included in our analysis.<sup>17</sup> The end-of-month market capitalizations used in defining the weights  $w_t^i$  are obtained from Thomson Reuters Institutional Brokers’ Estimate System (I/B/E/S) via Datastream. The plot of the weights in Figure 8 shows that the U.S. market accounts for around sixty percent through most of the sample period, with the Japanese market a distant second. This large weight assigned to the U.S. market in our definition of the “global” VRP index is also implicit in the aforementioned summary statistics in Panel C in Table 3, and the relatively high correlation of 0.89 between  $VRP_t^{global}$  and  $VRP_t^{U.S.}$ .

### 4.1 Individual Country Regressions

The results for the regressions obtained by replacing the country specific  $VRP_t^i$ ’s in equation (2) with the new  $VRP_t^{global}$  proxy,

$$h^{-1}r_{t,t+h}^i = a^i(h) + b^i(h)VRP_t^{global} + u_{t,t+h}^i , \quad (3)$$

are reported in Table 5. Comparing the results to the ones for the country specific regressions in Table 4, reveals even stronger commonalities and uniform patterns across countries. The “global” VRP proxy serves as a highly significant predictor variable for all of the different country returns, with  $t^{NW}$ -statistics systematically in excess of 4.0 at the 4 months horizon. Further increasing the horizon  $h$ ,  $VRP_t^{global}$  systematically becomes insignificant for predicting the longer 9 and 12 months returns.

These striking cross-country similarities are also evident from the plots of the estimated regression coefficients and the two NW-based standard error bands in Figure 9. Not only

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<sup>17</sup>This parallels the construction used in Harvey (1991) in the estimation of the world price of covariance risk.

do the individual country estimates for the  $b^i(h)$ 's look very similar, the confidence bands also tend to be tighter compared to the country specific regressions discussed above. Further along these lines, Figure 10 shows the general patterns in the predictability, as measured by the  $R^2(h)$ 's, to be very similarly shaped across countries, with peaks at the 4-5 months return horizon.<sup>18</sup>

These remarkable similarities in the estimates for the different countries, naturally suggest restricting the coefficients in equation (3) to be the same across countries, as a way to enhance the efficiency of the estimates and ensure a common reward for bearing “global” variance risk.

## 4.2 Panel Regressions

The estimation results from the panel regression that restricts the coefficients for the “global” variance risk premium to be the same across countries,

$$h^{-1}r_{t,t+h}^i = a(h) + b(h)VRP_t^{global} + u_{t,t+h}^i, \quad (4)$$

are reported in Table 6 (for additional details on calculating standard errors, see, e.g., Petersen, 2009).<sup>19</sup> As the table clearly shows, the use of panel regressions do indeed result in more accurate estimates, and a highly significant  $t^{NW}$ -statistics of 8.72 at the 4-months horizon. The average panel regression  $R^2(h)$ 's for the six countries also gradually rise from less than two percent at the one-month horizon to a large 6.73 percent for the 4-month returns, tapering off to zero for the longer 9-12 month return horizons.

These key empirical findings are succinctly summarized in Figure 11, which plots the panel regression estimates for the  $b(h)$ s based on the country specific VRP's and the “global” VRP proxy along with their two NW-based standard error bands (top two panels), and the

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<sup>18</sup>The relatively large weight assigned to the U.S. in our construction of the “global” variance risk premium means that fairly similar results are obtained by replacing the new  $VRP_t^{global}$  in the regressions in equation 3 with  $VRP_t^{S\&P500}$ . These additional results are available upon request. Comparable empirical results based on the U.S. variance risk premium have also recently been reported in concurrent independent work by Londono (2011), who ascribes the predictability to informational frictions along the lines of Rapach, Strauss, and Zhou (2010).

<sup>19</sup>We also experimented with the two-way cluster analysis in Cameron, Gelbach, and Miller (2011), resulting in very similar findings.

corresponding panel regression  $R^2(h)$ 's (bottom two panels). The  $VRP^{global}$ -based regressions (depicted in the right two panels) obviously result in sharper coefficient estimates and stronger average predictability across the six countries than do the individual country  $VRP^i$  regression (depicted in the left two panels).

The average panel regression  $R^2(h)$ 's, of course, mask important cross-country differences in the degree of predictability. We therefore also show in Figure 12 the country specific implied  $R^2(h)$ 's obtained by evaluating the individual country regressions in equation (3) at the more precisely estimated common  $\hat{a}(h)$  and  $\hat{b}(h)$  obtain from the panel regressions in equation (4). Comparing Figure 12 to the earlier Figure 10 for the individual country regressions, it is clear that the added precision afforded by restricting the  $a^i(h)$  and  $b^i(h)$  coefficients to be the same across countries sacrifices very little in terms of the implied predictability.

### 4.3 Robustness Checks

To assess the robustness of these striking international predictability patterns, the next panel in Table 6 reports the results obtained by including a capitalization weighted average of the country specific P/E ratios as an additional regressor in equation (4). Consistent with the results for the U.S. market in isolation reported in BTZ, the “global” P/E ratio adds nothing to the predictability afforded by  $VRP^{global}$  within the one-year horizons reported in the table, leaving all of the estimates for  $b(h)$  and the  $R^2(h)$ 's almost the same. The predictability of the “global” variance risk premium is effectively “orthogonal” to that documented in the existing literature based on more traditional macro-finance variables, such as the P/E ratio, dividend yields, and consumption-wealth ratios, which are typically only significant over longer multi-year return horizons (see, e.g., the classic studies by Fama and French, 1988; Campbell and Shiller, 1988b; Lettau and Ludvigson, 2001).<sup>20</sup>

To further highlight the predictive gains afforded by the use of our “global” VRP as opposed to the own country VRP's, the last two panels in Table 6 show the estimates

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<sup>20</sup>Further corroborating the results for the U.S. market in BTZ, we also found that including the implied “global” variance or the realized “global” variance together with the “global” variance risk premium resulted in mostly insignificant coefficient estimates. These additional results are available upon request.

obtained by including each individual country’s premium in a panel regression in place of  $VRP^{global}$ ,

$$h^{-1}r_{t,t+h}^i = a(h) + b(h)VRP_t^i + u_{t,t+h}^i . \quad (5)$$

While the results still point to overall efficiency gains from the use of the panel regression relative to the country specific regressions in Table 4, the magnitude of the return predictability is obviously much lower than for  $VRP^{global}$ . The “global” variance risk premium is clearly a much better predictor of the future returns for most of the countries than the individual country specific premia. Again, including the country specific P/E ratios in the same panel regression do not material affect the overall predictability as measured by the  $R^2$ s, nor the values of the estimated regression coefficients for the variance risk premia.

#### 4.4 Forward Looking Global Variance Risk Premium

Our proxy for the “global” variance risk premium underlying our main findings discussed above is based on a weighted average of the variance difference for each the countries. This directly mirrors the original proxy for the U.S. variance risk premium employed in BTZ, and the proxy used in the country specific regressions in Section 3. To assess the sensitivity of our results to this simple and easy-to-implement proxy, we briefly summarize the results obtained by replacing the model-free lagged monthly realized variances with forward looking model-based expectations in the way we define the “global” variance risk premium.

Specifically, let  $E_t(RV_{t,t+20}^i)$  denote the time  $t$  expectation of the one-month ahead return variation for country  $i$ . Additionally, let  $FVRP_t^i = IV_t^i - E_t(RV_{t,t+20}^i)$  denote the corresponding forward looking variance risk premia for country  $i$ . We then define a forward looking “global” variance risk premium by,

$$FVRP_t^{global} \equiv \sum_{i=1}^6 w_t^i FVRP_t^i .$$

In contrast to the  $VRP^{global}$  defined above,  $FVRP^{global}$  necessitates the use of a model for generating the forward expectations  $E_t(RV_{t,t+20}^i)$ . In the results reported on below, we follow Andersen, Bollerslev, and Diebold (2007) and Corsi (2009) in generating these forecasts from

HAR-RV type models in which we regress  $RV_{t,t+20}^i$  for each of the six countries on the daily, weekly, and monthly realized variances,  $RV_{t-1,t}^i$ ,  $RV_{t-5,t}^i$ , and  $RV_{t-20,t}^i$ , respectively, along with the options implied variances,  $IV_t^i$ , for all of the other six countries.<sup>21</sup>

The resulting  $FVRP^{global}$  is plotted in Figure 13 (bottom panel), together with the previously used simple  $VRP^{global}$  proxy (top panel). While the two series obviously differ, the general dynamic dependencies are obviously quite similar. Of course, the large negative spike in  $VRP^{global}$  observed at the height of the financial crisis is clearly diminished in the forward looking  $FVRP^{global}$ .

Turning to the predictive return regressions, the top panel in Table 7 reports the estimates from the same panel regressions in equation (4) using  $FVRP^{global}$  in place of  $VRP^{global}$ . While the NW-based  $t$ -statistics for the 1-6 month returns are all slightly lower than the comparable  $t^{NW}$ -statistics reported in the top panel in Table 6, they remain highly significant at any reasonable level. In fact, the statistical significance of the regressions based on  $FVRP^{global}$  extends to at least the 9 month horizon. The  $R^2$ s also show a similar hump shaped pattern to the ones in Table 6 and Figure 11, with the predictability now maximized at the slightly longer 5-6 month horizon. This shift in the location of the peak is also consistent with the results in Section 2.3, and the slightly larger first order autocorrelation of 0.41 for  $FVRP^{global}$  compared to 0.36 for  $VRP^{global}$ . The second panel in Table 7 again further corroborates our key empirical findings, and the idea that the predictability inherent in the “global” variance risk premium is essentially “orthogonal” to that in the “global” P/E ratio, which only kicks in over longer annual horizons.

To help better understand the economic mechanisms underlying these results, we next present a stylized two-country equilibrium model. This relatively simple model provides a possible rationale for why the estimated regression coefficients for the “global” variance risk premium are fairly similar across countries, and why, with the exception of the U.S., the

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<sup>21</sup>We make sure that all of the regressors are properly aligned to correct for the different time zones, so that none of the predictions involve any future information. We also experimented with the use of a standard VAR(1) model involving only the current monthly realized variation measures,  $RV_{t-20,t}^i$ , and options implied variation measures,  $IV_t^i$ , for generating  $E_t(RV_{t,t+20}^i)$ , resulting in qualitatively similar, albeit not as significant, predictive return regressions. Further details concerning these additional results are summarized in the Supplementary Appendix available upon request.

$R^2(h)$ 's for the panel regressions depicted in Figure 11 are generally larger for the “global” VRP than for the “local” VRP's.

## 4.5 Global Variance Risk in Equilibrium

Our two-country model is based on a direct extension of the “long-run risk” model in BTZ.<sup>22</sup> Specifically, denoting the geometric growth rate of consumption in country  $i$  by  $g_{t+1}^i \equiv \log(C_{t+1}^i/C_t^i)$ , we will assume that

$$g_{t+1}^i = \mu_g + \sigma_{g_i,t} z_{g_i,t+1}, \quad (6)$$

$$\sigma_{g_i,t+1}^2 = \alpha_\sigma \varphi_{q,i} + \nu_\sigma \sigma_{g_i,t}^2 + \varphi_{q,i} \sqrt{q_t} z_{\sigma,t+1} + \varphi_{h,\sigma} \sqrt{h_t} z_{\sigma_i,t+1}, \quad (7)$$

$$q_{t+1} = \alpha_q + \nu_q q_t + \varphi_q \sqrt{q_t} z_{q,t+1}, \quad (8)$$

$$h_{t+1} = \alpha_h + \nu_h h_t + \varphi_h \sqrt{h_t} z_{h,t+1}, \quad (9)$$

where  $\mu_g$  denotes mean growth rate, assumed to be constant and the same for the two countries,  $\sigma_{g_i,t}^2$  refers to the conditional variance of consumption growth for each of the countries. The convolution of  $q_t$  and  $h_t$  accounts for time-varying volatility-of-volatility, or economic uncertainty, with  $q_t$  responsible for the world-wide component and  $h_t$  determining the country-specific part. In parallel to existing “long-run risk” models, we will assume that  $z_{\sigma,t+1}$ ,  $z_{\sigma_i,t+1}$  and  $z_{q,t+1}$  are independent *i.i.d.*  $N(0,1)$  processes, and jointly independent of the two consumption growth shocks,  $z_{g_i,t+1}$ . For simplicity, we will fix the dynamic variance parameters  $\alpha_\sigma$  and  $\nu_\sigma$  to be the same across the two countries.<sup>23</sup> The system is normalized by fixing  $\varphi_{q,1}$  at unity. The scaling of the mean and volatility parameters for the second country by  $\varphi_{q,2}$ , in turn ensures that in the absence of idiosyncratic shocks, or  $\varphi_h=0$ , the two variance processes move proportional to each other. To complete the specification, we assume that

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<sup>22</sup>Even though the model explicitly excludes predictability in consumption growth, following the terminology of Bansal and Yaron (2004), we will refer to the basic setup as a “long-run risk” model. Alternative single country long-run risk models with two-factor

the conditional covariance between  $z_{g_i,t+1}$  and  $z_{g_j,t+1}$  is determined by the process

$$cv_{t+1,ij} = \alpha_{cv} + \nu_{cv}cv_{t,ij} + \varphi_{cv,ij}\sqrt{q_t}z_{\sigma,t+1}. \quad (10)$$

This trivially implies time-varying conditional correlations, unless  $\varphi_h=0$  and the remaining parameters are identical across the covariance and two variance processes.<sup>24</sup>

We further assume that the two markets are fully integrated and that there exists a representative agent with a claim on the world aggregate consumption, defined as the per capita weighted average consumption in each of the two countries, say  $C_t^{global}$ . Moreover, we assume that this agent is endowed with Epstein-Zin-Weil recursive preferences of the form

$$U_t = [(1 - \delta)(C_t^{global})^{\frac{1-\gamma}{\theta}} + \delta(E_t[U_{t+1}^{1-\gamma}])^{\frac{1}{\theta}}]^{\frac{\theta}{1-\gamma}}. \quad (11)$$

In the specific calibration reported on below, we follow Bansal and Yaron (2004) and BTZ in fixing the discount rate at  $\delta=0.997$ , the risk aversion parameter at  $\gamma=10$ , and the intertemporal elasticity of substitution at  $\varphi=1.5$ .

The parameters for the consumption dynamics are calibrated to mimic the U.S. as country “1”, and the U.K. as country “2”. In particular, following BTZ we fix the base parameters for the U.S. at  $\mu_g=0.0015$ ,  $\nu_\sigma=0.979$ ,  $\alpha_\sigma=0.0078^2(1 - \nu_\sigma)$ ,  $\nu_q=0.80$ ,  $\alpha_q=1.0 * 10e - 6(1 - \nu_q)$ , and  $\varphi_q=0.001$ , respectively. Additionally, we set the parameters for the country-specific volatility-of-volatility process at  $\varphi_{h,\sigma}=0.3 < 1$ ,  $\nu_h=\nu_q$ ,  $\alpha_h=E(q)(1 - \nu_h)$ , and  $\varphi_h=\varphi_q$ , respectively, implying a less persistent and overall less important influence of that shock on the variance compared to the world-wide shock. For simplicity, we take the weights used in the calculation of “global” consumption to be constant and equal to  $\omega_{US}=0.855$  and  $\omega_{UK}=0.145$ , corresponding to the consumption shares at the end of the sample.

The relevance of allowing for time-varying cross-country covariances is highlighted by Figure 14, which plots exponentially weighted moving average estimates of U.S. variances, and U.S.-U.K. covariances and correlations from 1951 to 2009.<sup>25</sup> Although the U.S.-U.K. consumption covariances clearly changes through time, the process is not as persistent as

<sup>24</sup>The consumption data discussed below strongly supports the notion of time-varying covariances (and correlations). By contrast, the aforementioned two-country model in Bansal and Shaliastovich (2010) postulates constant cross-country conditional covariances.

<sup>25</sup>The exponential weighted moving averages depicted in the figure are based on annual real total consump-

the process for the U.S. variance depicted in the top panel. We consequently set  $\nu_{cv}=0.85$  and  $\varphi_{cv,US,UK} = \varphi_{q,UK}^{1/2}\varphi_{q,US}^{1/2}$ . Finally, we set the parameter  $\varphi_{q,UK}^{1/2}=(2.5)^{1/2} \approx 1.581$  to reflect the generally higher variability of UK consumption growth.

Turning to the actual calibration results, the top two panels in Figure 15 show the implied regression coefficients for the “local” (dashed lines) and “global” (solid lines) VRP regressions for each of the two countries, while the bottom two panels show the implied  $R^2$ ’s from the “local” (dashed lines) and “global” (solid lines) VRP panel regressions.<sup>26</sup> The model-implied regressions in the figure generally match the qualitative features in the actual international return regressions quite well.

First, the implied slope coefficients for  $VRP^{global}$  in the two individual country regressions tend to be close across all horizons. For instance, at the four-month horizon, the model implied slope coefficients equal 0.34 and 0.33 for the U.S. and U.K., respectively, both of which are well within two standard errors of their corresponding estimates reported in Table 5. These numbers are also very close to the estimate of 0.29 and 0.34 for the six-country panel regressions reported in the top panels in Tables 6 and 7, respectively.

Second, the exposure to the “local” VRP is systematically lower than the exposure to the “global” VRP for the smaller country in the model (U.K.), directly mirroring the empirical results. Conversely, for the larger country (U.S.), the “local” VRP gives rise to marginally higher slope coefficients than the “global” VRP within the model, again directly mirroring the actual empirical results. Specifically, focussing again on the four-month horizon, the slope coefficient implied by the model equals 0.19 for the U.K. compared to 0.17 for the actual U.K. regression. In comparison, the model implied slope coefficient for the U.S. equals 0.40, compared to 0.34 for the actual “local” U.S. regression.

Third, looking at the  $R^2$ ’s from the corresponding panel regressions in the bottom two

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tion expenditures from the Penn World database, and a smoothing parameter equal to  $\lambda=1 - (1 - 0.06)^4$ . Specifically, for the U.S. variance  $\sigma_{US,t+1}^2=(1 - \lambda)\sigma_{US,t}^2 + \lambda(g_t^{US} - \widehat{\mu_{US}})^2$ , and the U.S.-U.K. covariance  $cv_{t+1}=(1 - \lambda)cv_t + \lambda(g_t^{US} - \widehat{\mu_{US}})(g_t^{UK} - \widehat{\mu_{UK}})$ , with the correlation defined accordingly.

<sup>26</sup>The calibrated model also implies equity premiums for the U.S. and U.K. of 7.17 percent and 4.50 percent, respectively, along with a world-wide risk free rate of 0.85 percent. Additional technical details concerning the solution of the model, together with explicit formulas for the regression coefficients and  $R^2$ ’s depicted in the figure, are relegated to Appendix A.



panels of Figure 15, both of the plots exhibit a hump shaped pattern with an apparent peak at the 2-4 month horizons. This overall shape closely matches that for the actual six-country panel regressions depicted in the bottom two panels in Figure 11. Of course, the values of the  $R^2$ 's from the theoretical model are somewhat muted compared to the six-country panel regressions  $R^2$ 's. Importantly, however, the model implied panel regression  $R^2$ 's based on  $VRP^{global}$  uniformly dominate the “local” VRP panel regression  $R^2$ 's. Again, these theoretical implications directly mirror the empirical results for the six-country panel regressions in Figure 11. Intuitively, the “global” VRP effectively isolates the aggregate world-wide economic uncertainty that is being priced in both markets, in turn providing much better overall predictions for the future returns than the “local” VRP for the smaller country.<sup>27</sup>

In a sum, the qualitative implications from our stylized equilibrium model are generally in line with the international predictability patterns documented in the data. Some of the quantitative implications from the model admittedly fall short in terms of explaining the magnitude of the effects. However, we purposely kept the model relatively simple, and it is certainly possible that by extending the basic setup to include additional sources of covariance, or correlation, risks, a full-fledged risk-based explanation for the new international evidence might be possible.

## 5 Conclusion

A number of recent studies have argued that aggregate U.S. stock market return is predictable over relatively short 3-5 month horizons by the difference between options implied and actual realized variation, or the so-called variance risk premium. We show that this newly documented predictability is not due to finite sample biases in the statistical inference procedures, and that the apparent hump-shaped pattern in the degree of predictability documented in over-lapping monthly returns regressions is entirely consistent with the im-

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<sup>27</sup>We also experimented with other calibrations and model specifications. In particular, restricting the covariance to be proportional to the U.S. variance  $cov_{t,US,UK} = \sqrt{\varphi_{qUK}} \sigma_{gUS}^2 \rho$ , and fixing the implied constant conditional correlation at  $\rho=0.18$  as in Bansal and Shaliastovich (2010), result in dramatically lower  $R^2$ 's (less than 0.03 percent across all return horizons) for  $VRP^{global}$ .

plications from an empirically realistic bivariate daily time series model for the returns and variance risk premia.

Further corroborating the existing empirical evidence for the U.S., we show that the same basic predictive relationship between future returns and current variance risk premia holds true with more recent “out-of-sample” data through 2011. We also show that the same basic results hold true for a set of five other countries, although the magnitude of the predictability and the statistical significance of the own country variance risk premium tend to be somewhat muted relative to those observed for the U.S.

Meanwhile, employing a capitalization weighted “global” variance risk premium results in very similar shaped predictability patterns across return horizons for *all* of the countries in our sample, and uniformly larger  $t$ -statistics. Further restricting the regression coefficients and the compensation for “global” variance risk to be the same across countries, we find even stronger results and highly significant test statistics, with the degree of predictability maximized at the 4-5 month horizon. Based on the implications from a stylized equilibrium model, we argue that the “global” variance risk premium may be seen as a proxy for world-wide aggregate economic uncertainty, and that this “global” variance risk premium generally provides more accurate predictions of the future individual country returns than the own country variance risk premia.

Alternatively, the “global” variance risk premium may be interpreted as a measure of aggregate risk aversion (e.g., Bekaert, Engstrom, and Xing, 2009), or a summary measure of world-wide disagreements in beliefs (e.g., Buraschi, Trojani, and Vedolin, 2010). All of these different economic mechanisms likely play some role in generating the strong international return predictability embodied in the “global” variance risk premium first documented here. We leave it for future research to sort out this important question.

## A Two-Country Equilibrium Model Solution

Following Epstein and Zin (1989), the logarithm of the world unique intertemporal marginal rate of substitution,  $m_{t+1} = \log(M_{t+1})$ , must satisfy,

$$m_{t+1} = \theta \log(\delta) - \theta \psi^{-1} g_{t+1} + (\theta - 1) r_{t+1}, \quad (\text{A.1})$$

where  $r_{t+1}$  refers to the time  $t$  to  $t + 1$  logarithmic return on the “global” consumption asset, and  $g_{t+1}$  denotes the corresponding “global” consumption growth rate.<sup>28</sup> Further, utilizing the standard Campbell and Shiller (1988a) log-linearization technique, the “world” and country specific returns may be expressed as,

$$r_{t+1} = k_0 + k_1 w_{t+1} - w_t + g_{t+1}, \quad (\text{A.2})$$

$$r_{t+1}^i = k_{i,0} + k_{i,1} w_{t+1}^i - w_t^i + g_{t+1}^i, \quad (\text{A.3})$$

where  $w_t$  and  $w_t^i$  denote the logarithmic price-consumption ratios for the “world” and the two individual countries, respectively.<sup>29</sup> Following the standard approach in the “long-run risk” literature, we proceed by conjecturing solutions to  $w_t$  and  $w_t^i$  of the form,<sup>30</sup>

$$w_{t+1} = A_0 + \sum A_{\sigma_j} \sigma_{g_j,t+1}^2 + A_q q_{t+1} + A_{cv,ij} cv_{t+1,ij} + A_h h_{t+1}, \quad (\text{A.4})$$

$$w_{t+1}^i = A_{i,0} + \sum A_{i,\sigma_j} \sigma_{g_j,t+1}^2 + A_{i,q} q_{t+1} + A_{i,cv,ij} cv_{t+1,ij} + A_{i,h} h_{t+1}. \quad (\text{A.5})$$

Combining the equations for  $r_{t+1}^i$  and  $w_{t+1}^i$  above, with equation (6) for  $g_{t+1}^i$  in the main text, the equilibrium return for country  $i$  may alternatively be expressed as,

$$\begin{aligned} r_{t+1}^i = & c_{i,r} + \sum_{l=1}^2 A_{r_i,gl} \sigma_{g_l,t}^2 + A_{r_i,q} q_t + A_{r_i,cv,ij} cv_{t,ij} + A_{r_i,h} h_t + \sigma_{g_i,t} z_{g_i,t+1} \\ & + \sqrt{q_t} k_{i,1} [A_{i,\varphi} z_{\sigma,t+1} + A_{i,q} \varphi_q z_{q,t+1}] + \sqrt{h_t} k_{i,1} [\sum A_{i,\sigma_j} \varphi_{h,\sigma} z_{\sigma_j,t+1} + A_{i,h} \varphi_h z_{h,t+1}] \end{aligned} \quad (\text{A.6})$$

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<sup>28</sup>For notational simplicity, here and throughout the Appendix, we omit the “global” superscript on the relevant variables.

<sup>29</sup>For the calibration exercise discussed in the main text we set  $k_1 = k_{US,1} = k_{UK,1} = 0.9$ . The constants  $k_0$  and  $k_{i,0}$  only enter the expressions for  $A_0$  and  $A_{i,0}$  below, which are not actually needed for the calculations of the regression coefficients,  $R^2$ 's, and equity premia.

<sup>30</sup>In the following, unless explicitly noted, all of the summations are over the two countries, running from  $j = 1$  to 2.

where  $c_{i,r} = -\log(\delta) + \varphi^{-1}\mu_g$ ,  $A_{r_i,g_j} = A_{i,\sigma_j}(k_{i,1}\nu_\sigma - 1)$ ,  $A_{r_i,q} = A_{i,q}(k_{i,1}\nu_q - 1)$ ,  $A_{r_i,h} = A_{i,h}(k_{i,1}\nu_h - 1)$ ,  $A_{r_i,cv,ij} = A_{i,cv,ij}(k_{i,1}\nu_{cv} - 1)$ , and  $A_{i,\varphi} = \sum A_{i,\sigma_j}\varphi_{q_j} + A_{i,cv,ij}\varphi_{cv,ij}$ .

Next, utilizing the standard no-arbitrage condition  $E_t(\exp(r_{t+1} + m_{t+1})) = 1$ , the parameters for the “world” in equation (A.4) may be solved as,<sup>31</sup>

$$\begin{aligned} A_0 &= \frac{\log(\delta) + (1 - \varphi^{-1})\mu_g + k_0 + k_1[\sum A_{\sigma_j}\alpha_\sigma\varphi_{q,j} + A_q\alpha_q + A_{cv,ij}\alpha_{cv}]}{1 - k_1}, \\ A_{cv,ij} &= \frac{(\gamma - 1)^2\omega_i\omega_j}{\theta(1 - k_1\nu_{cv})}, \\ A_{\sigma_j} &= \frac{(\gamma - 1)^2\omega_j^2}{2\theta(1 - k_1\nu_\sigma)}, \\ A_q &= \theta^{-1}\varphi_q^{-2}k_1^{-2}((1 - k_1\nu_q) - [(1 - k_1\nu_q)^2 - \theta^2k_1^4\varphi_q^2(\sum A_{\sigma_j}\varphi_{q_j} + A_{cv,ij}\varphi_{cv,ij})^2]^{1/2}), \\ A_h &= \theta^{-1}\varphi_h^{-2}k_1^{-2}((1 - k_1\nu_h) - [(1 - k_1\nu_h)^2 - \theta^2k_1^4\varphi_h^2\varphi_{h,\sigma}^2\sum A_{\sigma_j}^2]^{1/2}). \end{aligned}$$

Similarly, the parameters for the individual countries in equation (A.5) may be solved as,<sup>32</sup>

$$\begin{aligned} A_{i,0} &= \frac{\log(\delta) + (1 - \varphi^{-1})\mu_g + k_{i,0} + k_{i,1}[\sum A_{i,\sigma_j}\alpha_\sigma\varphi_{q,j} + A_{i,q}\alpha_q + A_{i,cv,ij}\alpha_{cv,ij}]}{1 - k_{i,1}}, \\ A_{i,cv,ij} &= A_{cv,ij} + \frac{(2\gamma - 1)\omega_i\omega_j - \gamma\omega_j}{(1 - k_{i,1}\nu_{cv})}, \\ A_{i,\sigma_j} &= (1 - \theta)A_{\sigma_j}\frac{1 - k_{i,1}\nu_\sigma}{1 - k_{i,1}\nu_\sigma} + \frac{\gamma^2\omega_j^2 + I_{i=j}(-2\gamma\omega_j + 1)}{2(1 - k_{i,1}\nu_\sigma)}, \\ A_{i,q} &= \frac{k_1}{k_{i,1}}(1 - \theta)A_q + \frac{(1 - k_{i,1}\nu_q)}{\varphi_q^2k_{i,1}^2} \\ &\quad - \varphi_q^{-2}k_{i,1}^{-2}((1 - k_{i,1}\nu_q)^2 - \theta^2k_{i,1}^2\varphi_q^2\{k_1^2(\sum A_{\sigma_j}\varphi_{q_j} + A_{cv,ij}\varphi_{cv,ij})^2 - 2(\theta - 1)A_q(1 - \frac{k_1}{k_{i,1}}) \\ &\quad + \frac{2}{\theta^2}[0.5(\sum A_{i,\sigma_j}\varphi_{q_j} + A_{i,cv,ij}\varphi_{cv,ij})^2k_{i,1}^2 + (0.5 - \theta)k_1^2(\sum A_{\sigma_j}\varphi_{q,j} + A_{cv,ij}\varphi_{cv,ij})^2 \\ &\quad + (\theta - 1)k_1k_{i,1}(\sum A_{\sigma_j}\varphi_{q_j} + A_{cv,ij}\varphi_{cv,ij})(\sum A_{i,\sigma_j}\varphi_{q_j} + A_{i,cv,ij}\varphi_{cv,ij})]\}^{1/2}), \\ A_{i,h} &= \frac{k_1}{k_{i,1}}(1 - \theta)A_h + \frac{(1 - k_{i,1}\nu_h)}{\varphi_h^2k_{i,1}^2} \\ &\quad - \varphi_h^{-2}k_{i,1}^{-2}((1 - k_{i,1}\nu_h)^2 - \theta^2k_{i,1}^2\varphi_h^2\{k_1^2\sum A_{\sigma_j}^2\varphi_{h,\sigma}^2 - 2(\theta - 1)A_h(1 - \frac{k_1}{k_{i,1}}) \\ &\quad + \frac{2}{\theta^2}\varphi_{h,\sigma}^2[0.5k_{i,1}^2\sum A_{i,\sigma_j}^2 + (0.5 - \theta)k_1^2\sum A_{\sigma_j}^2 + (\theta - 1)k_1k_{i,1}\sum A_{\sigma_j}A_{i,\sigma_j}]\}^{1/2}). \end{aligned}$$

Going one step further and building on the derivations in BTZ, the two country specific VRP's may be approximated as,

$$VRP_t^i \approx (\theta - 1)k_1(A_{vrp_i,q}q_t + A_{vrp_i,h}h_t), \quad (\text{A.7})$$

where  $A_{vrp_i,q} = k_{i,1}^2 A_q \varphi_q^2 (A_{i,\varphi}^2 + A_{i,q}^2 \varphi_q^2) + A_\varphi \varphi_{q,i}$ ,  $A_{vrp_i,h} = k_{i,1}^2 A_h \varphi_h^2 (\sum A_{i,\sigma_j}^2 \varphi_{h,\sigma}^2 + A_{i,h}^2 \varphi_h^2) + A_{\sigma_i} \varphi_{h,\sigma}^2$ .

Based on these expressions, it is now possible to derive the slope coefficients from regressing country  $i$ 's return on country  $j$ 's VRP,

$$\beta_{i,j}(hr) = \frac{A_{r_i,q} A_{vrp_j,q} \text{Var}(q_t) \frac{1-\nu_q^{hr}}{1-\nu_q} + A_{r_i,h} A_{vrp_j,h} \text{Var}(h_t) \frac{1-\nu_h^{hr}}{1-\nu_h}}{hr(\theta - 1)k_1(A_{vrp_j,q}^2 \text{Var}(q_t) + A_{vrp_j,h}^2 \text{Var}(h_t))}, \quad (\text{A.8})$$

as well as the slope coefficient from regressing country  $i$ 's return on the global VRP,

$$\beta_i(hr) = \frac{A_{r_i,q} A_{vrp,q} \text{Var}(q_t) \frac{1-\nu_q^{hr}}{1-\nu_q} + A_{r_i,h} A_{vrp,h} \text{Var}(h_t) \frac{1-\nu_h^{hr}}{1-\nu_h}}{hr(\theta - 1)k_1(A_{vrp,q}^2 \text{Var}(q_t) + A_{vrp,h}^2 \text{Var}(h_t))}, \quad (\text{A.9})$$

The final expressions for the “global” and “local” panel regressions discussed in the main text may be derived analogously. In particular, it is possible to show that

$$R_{global}^2(hr) = \left( \frac{1}{2} \sum \beta_j(hr) \right)^2 \frac{\text{Var}(VRP_t^{global})}{\frac{1}{2} \sum \text{Var}(\sum_{m=1}^{hr} r_{t+m}^j)}, \quad (\text{A.10})$$

and

$$R_{local}^2(hr) = \left( \sum \text{Var}^2(VRP_t^j) \right)^{-2} \left( \sum \beta_{j,j}(hr) \text{Var}^2(VRP_t^j) \right)^2 \frac{\sum \text{Var}(VRP_t^j)}{\sum \text{Var}(\sum_{m=1}^{hr} r_{t+m}^j)}, \quad (\text{A.11})$$

where  $\text{Var}(VRP_t^j) = (\theta - 1)^2 k_1^2 (A_{vrp_j,q}^2 \text{Var}(q_t) + A_{vrp_j,h}^2 \text{Var}(h_t))$ ,

$$\text{Var}\left(\sum_{m=1}^{hr} r_{t+m}^i\right) = hr \text{Var}(r_{t+1}^i) + 2 \sum_{s=1}^{hr-1} (hr - s)(A_{i,s} + B_{i,s}),$$

$$\begin{aligned} \text{Var}(r_{t+1}^i) &= A_{r_i,q}^2 \text{Var}(q_t) + (A_{r_i,g_i}^2 + A_{r_i,g_j}^2 \frac{\varphi_{q,j}^2}{\varphi_{q,i}^2} + 2A_{r_i,g_i} A_{r_i,g_j} \frac{\varphi_{q,j}}{\varphi_{q,i}}) \text{Var}(\sigma_{g_i,t}^2) + A_{r_i,cv,ij}^2 \text{Var}(cv_{t,ij}) \\ &\quad + A_{r_i,h}^2 \text{Var}(h_t) + 2 \sum_{l=1}^2 A_{r_i,gl} A_{r_i,cv,ij} \text{Cov}(\sigma_{gl,t}^2, cv_{t,ij}) + k_{i,1}^2 [(A_{i,\varphi}^2 + A_{i,q}^2 \varphi_q^2) E(q_t)] \\ &\quad + k_{i,1}^2 [(\sum A_{i,\sigma_j}^2 \varphi_{h,\sigma}^2 + A_{i,h}^2 \varphi_h^2) E(h_t)] + E(\sigma_{g_i,t}^2), \end{aligned}$$

$$\begin{aligned}
A_{i,s} = & A_{r_i,q}^2 \nu_q^s \text{Var}(q_t) + A_{r_i,h}^2 \nu_h^s \text{Var}(h_t) + \nu_\sigma^s (A_{r_i,g_i}^2 + A_{r_i,g_j}^2 \frac{\varphi_{q,j}^2}{\varphi_{q,i}^2} + 2A_{r_i,g_i} A_{r_i,g_j} \frac{\varphi_{q,j}}{\varphi_{q,i}}) \text{Var}(\sigma_{g_i,t}^2) \\
& + A_{r_i,cv,ij}^2 \nu_{cv}^s \text{Var}(cv_{t,ij}) + \sum_{l=1}^2 A_{r_i,g_l} A_{r_i,cv,ij} (\nu_{cv}^s + \nu_\sigma^s) \text{Cov}(\sigma_{g_l,t}^2, cv_{t,ij}),
\end{aligned}$$

$$\begin{aligned}
B_{i,s} = & k_{i,1} E(q_t) (\nu_\sigma^{s-1} \sum_{l=1}^2 A_{r_i,g_l} A_{i,\varphi} \varphi_{q_l} + \nu_q^{s-1} A_{r_i,q} A_{i,q} \varphi_q^2 + \nu_{cv}^{s-1} A_{r_i,cv,ij} A_{i,\varphi} \varphi_{cv,ij}) \\
& + k_{i,1} E(h_t) (\nu_\sigma^{s-1} \sum_{l=1}^2 A_{r_i,g_l} A_{i,\sigma_l} \varphi_{h,\sigma} + \nu_h^{s-1} A_{r_i,h} A_{i,h} \varphi_h^2),
\end{aligned}$$

and the model-implied moments entering the above expressions are given by,

$$E(q_t) = E(h_t) = \frac{\alpha_q}{1 - \nu_q}, \quad E(\sigma_{g_i,t}^2) = \frac{\alpha_\sigma \varphi_{q,i}}{1 - \nu_\sigma}, \quad E(\sigma_{g,t}^2) = \frac{\alpha_\sigma \sum \omega_i \varphi_{q,i}}{1 - \nu_\sigma}, \quad E(cv_{t,ij}) = \frac{\alpha_{cv}}{1 - \nu_{cv}},$$

$$\text{Var}(q_t) = \frac{\varphi_q^2 E(q_t)}{1 - \nu_q^2}, \quad \text{Var}(h_t) = \frac{\varphi_h^2 E(h_t)}{1 - \nu_h^2}, \quad \text{Var}(\sigma_{g_i,t}^2) = \frac{(\varphi_{q_i}^2 + \varphi_{h,\sigma}^2) E(q_t)}{1 - \nu_\sigma^2}, \quad \text{Var}(cv_{t,ij}) = \frac{\varphi_{cv,ij}^2 E(q_t)}{1 - \nu_{cv}^2},$$

$$\text{Cov}(\sigma_{g_i,t}^2, \sigma_{g_j,t}^2) = \frac{\varphi_{q,i} \varphi_{q,j} E(q_t)}{1 - \nu_\sigma^2}, \quad \text{Cov}(\sigma_{g_l,t}^2, cv_{t,ij}) = \frac{\varphi_{q_l} \varphi_{cv,ij} E(q_t)}{1 - \nu_\sigma \nu_{cv,ij}}.$$

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**Table 1 Simulated Size and  $R^2$** 

The table reports the simulated 95-percentiles in the finite sample distributions of  $t^{NW}$  and  $t^{HD}$  for testing the hypothesis that  $b_s(h) = 0$  based on the return predictability regression in equation (1), along with the adjusted  $R^2$  from the regression. The data are generated from the VAR-GARCH-DCC model discussed in the main text, restricting the coefficients in the conditional mean equation for the returns to be equal to zero. The “daily” return regressions are based on 2,954 observations, while the “weekly” and “monthly” regressions involve 598 and 149 observations, respectively. All of the simulations are based on a total of 2,000 replications.

$h$	$t^{NW}$	$t^{HD}$	$adj.R^2$	$h$	$t^{NW}$	$t^{HD}$	$adj.R^2$	$h$	$t^{NW}$	$t^{HD}$	$adj.R^2$
Daily				Weekly				Monthly			
20	2.445	2.182	3.036	4	2.434	2.212	2.971	1	2.260	2.276	3.017
40	2.602	2.112	4.804	8	2.600	2.078	4.800	2	2.520	2.187	4.837
60	2.815	2.085	5.756	12	2.805	2.016	5.790	3	2.788	2.083	5.774
80	2.969	2.107	6.324	16	2.967	2.031	6.345	4	2.941	2.106	6.315
120	3.054	2.152	7.639	24	3.095	2.098	7.615	6	3.220	2.124	7.502
180	3.289	2.171	8.594	36	3.322	2.113	8.482	9	3.314	2.163	8.192
240	3.400	2.229	8.951	48	3.476	2.146	8.682	12	3.509	2.186	8.679

**Table 2 Simulated Power**

The table reports the simulated power of the size-adjusted 5-percent  $t^{NW}$  and  $t^{HD}$  statistics for testing the null hypothesis of no predictability and  $b_s(h) = 0$  in the return regression in equation (1). The data are generated from the VAR-GARCH-DCC model discussed in the main text. The “daily” return regressions are based on 2,954 observations, while the “weekly” and “monthly” regressions involve 598 and 149 observations, respectively. All of the simulations are based on a total of 2,000 replications.

$h$	$pw^{NW}$	$pw^{HD}$	$h$	$pw^{NW}$	$pw^{HD}$	$h$	$pw^{NW}$	$pw^{HD}$
Daily			Weekly			Monthly		
20	0.919	0.873	4	0.910	0.852	1	0.886	0.807
40	0.888	0.808	8	0.877	0.799	2	0.845	0.762
60	0.804	0.725	12	0.793	0.729	3	0.768	0.711
80	0.710	0.630	16	0.709	0.639	4	0.686	0.627
120	0.567	0.474	24	0.553	0.481	6	0.507	0.497
180	0.375	0.352	36	0.371	0.352	9	0.368	0.350
240	0.288	0.283	48	0.285	0.289	12	0.277	0.302

**Table 3 Summary Statistics**

The monthly excess returns are in annualized percentage form. The variance risk premia are in monthly percentage-squared form. The “global” index of variance risk premium are defined in the main text. The sample period extends from January 2000 to December 2011.

**Panel A: Excess Returns and Variance Risk Premia**

	CAC 40		DAX 30		FTSE 100		Nikkei 225		SMI		S&P 500		Global Index
	$r_t - r_{f,t}$	$VRP_t$	$r_t - r_{f,t}$	$VRP_t$	$r_t - r_{f,t}$	$VRP_t$	$r_t - r_{f,t}$	$VRP_t$	$r_t - r_{f,t}$	$VRP_t$	$r_t - r_{f,t}$	$VRP_t$	$VRP_t$
Mean	-8.35	2.75	-4.73	4.68	-4.69	7.55	-7.44	12.32	-2.49	6.45	-2.88	7.40	7.54
Std. Dev	67.44	41.69	82.78	33.43	52.32	32.16	71.70	38.47	51.90	28.10	57.52	35.47	32.59
Skewness	-0.58	-4.84	-0.90	-2.83	-0.63	-5.56	-0.75	-4.88	-0.70	-3.25	-0.61	-4.71	-5.41
Kurtosis	3.60	41.98	5.50	15.98	3.55	50.72	4.65	42.71	3.50	23.86	3.93	35.55	47.00
AR(1)	0.13	0.30	0.09	0.10	0.06	0.34	0.13	0.16	0.27	0.14	0.15	0.39	0.36

**Panel B: Correlations for Excess Returns**

	CAC 40	DAX	FTSE 100	Nikkei 225	SMI	S&P 500
CAC 40	1.00	0.93	0.90	0.60	0.84	0.87
DAX		1.00	0.85	0.57	0.80	0.83
FTSE 100			1.00	0.62	0.80	0.88
Nikkei 225				1.00	0.58	0.64
SMI					1.00	0.78
S&P 500						1.00

**Panel C: Correlations for Variance Risk Premia**

	CAC 40	DAX	FTSE 100	Nikkei 225	SMI	S&P 500	Global
CAC 40	1.00	0.84	0.89	0.65	0.79	0.82	0.85
DAX		1.00	0.78	0.54	0.86	0.70	0.91
FTSE 100			1.00	0.73	0.84	0.88	0.65
Nikkei 225				1.00	0.60	0.64	0.82
SMI					1.00	0.69	0.82
S&P 500						1.00	0.89
Global							1.00

**Table 4 Country Specific Regressions**

The results are based on the monthly regression in equation (2).  $t^{NW}$ -statistics are reported in parentheses. The sample period extends from January 2000 to December 2011.

Index	Horizon	1	2	3	4	5	6	9	12
CAC 40	Constant	-9.00 ( -1.50)	-9.09 ( -1.51)	-9.17 ( -1.52)	-9.49 ( -1.54)	-9.47 ( -1.49)	-9.13 ( -1.42)	-8.33 ( -1.24)	-7.93 ( -1.15)
	$VRP_t^i$	0.24 ( 2.18)	0.22 ( 2.63)	0.22 ( 3.45)	0.22 ( 4.43)	0.18 ( 4.66)	0.13 ( 3.19)	0.05 ( 1.41)	0.04 ( 0.90)
	$Adj.R^2$	1.42	2.66	3.99	5.35	3.98	2.15	-0.15	-0.42
DAX 30	Constant	-4.82 ( -0.61)	-5.45 ( -0.71)	-5.42 ( -0.72)	-5.91 ( -0.81)	-6.01 ( -0.82)	-5.15 ( -0.69)	-4.09 ( -0.53)	-3.89 ( -0.50)
	$VRP_t^i$	0.02 ( 0.11)	0.17 ( 0.87)	0.18 ( 1.36)	0.25 ( 2.11)	0.25 ( 2.71)	0.16 ( 1.75)	0.08 ( 1.55)	0.11 ( 2.26)
	$Adj.R^2$	-0.71	0.16	0.70	2.62	3.21	1.06	-0.12	0.75
FTSE 100	Constant	-4.96 ( -1.03)	-5.44 ( -1.15)	-6.02 ( -1.33)	-6.43 ( -1.40)	-6.42 ( -1.36)	-6.09 ( -1.27)	-5.32 ( -1.07)	-5.05 ( -0.98)
	$VRP_t^i$	0.04 ( 0.35)	0.07 ( 0.95)	0.14 ( 3.12)	0.17 ( 4.09)	0.16 ( 3.95)	0.13 ( 2.31)	0.04 ( 1.01)	0.01 ( 0.29)
	$Adj.R^2$	-0.67	-0.40	1.43	3.44	3.18	2.05	-0.39	-0.74
Nikkei 225	Constant	-7.29 ( -1.09)	-7.79 ( -1.20)	-8.40 ( -1.29)	-8.23 ( -1.30)	-7.92 ( -1.25)	-7.32 ( -1.15)	-6.02 ( -0.91)	-5.42 ( -0.81)
	$VRP_t^i$	-0.01 ( -0.12)	0.02 ( 0.16)	0.10 ( 1.12)	0.12 ( 1.37)	0.11 ( 1.35)	0.09 ( 1.11)	0.02 ( 0.39)	0.02 ( 0.42)
	$Adj.R^2$	-0.71	-0.70	0.06	0.58	0.47	0.22	-0.66	-0.71
SMI	Constant	-2.68 ( -0.45)	-3.72 ( -0.64)	-3.96 ( -0.68)	-4.78 ( -0.84)	-5.21 ( -0.92)	-5.01 ( -0.88)	-4.39 ( -0.75)	-4.30 ( -0.71)
	$VRP_t^i$	0.03 ( 0.22)	0.12 ( 1.08)	0.14 ( 1.35)	0.22 ( 2.13)	0.24 ( 2.97)	0.20 ( 2.55)	0.13 ( 2.19)	0.12 ( 2.99)
	$Adj.R^2$	-0.69	-0.08	0.42	2.97	4.09	3.07	1.34	1.61
S&P 500	Constant	-6.58 ( -1.45)	-6.19 ( -1.32)	-6.27 ( -1.35)	-6.03 ( -1.24)	-6.11 ( -1.23)	-5.25 ( -1.03)	-4.05 ( -0.76)	-3.61 ( -0.66)
	$VRP_t^i$	0.50 ( 4.17)	0.38 ( 4.36)	0.37 ( 6.39)	0.34 ( 5.37)	0.30 ( 5.13)	0.20 ( 3.26)	0.06 ( 1.30)	0.03 ( 0.61)
	$Adj.R^2$	8.88	8.71	13.02	12.83	10.75	5.25	0.09	-0.53

**Table 5 “Global” Variance Risk Premium Regressions**

The results are based on the monthly regression in equation (3).  $t^{NW}$ -statistics are reported in parentheses. The sample period extends from January 2000 to December 2011.

Index	Horizon	1	2	3	4	5	6	9	12
CAC 40	Constant	-10.84 ( -1.78)	-10.94 ( -1.81)	-10.88 ( -1.81)	-11.05 ( -1.81)	-10.99 ( -1.73)	-10.11 ( -1.57)	-8.66 ( -1.30)	-8.00 ( -1.17)
	$VRP_t^{global}$	0.33 ( 2.88)	0.33 ( 3.36)	0.32 ( 5.50)	0.32 ( 6.91)	0.28 ( 4.94)	0.19 ( 2.85)	0.07 ( 1.47)	0.03 ( 0.67)
	$Adj.R^2$	1.84	3.86	5.42	7.15	6.06	2.90	-0.13	-0.65
DAX 30	Constant	-6.86 ( -0.93)	-7.07 ( -0.95)	-7.03 ( -0.97)	-7.26 ( -1.00)	-7.28 ( -0.97)	-6.01 ( -0.79)	-4.21 ( -0.54)	-3.57 ( -0.45)
	$VRP_t^{global}$	0.28 ( 2.20)	0.32 ( 2.21)	0.33 ( 4.51)	0.36 ( 6.16)	0.34 ( 3.52)	0.23 ( 2.14)	0.07 ( 1.06)	0.04 ( 0.69)
	$Adj.R^2$	0.53	2.28	3.93	6.26	6.34	2.76	-0.25	-0.59
FTSE 100	Constant	-6.06 ( -1.36)	-6.26 ( -1.39)	-6.51 ( -1.48)	-6.63 ( -1.46)	-6.78 ( -1.45)	-6.30 ( -1.32)	-5.42 ( -1.09)	-5.07 ( -0.99)
	$VRP_t^{global}$	0.18 ( 1.69)	0.17 ( 1.76)	0.20 ( 3.32)	0.20 ( 4.43)	0.20 ( 3.28)	0.15 ( 2.10)	0.05 ( 1.11)	0.01 ( 0.30)
	$Adj.R^2$	0.57	1.48	3.83	5.09	5.46	3.26	-0.13	-0.72
Nikkei 225	Constant	-8.59 ( -1.23)	-8.54 ( -1.27)	-8.88 ( -1.39)	-8.50 ( -1.35)	-8.24 ( -1.29)	-7.38 ( -1.15)	-5.81 ( -0.88)	-5.21 ( -0.79)
	$VRP_t^{global}$	0.15 ( 1.16)	0.13 ( 1.69)	0.23 ( 3.85)	0.23 ( 4.37)	0.20 ( 2.73)	0.14 ( 1.60)	0.01 ( 0.09)	0.00 ( 0.05)
	$Adj.R^2$	-0.23	-0.13	1.95	2.70	2.03	0.84	-0.75	-0.77
SMI	Constant	-3.78 ( -0.67)	-4.79 ( -0.87)	-5.15 ( -0.94)	-5.43 ( -0.98)	-5.67 ( -1.00)	-5.20 ( -0.91)	-3.95 ( -0.67)	-3.64 ( -0.60)
	$VRP_t^{global}$	0.17 ( 1.64)	0.24 ( 3.73)	0.27 ( 4.97)	0.29 ( 5.17)	0.27 ( 6.74)	0.21 ( 4.50)	0.06 ( 1.69)	0.03 ( 0.77)
	$Adj.R^2$	0.45	2.86	5.20	7.34	7.52	4.57	-0.12	-0.63
S&P 500	Constant	-6.42 ( -1.40)	-6.16 ( -1.31)	-6.37 ( -1.38)	-6.26 ( -1.32)	-6.19 ( -1.27)	-5.40 ( -1.08)	-4.22 ( -0.80)	-3.81 ( -0.70)
	$VRP_t^{global}$	0.47 ( 3.82)	0.37 ( 4.22)	0.38 ( 5.92)	0.35 ( 5.96)	0.31 ( 4.52)	0.22 ( 2.89)	0.09 ( 1.50)	0.05 ( 1.01)
	$Adj.R^2$	6.36	6.86	11.26	12.09	9.94	5.46	0.55	-0.08

**Table 6 Panel Regressions**

The results are based on the monthly “global” and country-specific panel regressions in equations (4) and (5), respectively. NW-based t-statistics are reported in parentheses. The sample period extends from January 2000 to December 2011.

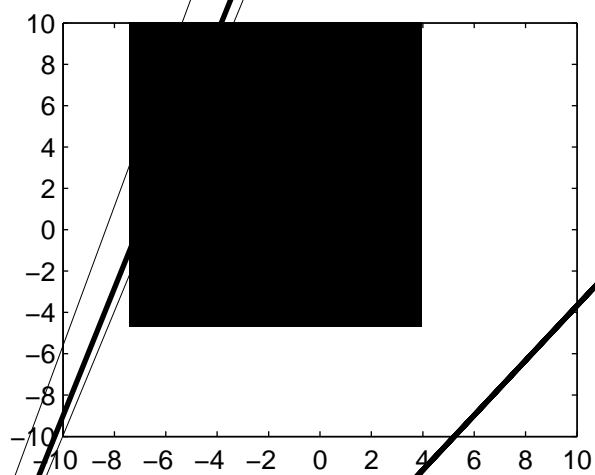
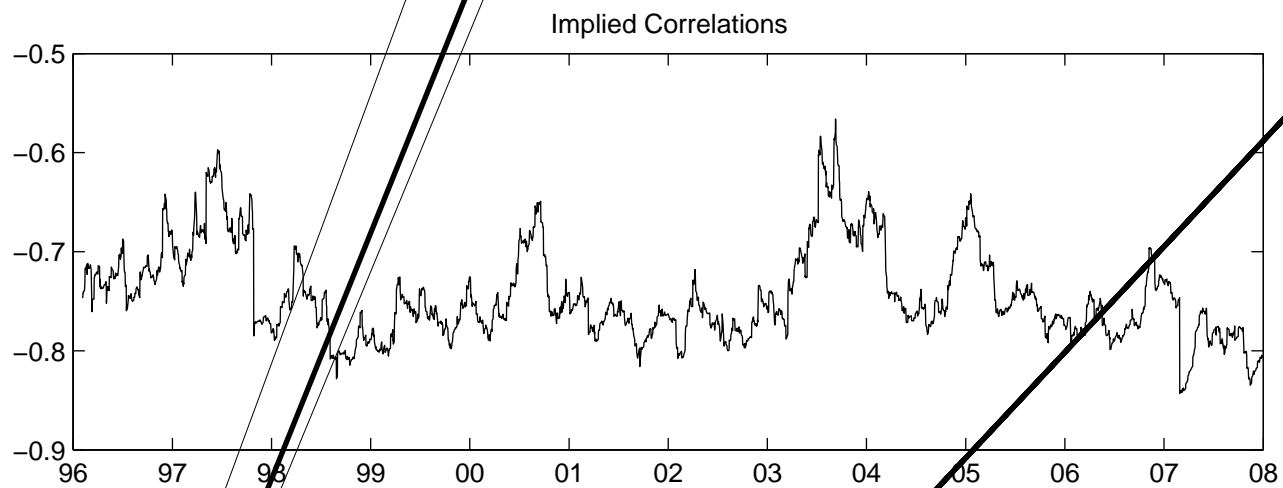
	“Global” Regressors							
Horizon	1	2	3	4	5	6	9	12
Constant	-7.09 ( -2.55)	-7.30 ( -2.70)	-7.47 ( -2.89)	-7.52 ( -2.89)	-7.52 ( -3.12)	-6.73 ( -2.95)	-5.38 ( -3.05)	-4.88 ( -3.42)
$VRP_t^{global}$	0.26 ( 4.15)	0.26 ( 5.79)	0.29 ( 6.78)	0.29 ( 8.72)	0.27 ( 7.35)	0.19 ( 5.59)	0.06 ( 2.20)	0.03 ( 1.07)
$Adj.R^2$	1.64	2.90	5.22	6.73	6.24	3.53	0.36	0.01
Constant	8.99 ( 0.34)	5.13 ( 0.23)	7.40 ( 0.33)	14.56 ( 0.67)	16.15 ( 0.72)	15.88 ( 0.77)	12.32 ( 0.77)	3.31 ( 0.31)
$VRP_t^{global}$	0.28 ( 4.70)	0.27 ( 7.61)	0.30 ( 8.63)	0.31 ( 10.94)	0.29 ( 9.66)	0.21 ( 7.93)	0.07 ( 3.12)	0.03 ( 1.34)
$\log(P_t/E_t)^{global}$	-7.38 ( -0.60)	-5.69 ( -0.54)	-6.81 ( -0.66)	-10.10 ( -1.02)	-10.81 ( -1.07)	-10.31 ( -1.11)	-8.05 ( -1.12)	-3.72 ( -0.82)
$Adj.R^2$	1.63	2.89	5.32	7.18	6.89	4.20	0.89	0.06
	Country-Specific Regressors							
Horizon	1	2	3	4	5	6	9	12
Constant	-6.14 ( -2.04)	-6.47 ( -2.15)	-6.62 ( -2.40)	-6.88 ( -2.64)	-6.87 ( -2.91)	-6.32 ( -2.79)	-5.38 ( -2.67)	-5.05 ( -2.98)
$VRP_t^i$	0.15 ( 3.12)	0.17 ( 3.40)	0.20 ( 5.25)	0.22 ( 6.97)	0.20 ( 5.46)	0.15 ( 3.94)	0.06 ( 2.09)	0.05 ( 1.98)
$Adj.R^2$	0.58	1.35	2.73	4.30	4.11	2.49	0.54	0.44
Constant	7.96 ( 1.30)	8.20 ( 1.34)	7.65 ( 1.25)	7.28 ( 1.29)	6.89 ( 1.40)	6.38 ( 1.28)	5.09 ( 1.35)	1.97 ( 0.67)
$VRP_t^i$	0.16 ( 3.88)	0.18 ( 4.44)	0.21 ( 6.67)	0.23 ( 8.99)	0.21 ( 6.44)	0.16 ( 4.54)	0.07 ( 2.82)	0.06 ( 3.14)
$\log(P_t^i/E_t^i)$	-6.86 ( -2.43)	-7.12 ( -2.71)	-6.92 ( -2.61)	-6.86 ( -2.79)	-6.66 ( -2.97)	-6.14 ( -2.82)	-5.05 ( -2.83)	-3.38 ( -2.28)
$Adj.R^2$	0.72	1.73	3.29	5.01	4.91	3.26	1.25	0.81

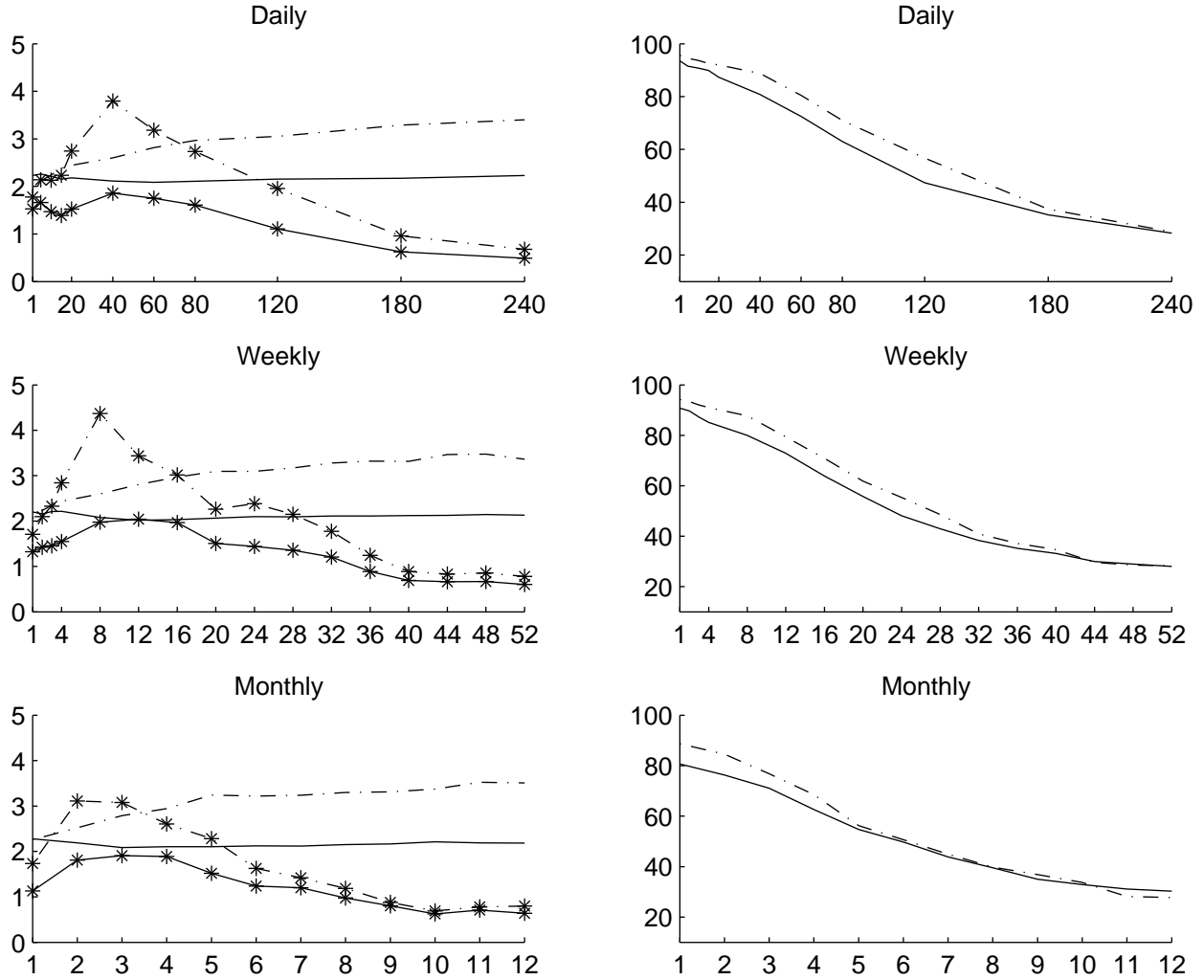
**Table 7 Panel Regressions with “Global” Forward VRP**

The results are based on the monthly “global” panel regression in equation (4) with  $FVRP_t^{global}$  in place of  $VRP_t^{global}$ . NW-based t-statistics are reported in parentheses. The sample period extends from January 2000 to December 2011.

Horizon	1	2	3	4	5	6	9	12
Constant	-8.92 ( -2.82)	-8.91 ( -3.12)	-8.45 ( -3.10)	-8.64 ( -3.34)	-9.05 ( -3.62)	-8.81 ( -3.88)	-7.15 ( -3.66)	-6.46 ( -3.55)
$FVRP_t^{global}$	0.38 ( 2.52)	0.36 ( 3.47)	0.32 ( 4.03)	0.34 ( 4.98)	0.39 ( 5.89)	0.37 ( 5.36)	0.23 ( 3.75)	0.18 ( 2.35)
$Adj.R^2$	1.84	3.01	3.47	4.79	7.28	7.93	4.08	3.32
Constant	9.67 ( 0.35)	6.05 ( 0.24)	6.20 ( 0.27)	14.05 ( 0.69)	22.14 ( 1.10)	24.65 ( 1.31)	20.14 ( 1.43)	10.19 ( 1.18)
$FVRP_t^{global}$	0.40 ( 2.84)	0.38 ( 4.37)	0.34 ( 5.25)	0.37 ( 7.83)	0.43 ( 8.92)	0.42 ( 7.74)	0.27 ( 6.33)	0.20 ( 3.59)
$\log(P_t/E_t)^{global}$	-8.59 ( -0.67)	-6.90 ( -0.60)	-6.75 ( -0.64)	-10.45 ( -1.12)	-14.35 ( -1.58)	-15.37 ( -1.81)	-12.50 ( -1.99)	-7.61 ( -2.08)
$Adj.R^2$	1.86	3.04	3.56	5.27	8.47	9.52	5.50	3.93

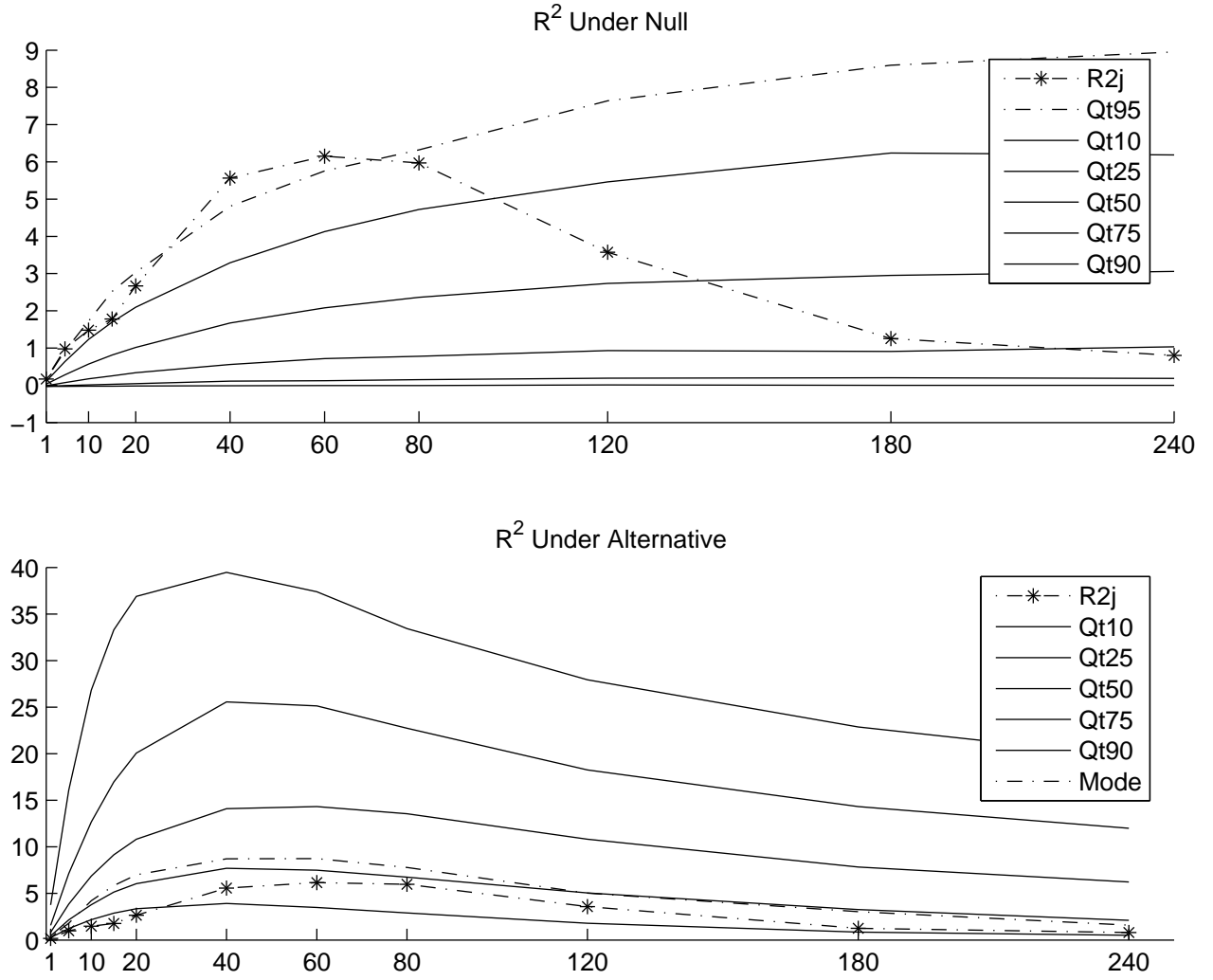






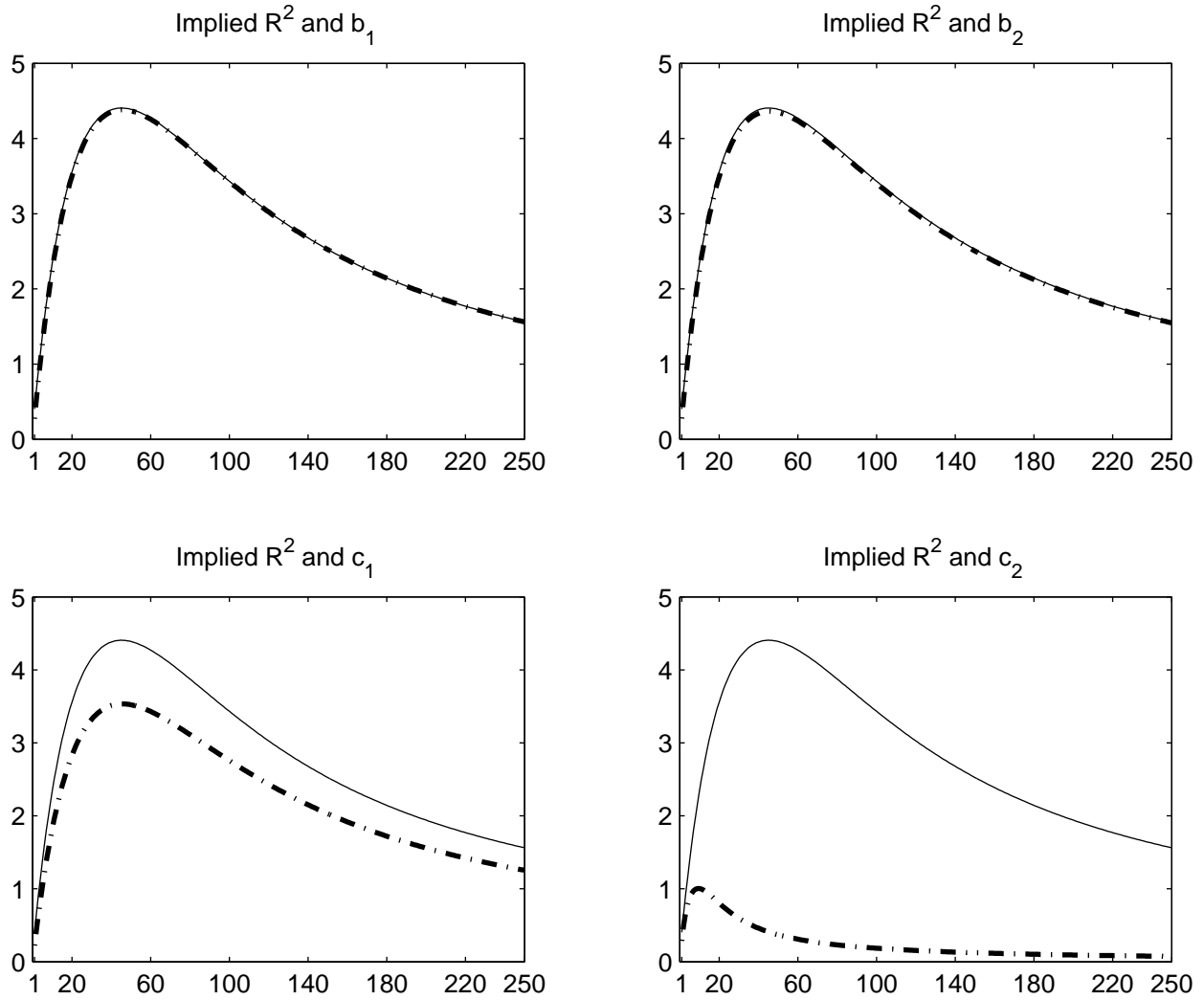
**Figure 2 Simulated Size and Power**

The upper left panel reports the 95-percentiles in the finite-sample distributions of the  $t^{NW}$  (dash line) and  $t^{HD}$  (solid line) based on simulated “daily” data from the restricted VAR-GARCH-DCC model under the null of no predictability. The dashed and solid star lines refer to the corresponding  $t$ -statistics for actual daily U.S. S&P 500 returns spanning February 1, 1996 to December 31, 2007. The middle and bottom two left panels give the results for the simulated “weekly” and “monthly” data, together with the results based on the actual weekly and monthly S&P 500 returns. The right three panels give simulated “daily,” “weekly” and “monthly” percentage power based on the unrestricted VAR-GARCH-DCC model and the size-adjusted 5-percent  $t^{NW}$  (dashed line) and  $t^{HD}$  (solid line) statistics.



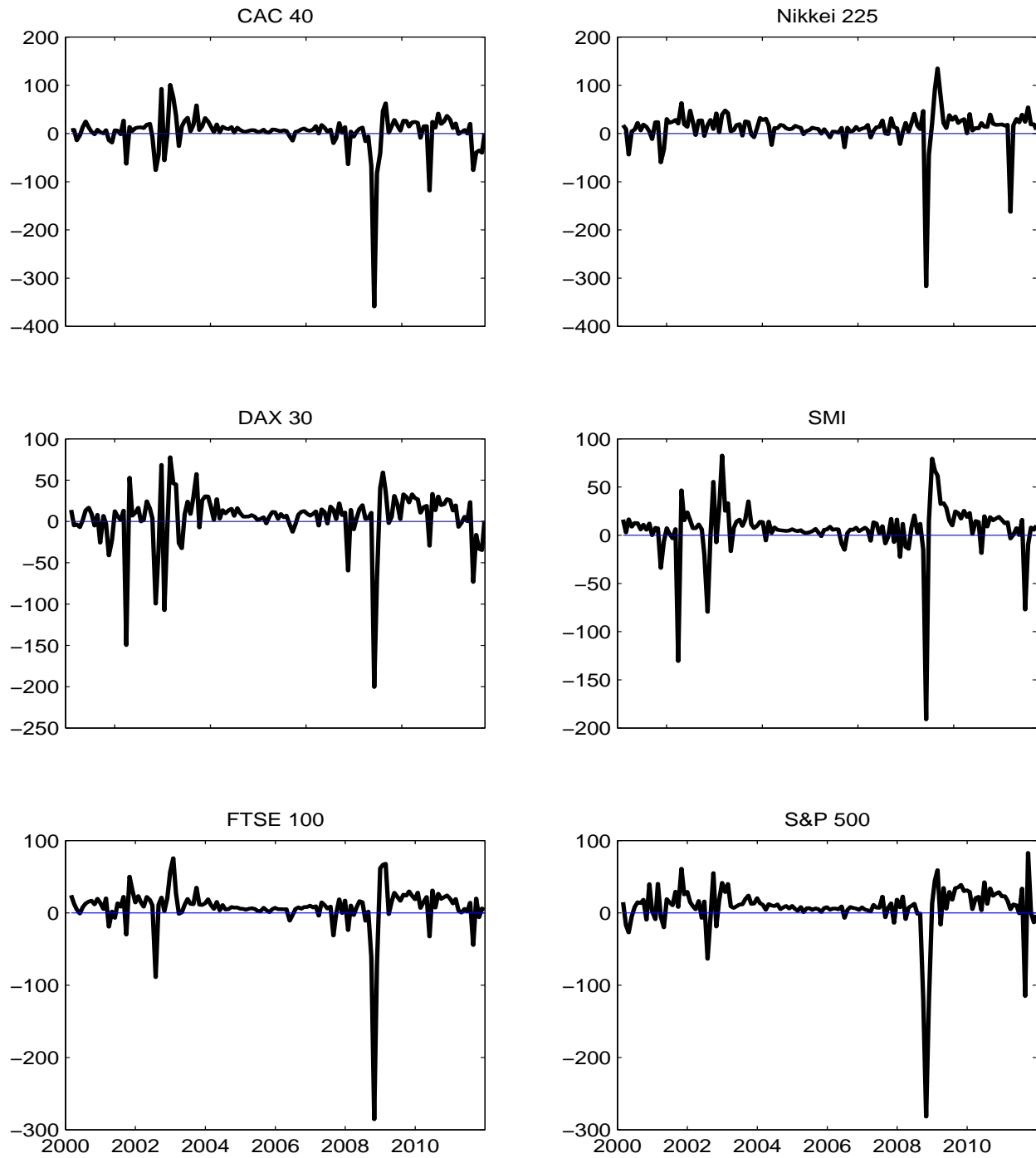
**Figure 3 Simulated  $R^2$**

The top panel in the figure plots the quantiles in the finite-sample distribution of the  $R^2$  from the return regression in equation (1) and simulated “daily” data from the restricted VAR-GARCH-DCC model under the null of no predictability. The star dashed line refer to the corresponding  $R^2$ ’s in actual daily U.S. S&P 500 returns spanning February 1, 1996 to December 31, 2007. The bottom panel reports the quantiles in the simulated finite-sample distribution based on the unrestricted VAR-GARCH-DCC model.



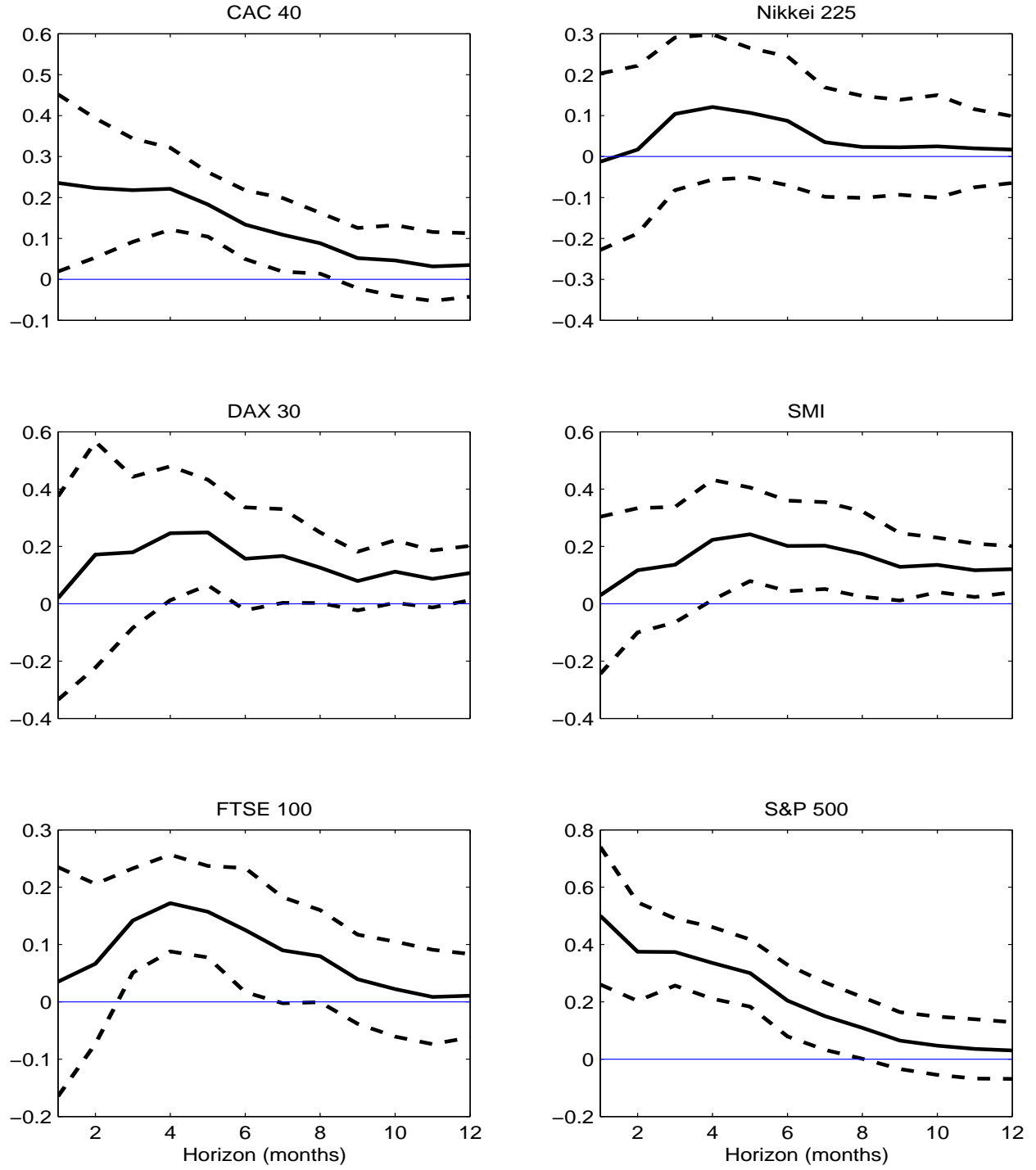
**Figure 4 Implied  $R^2$**

The solid lines in each of the four panels show the  $R^2(h)$ 's implied by the formula in Section 2.3 in the main text and the estimated unrestricted VAR-GARCH-DCC model. The dashed lines in each of the four panels show the implied  $R^2(h)$ 's for a 10-percent decrease in the values of the  $b_1$ ,  $b_2$ ,  $c_1$ , and  $c_2$  VAR coefficients, respectively.



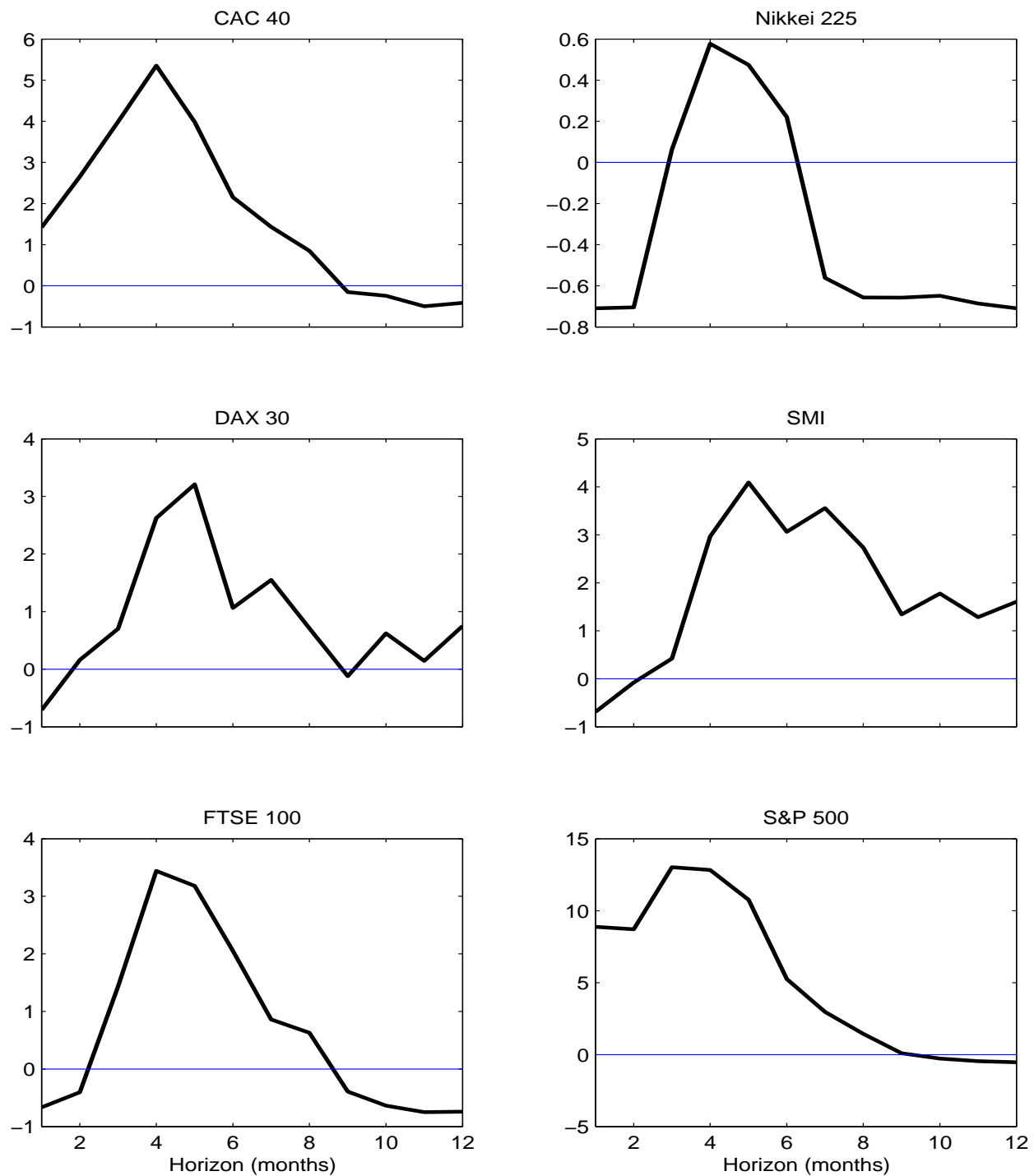
**Figure 5 Variance Risk Premia**

The figure shows the monthly proxies for the variance risk premia  $VRP_t^i$  for France (CAC 40), Japan (Nikkei 225), Germany (DAX 30), Switzerland (SMI 20), the U.K. (FTSE 100), and the U.S. (S&P 500). The risk premia are constructed by subtracting the actual realized variation from the model-free options implied variation. The sample period spans January 2000 to December 2011



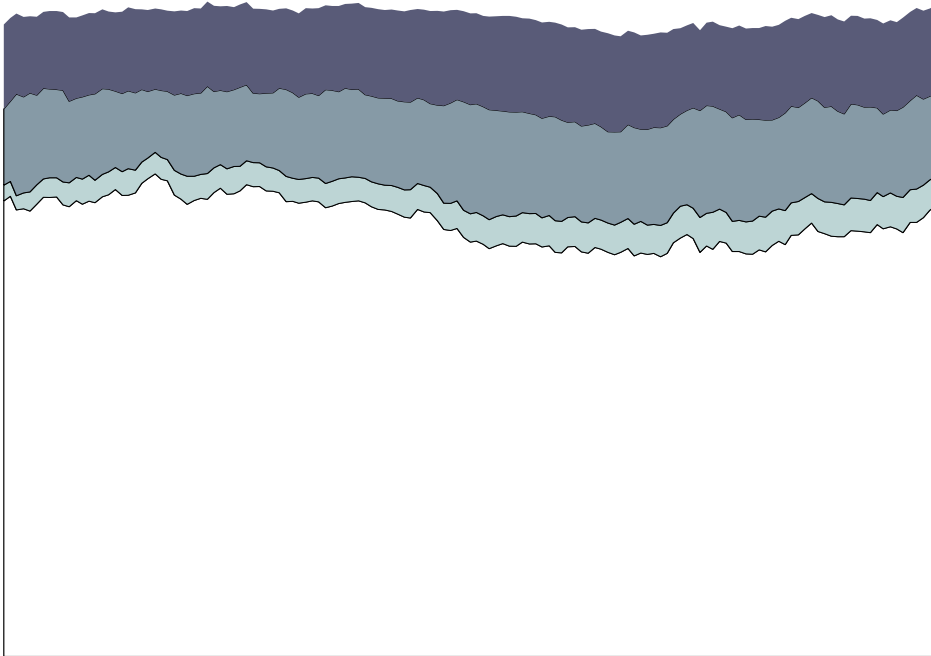
**Figure 6 Country Specific Regression Coefficients**

The figure shows the estimated regression coefficients for  $VRP_t^i$  for each of the country specific return regressions reported in Table 4, together with two NW-based standard error bands. The regressions are based on monthly data from January 2000 to December 2011.

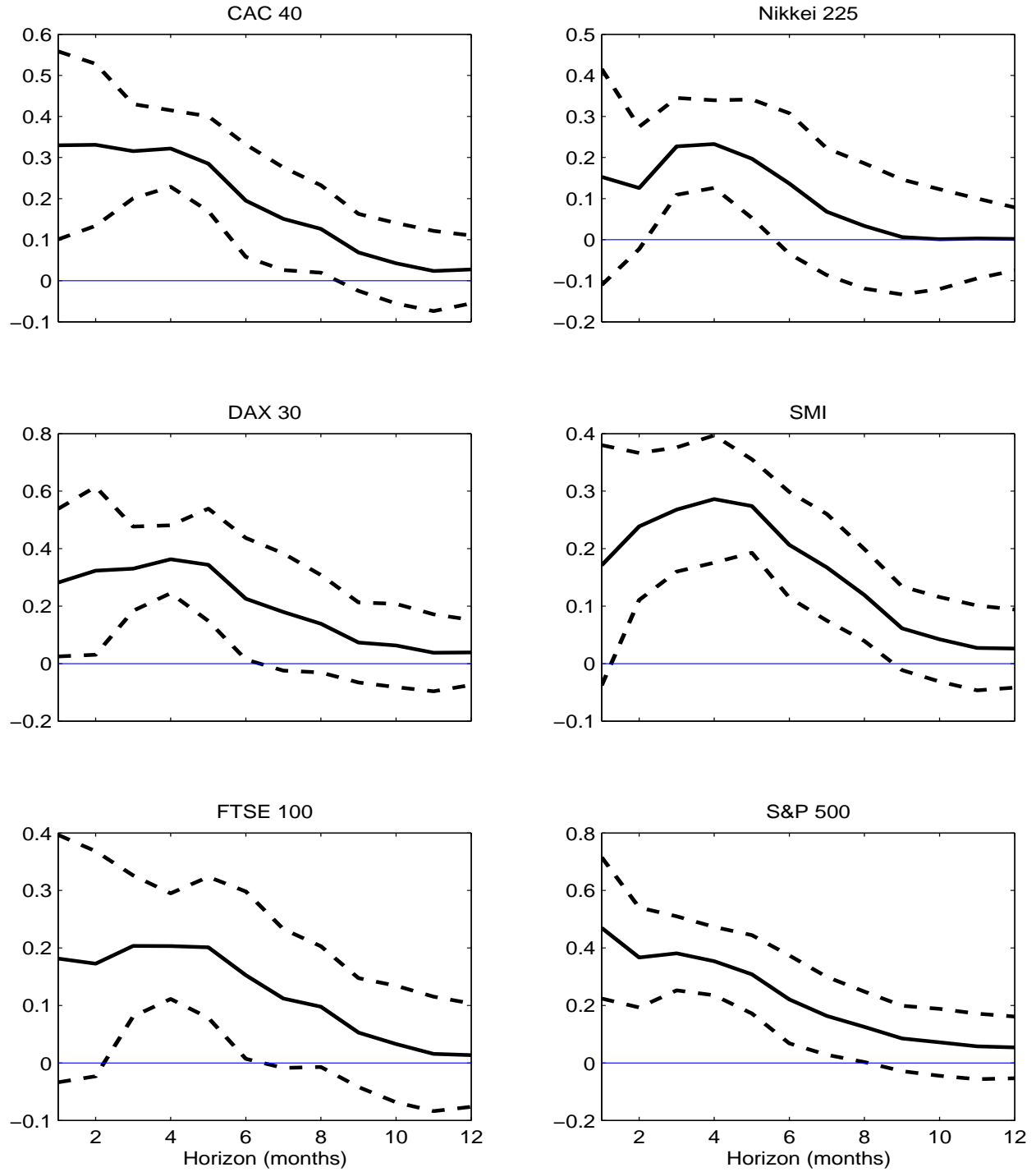


**Figure 7 Country Specific Regression  $R^2$ 's**

The figure shows the adjusted  $R^2(h)$ 's for the country specific return regressions reported in Table 4. The regressions are based on monthly data from January 2000 to December 2011.







**Figure 9 “Global” VRP Regression Coefficients**

The figure shows the coefficient estimates for  $VRP_t^{global}$  from the return regressions reported in Table 5, together with two NW-based standard error bands. The regressions are based on monthly data from January 2000 to December 2011.

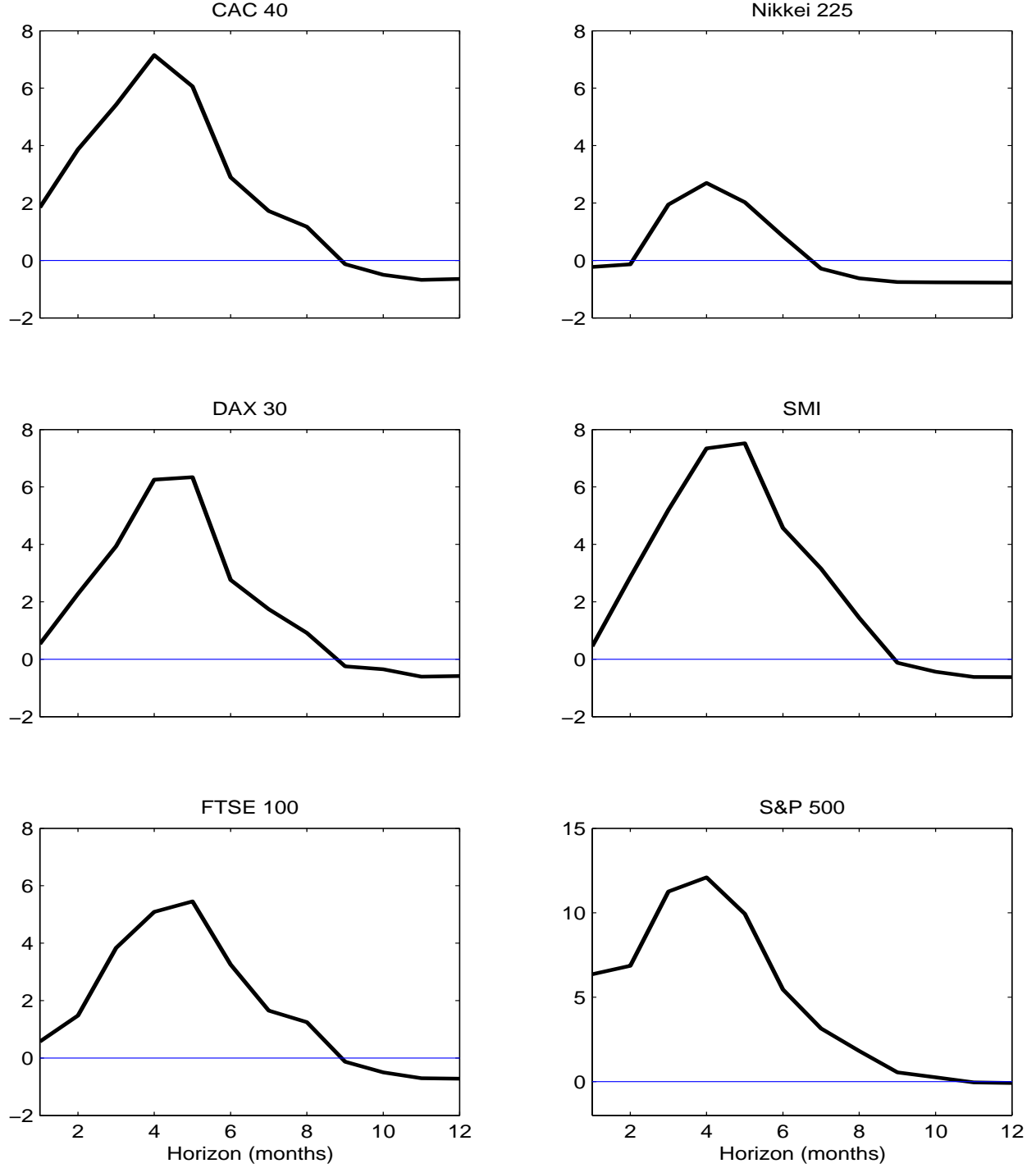
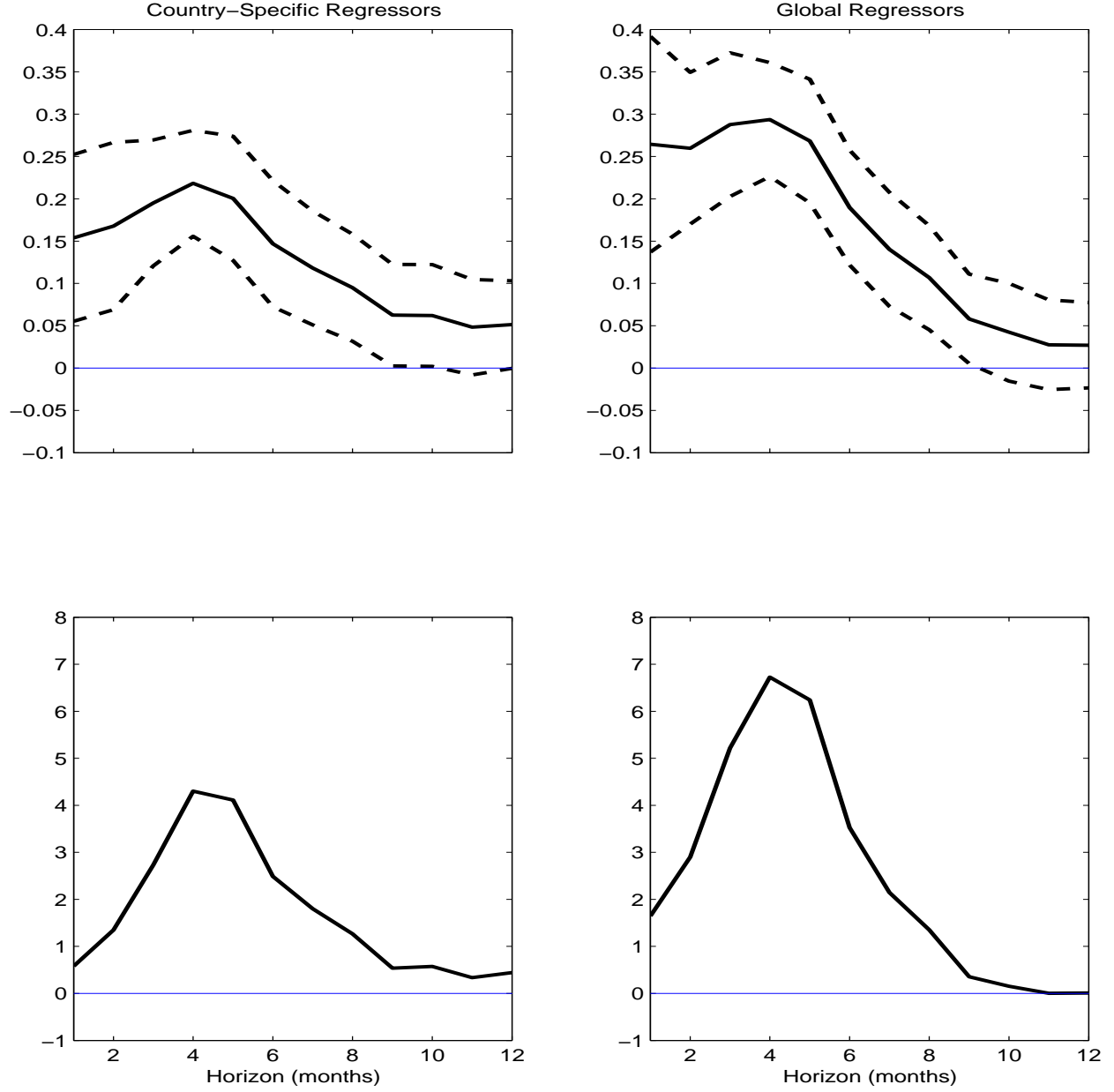


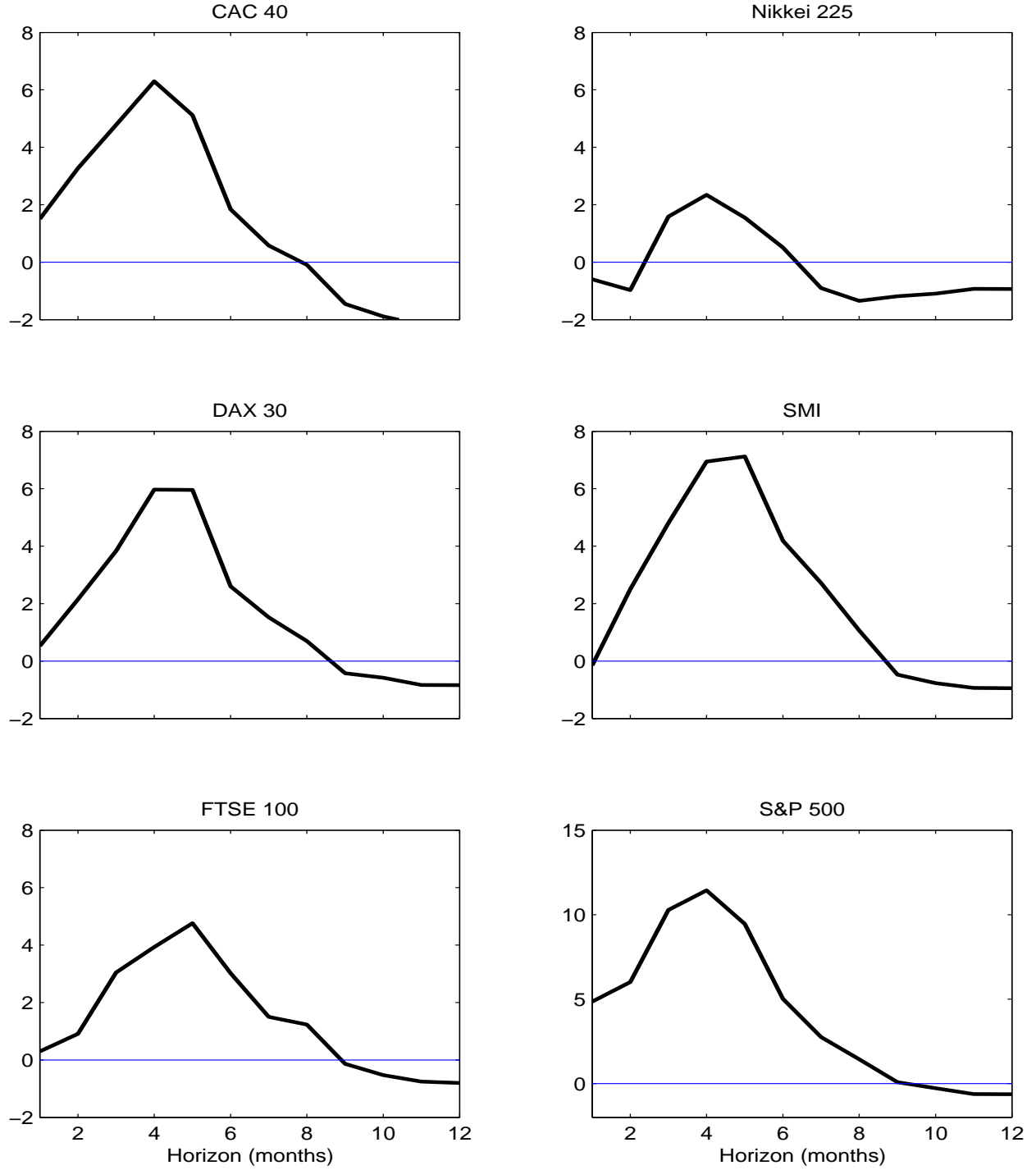
Figure 10 “Global” VRP Regression  $R^2$ 's

The figure shows the adjusted  $R^2(h)$ 's from regressing the individual country returns on  $VRP_t^{global}$  reported in Table 5. The regressions are based on monthly data from January 2000 to December 2011.



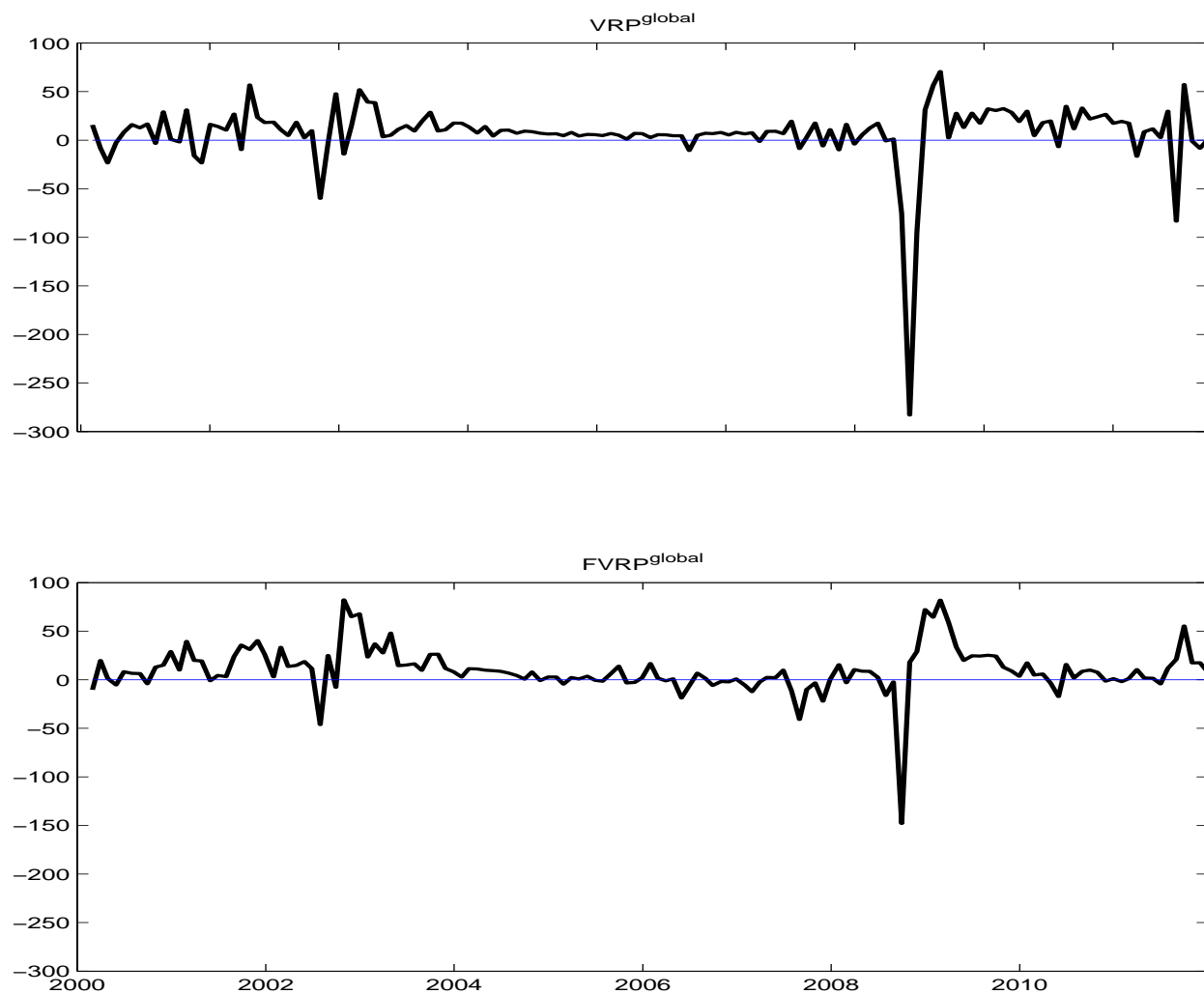
**Figure 11 Panel Regression Coefficients and  $R^2$ 's**

The top two panels show the estimated panel regression coefficients from regressing the returns on the individual country variance risk premia  $VRP_t^i$  and the “global” variance risk premium  $VRP_t^{global}$ , respectively, reported in Table 6, together with two NW-based standard error bands. The bottom two panels show the  $R^2(h)$ 's from the same two panel regressions. The regressions are based on monthly data from January 2000 through December 2011.



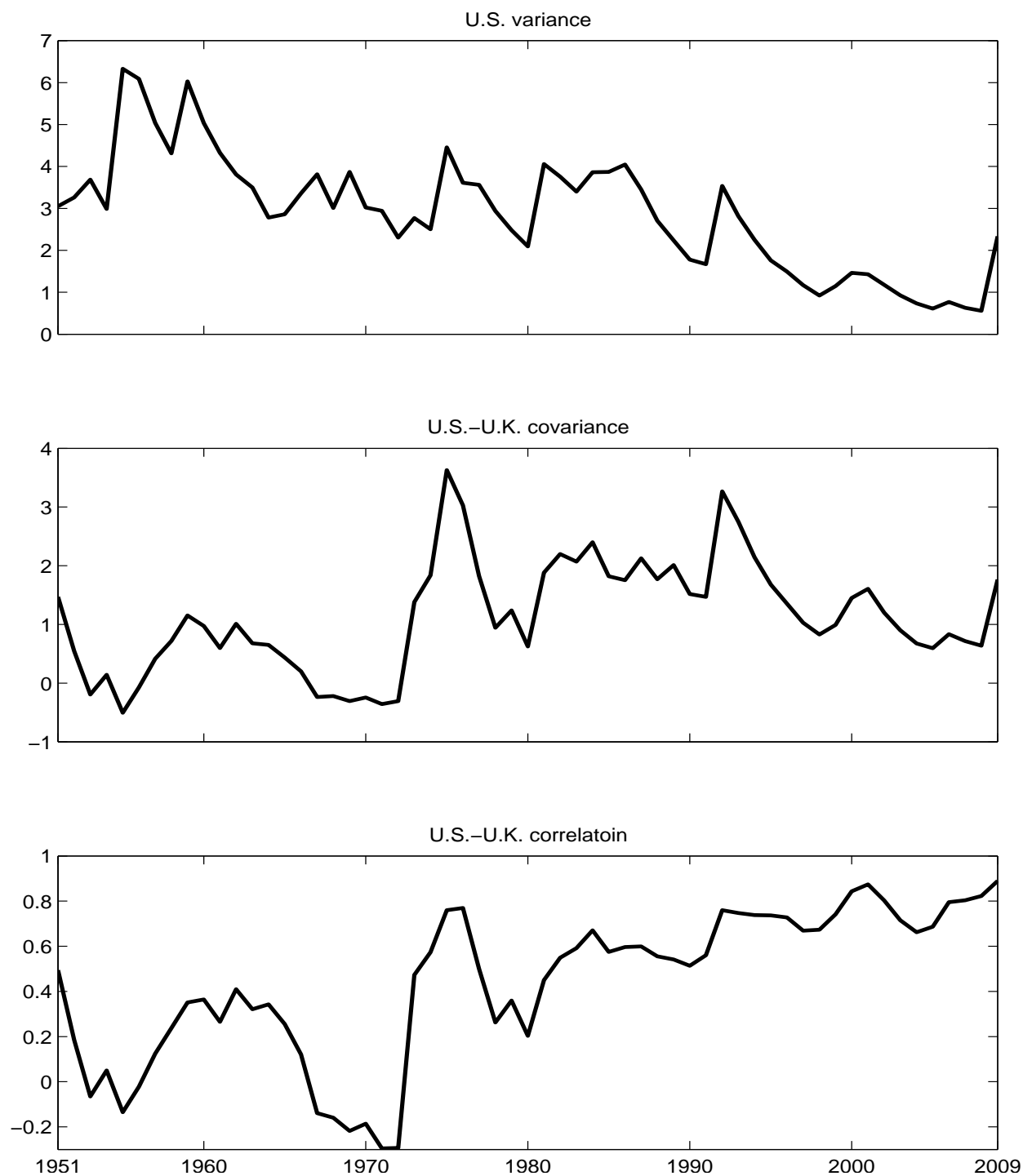
**Figure 12 “Global” VRP Panel Regression  $R^2$ 's**

The figure shows the adjusted  $R^2(h)$ 's implied by the  $VRP_t^{global}$  panel regressions reported in the top panel in Table 6. The regressions are based on monthly data from January 2000 to December 2011.



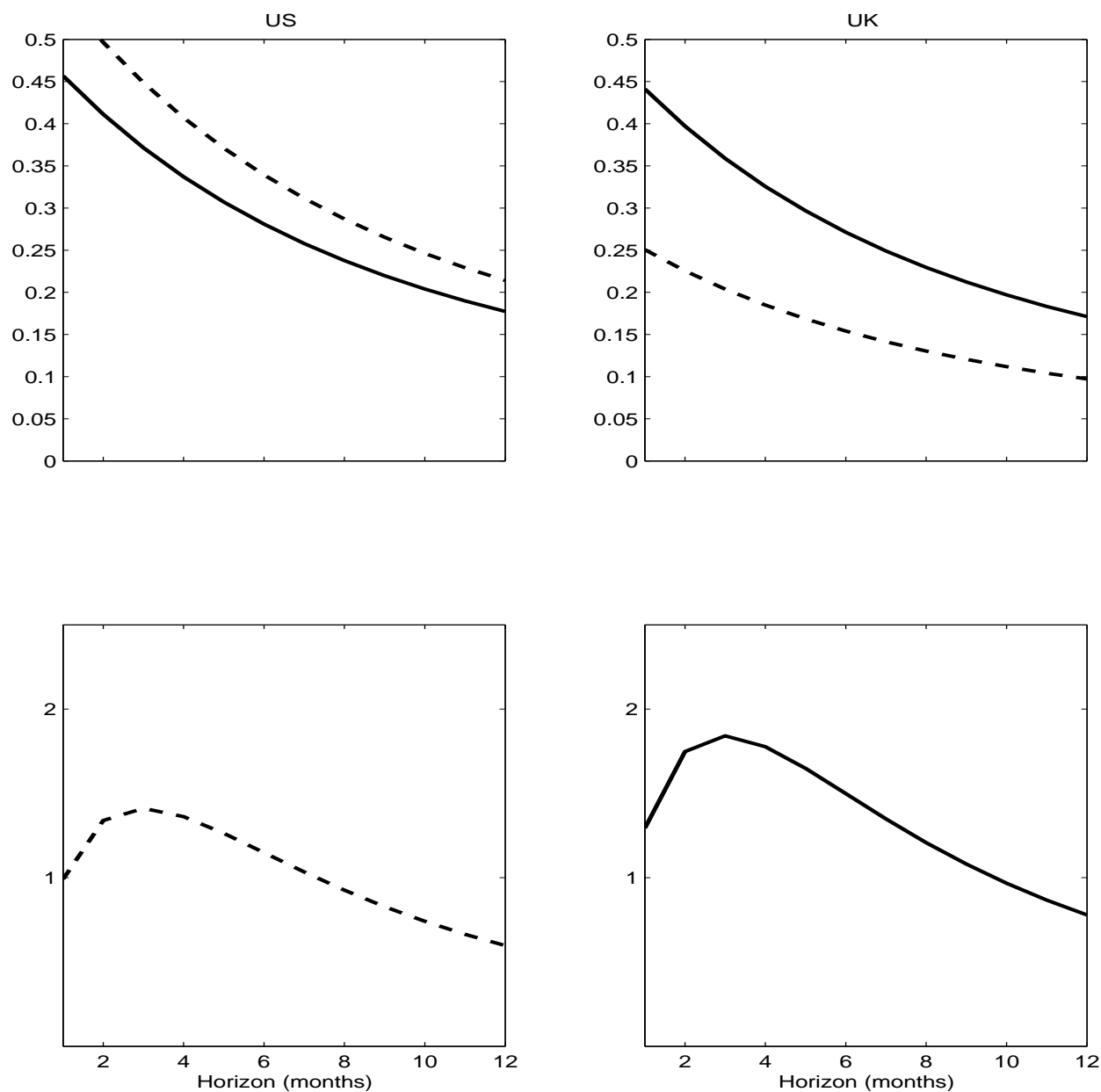
**Figure 13 Variance Risk Premia**

The figure shows our proxies for the monthly “global” variance risk premia  $VRP_t^{global}$  (top panel) and  $FVRP_t^i$  (bottom panel) as defined in the main text. The sample period spans January 2000 to December 2011



**Figure 14 Consumption Growth Variances, Covariances, and Correlations**

The figure shows exponentially weighted moving average estimates for U.S. consumption growth variances, and covariances and correlations with U.K. consumption growth. The estimates are based on annual total real consumption expenditures from 1951 to 2009, and a exponential smoothing parameter of  $\lambda=1 - (1 - 0.06)^4$ . The variances and covariances are both scaled by a factor of  $10^4$ .



**Figure 15 Equilibrium VRP Regression Coefficients and  $R^2$ 's**

The figure shows the implications from the calibrated stylized two-country general equilibrium model. The upper two panels plot the slope coefficients in the country specific regressions for each of the two countries based on the “local” VRP’s (dashed lines) and “global” VRP (solid lines). The lower two panels show the implied panel regression  $R^2$ ’s based on the “local” (dashed line) and “global” (solid line) VRP’s, respectively.