Forecasting International Equity Correlations

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An important component of asset allocation decisions is the future correlation structure of equity returns. Other studies have found that correlations change through time. Examination of the changing cross-country correlations in the G–7 countries provides clues as to why they change. Equity cross-correlations are related to the coherence between business cycles in the respective countries. Correlations are higher during recessions than during growth periods. Correlations are low when two countries' business cycles are out of phase. A semicorrelation metric differentiates equity comovements in bull and bear markets and provides a method for forecasting multiperiod equity correlations. Two applications are investigated: out-of-sample global portfolio allocation and derivative instruments.

Evidence suggests that U.S. equity market correlations with other G–7 countries have generally declined in recent years. How do we interpret this decline in correlation? Does it mean that future correlations will be lower? These are important questions because the structure of international equity correlations plays an important role in asset management.

At first inspection, the recent decline in equity correlations is somewhat surprising. The increasing globalization of capital markets during the past decade might lead us to expect higher, rather than lower, correlations. Increased globalization, however, or international market integration does not necessarily imply increased correlation between equity markets. Two countries may be completely integrated in that investors in both countries have unrestricted access to the two capital markets, but the industry mixes within each country may be sufficiently different to induce low equity correlation.

The change in correlations through time is linked to economic activity. For example, equity correlations are higher than usual if two countries are simultaneously in economic recession; they are lower when the two countries' business cycles are out of phase.

The coherence of real economic activity explains recent declines in correlations. For example, the United States fell into recession in 1990 and European countries followed in 1991 and 1992. The drop in the U.S. market correlation with Canada's market is likely a result of Canada entering a prolonged recession in 1989 and barely emerging by the end of 1993. In contrast, the official length of the U.S. recession, according to the National Bureau of Economic Research (NBER), was only five quarters. Thus, the international business cycles of the United States and both Canada and the European countries were out of phase by at least one year. This phase incongruity accounts for the lower equity market correlations between the United States and Canada and the United States and Europe. The correlations are also lower in common growth stages than in common recession stages.

We used semicorrelation analysis to examine whether correlations are different when the data are segmented by *ex post* return. This measure is constructed in the same way as the semivariance measure.[1] The semicorrelation analysis provides a measure of equity comovements in common up, common down, and mixed markets.

Understanding how correlation varies in different states of the world is important for predicting future correlation. We constructed models to forecast one-year through five-year correlations that explicitly take into account variables that proxy for expected economic activity (phase of the business cycle), expected stock returns, and persistence in correlations. An analysis of quantitative asset allocation indicates that using forecasted correlations, rather than a naive historical measure,

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will change allocation weights. This finding has implications for the valuation of derivative securities.

EQUITY CORRELATIONS IN DIFFERENT MARKET PHASES

In Sharpe's discussion of standard deviation, he remarks:[2]

> But why count happy surprises—those above the expected value—at all in a measure of risk? Why not just consider the deviations below the expected return? Measures that do so have much to recommend them. But if a distribution is symmetric, the results will be the same, since the left side is a mirror image of the right! And in general, a list of portfolios ordered on the basis of "downside risk" will differ little if at all from one ordered on the basis of standard deviation.

This same observation can be applied to correlation. If returns are drawn from symmetric distributions, correlations in up markets and down markets should be indistinguishable from each other. A long history of research reaching back to Fama, however, suggests that stock returns are not symmetric. Recent evidence presented for U.S. stocks by Richardson and Smith, for developed equity markets by Harvey and Zhou, and for emerging market assets by Harvey suggest that return distributions are not symmetric.[3]

Knowing how stocks will comove in different market scenarios is important for portfolio management. Indeed, Harlow and Rao and, later, Harlow showed that portfolios constructed so as to take asymmetry explicitly into account outperform the usual mean–variance portfolios.[4] In this regard, the usual measure of correlation represents average comovement in both up and down markets. Separate correlation estimates in different return environments permit detection of whether correlation increases or decreases in down markets. Increased correlation in down markets reduces the benefit of portfolio diversification.

Measuring correlation in up and down markets follows the insight of Sharpe; the subsequent work on semivariance by Bookstaber and Clarke, by Lewis, and by Josephy and Aczel; and the work on mean lower partial moments by Harlow and Rao and by Harlow.[5] For the present analysis, the measure of correlation is conditional on the realized return. That is, we calculated an unconditional correlation for months with below-average return (negative semicorrelation) and for months with above-average performance (positive semicorrelation).

Unlike volatility, correlation involves returns on two assets. This leads to a four-way classification of markets: up–up, down–down, up–down, and down–up. Trivially, the up–down and down–up, or mixed, states will deliver negative correlation. There is no statistical reason why the returns above the mean should have a different correlation from the returns below the mean, but we found that the correlations differ substantially.

The top section of Table 1 presents the returns-state analysis for U.S.-based correlations. The returns shown are U.S. dollar returns for the Morgan Stanley Capital International (MSCI) indexes from January 1970 through December 1993. For each of the other six G–7 countries, correlations with U.S. returns are higher in down–down states (negative semicorrelation) than in up–up or mixed states. The average negative semicorrelation is nearly double the positive semicorrelation. Some of the differences are dramatic. For example, the United States–German correlation is 9 percent in up–up states and 52 percent in down–down states.

The difference in state-based correlations is not just related to cross-equity correlations. The bottom line of Table 1 presents the semicorrelation analysis of two domestic (U.S.) assets: equities and long-term government bonds. Consistent with the equity analysis, the correlation of equities and bonds is more than double in negative-returns states.[6]

The asymmetry in the correlation structure is not being driven by the October 1987 observation. Many researchers (e.g., Roll[7]) have found that international correlations increased with the October 1987 crash. When this observation is removed from the data set, however, the average negative semicorrelation for the United States and the other G–7 countries (42 percent compared with 49 percent including the crash observation) is still well above the positive semicorrelation of 26 percent.

Based on the October 1987 observation, some researchers have argued that correlations increase in big down markets. We found the correlations to be generally higher in down markets, but the move down need not be big. The implication for portfolio management is clear. If a portfolio is formed based on average correlations, which implicitly assumes symmetry, the performance of the investment could be worse than expected in down markets because the correlations increase. The lesson is that portfolios need to be constructed on the basis of expected correlation rather than past averages.

Table 1. Semicorrelation in the G–7 Equity Markets

Asset Pair		Up–Up Returns Correlation	Down–Down Returns Correlation	Out-of-Phase Returns Correlation	Total Correlation
United States	Canada	54.0	60.6 [50.0]	−47.4	69.8
	France	26.6	48.3 [39.7]	−57.6	42.8
	Germany	8.6	52.3 [41.2]	−61.0	34.8
	Italy	10.5	31.2 [27.1]	−59.1	22.8
	Japan	21.0	41.2 [44.7]	−53.8	26.0
	United Kingdom	32.2	57.9 [47.3]	−60.1	50.2
	Average vs. 6	25.5	48.6 [41.6]	−56.4	41.1 [38.7]
Canada	France	16.7	49.2 [41.2]	−56.2	42.2
	Germany	−15.1	36.8 [26.0]	−58.6	30.5
	Italy	−10.0	33.4 [30.6]	62.7	29.9
	Japan	23.9	28.0 [26.7]	−52.2	27.6
	United Kingdom	33.1	56.0 [46.7]	−60.2	51.8
	Average vs. 6	17.1	44.0 [36.9]	−56.2	42.0 [39.8]
France	Germany	29.3	66.3 [63.0]	−53.0	60.0
	Italy	28.6	40.1 [38.6]	−69.9	45.1
	Japan	12.9	26.3 [24.7]	−53.4	40.2
	United Kingdom	41.6	54.3 [48.9]	−52.6	53.6
	Average vs. 6	25.9	47.5 [42.7]	−57.1	47.3 [45.7]
Germany	Italy	7.3	38.4 [36.5]	−62.1	38.6
	Japan	4.6	24.3 [21.9]	−46.9	39.7
	United Kingdom	21.7	40.2 [31.1]	−62.1	42.4
	Average vs. 6	9.4	43.1 [36.6]	−57.3	41.0 [38.9]
Italy	Japan	7.0	26.5 [25.5]	−55.9	39.7
	United Kingdom	10.1	40.7 [40.0]	−67.7	35.5
	Average vs. 6	8.9	35.2 [33.0]	−62.9	35.3 [34.1]
Japan	United Kingdom	12.2	20.9 [17.5]	−54.4	36.5
	Average vs. 6	13.5	27.9 [26.8]	−52.8	34.9 [34.1]
United Kingdom	Average vs. 6	25.2	45.0 [38.6]	−60.0	45.0 [43.3]
U.S. stocks	U.S. bonds	12.7	27.0	−59.6 [−59.5]	37.0 [41.9]

Notes: Semicorrelation measures the correlation in three states of the world: up–up (returns in both countries above the mean), down–down (returns in both countries below the mean), and out of phase (one country above the mean and the other below). Correlations are based on U.S. dollar returns on the MSCI total return indexes. The U.S. bond returns are a U.S. government bond portfolio reported by Ibbotson Associates. Correlations in brackets are calculated without the October 1987 observation. The sample is for January 1970–December 1993.

CORRELATION AND THE BUSINESS CYCLE

To understand and to forecast correlation, analysts must understand how correlation interacts with the business cycle. Correlation is linked to the business cycle because expected stock returns are linked to the business cycle. Research suggests that expected returns are high during recessions and low during recoveries. Thus, changing economic scenarios may influence the correlation structure.

Because correlation is a measure of the comovement of stock returns in two markets, business cycles in both markets may influence the correlation. Similar to the semicorrelation measure, correlations were classified into three business cycle categories: recession–recession, growth–growth, and out of phase.

The dating of the business cycles for the G–7 countries is problematic because only the United States (through the NBER) officially dates the peaks and troughs of business cycles. We used the "growth cycle" peaks and troughs from the Center for International Business Cycle Research (CIBCR) at Columbia University as a proxy for business cycle peaks and troughs. These are not, however, the same as the NBER's business cycle turning points for the United States. The CIBCR measure is designed to capture periods of above-average and of below-average growth.

The top section of Table 2 presents the business-cycle-induced variation in the correlations of returns for the other six G–7 countries with U.S. equity returns. The international cross-correlations are highest when both economies are contracting (down–down returns). Even the U.S. equity–U.S. bond correlation is higher during periods of below-average growth. International correlations are lowest in times when both economies are expanding (up–up returns). Correlations are also low when the business cycles are out of phase. For example,

Table 2. International Equity Markets' Correlations through Business Cycles

Asset Pair		Up–Up Returns Correlation	Down–Down Returns Correlation	Out-of-Phase Returns Correlation	Total Correlation
United States	Canada	73.7	71.2	62.4	69.8
	France	35.8	53.1	37.1	42.8
	Germany	2.4	49.2	35.8	34.8
	Italy	9.6	28.2	23.8	22.8
	Japan	27.2	20.3	39.5	26.0
	United Kingdom	45.9	54.8	38.0	50.2
	Average vs. 6	32.4	44.9	39.5	41.1
Canada	France	43.9	53.4	33.3	42.2
	Germany	3.9	40.2	35.6	30.5
	Italy	25.7	24.2	18.7	29.9
	Japan	18.4	24.2	35.4	27.6
	United Kingdom	55.3	56.9	38.8	51.8
	Average vs. 6	29.5	43.2	32.4	36.4
France	Germany	49.6	62.7	65.8	60.0
	Italy	43.5	23.0	66.4	45.1
	Japan	36.0	32.2	53.7	40.2
	United Kingdom	41.7	61.6	57.1	53.6
	Average vs. 6	42.9	46.7	55.3	47.3
Germany	Italy	44.5	27.7	46.3	38.6
	Japan	33.1	37.3	53.4	39.7
	United Kingdom	38.0	44.9	45.6	42.4
	Average vs. 6	28.6	43.6	47.1	41.0
Italy	Japan	25.7	43.2	55.1	39.7
	United Kingdom	42.9	31.2	39.8	35.5
	Average vs. 6	36.5	33.3	45.3	35.3
Japan	United Kingdom	37.6	35.9	39.6	36.5
	Average vs. 6	30.2	34.5	47.4	34.9
United Kingdom	Average vs. 6	43.6	47.6	43.2	45.0
U.S. stocks	U.S. bonds	39.6	43.4	—	41.9

Notes: Correlations are measured in three possible business cycle states: up–up (growth in both countries above the mean), down–down (growth in both countries below the mean), and out of phase (one country's growth above the mean and the other below). Correlations are based on U.S. dollar returns on the MSCI total return indexes. The U.S. bond return is based on a U.S. government bond portfolio reported by Ibbotson Associates. The growth cycle dates are from the CIBCR at Columbia University. The sample is for January 1970–December 1993.

the United States–United Kingdom correlation is 46 percent in expansions and 55 percent in recessions; in periods when growth in the two countries is out of phase, the correlation is 38 percent.

The relationship between correlation and economic growth is not just a phenomenon linked to U.S. returns. The other sections of Table 2 suggest that correlations are highest in joint recessions in all of the countries except for Italy, for which the difference between up–up and down–down correlations is not significant, perhaps because the dating of the growth cycles in Italy is the most problematic. The CIBCR estimates that Italy has had seven growth cycle recessions since 1969.

Indeed, all of these results could be sensitive to the way the CIBCR classifies the growth cycle. As a result of the definitions of above- and below-average growth, CIBCR classifies as many contractionary months as expansionary months. The contractionary months are not necessarily associated with recessions.

To assess the sensitivity of our analysis to the definition of up and down cycles, we replicated the top section of Table 2 using only the NBER turning points for the United States. As a result, the three-way classification based on the growth cycles of two countries is reduced to a two-way classification based on whether or not the United States is in recession.

The results, presented in Table 3, are consistent with the previous analysis. In U.S. recessions, the average U.S. equity correlation is 52 percent; in recoveries, the correlation falls to 36 percent (23 percent without the 1987 crash observation). These results reinforce the idea that correlation is related to the business cycle. They imply that the same forces that shape expected returns may affect correlations.

Table 3. The U.S. Business Cycle and International Equity Correlations

Asset Pair		Recovery Returns Correlation	Recession Returns Correlation	Total Correlation
United States	Canada	67.2	73.5	69.8
	France	37.1	54.8	42.8
	Germany	27.7	49.2	34.8
	Italy	14.7	42.5	22.8
	Japan	22.5	32.5	26.0
	United Kingdom	44.9	57.6	50.2
	Average vs. 6	35.7	51.7	41.1
U.S. stocks	U.S. bonds	41.1	44.4	41.9

Notes: Correlations are measured in two possible business cycle states: U.S. recovery and U.S. recession. Correlations are based on U.S. dollar returns on the MSCI total return indexes. The U.S. bond returns are based on the U.S. government bond return portfolio reported by Ibbotson Associates. The business cycle dates are from the NBER. The sample is for January 1970–December 1993.

IS CORRELATION CONSTANT?

Many researchers have confirmed that expected stock returns move with the business cycle (e.g., see Keim and Stambaugh, Campbell, and Fama and French[8]). Others have found justification for business-cycle-related influences in volatility measures (Black, Schwert, and Nelson[9]). No one, however, has linked the time variation in correlation to the phases of the business cycle.

Indeed, little is known about the stochastic properties of correlation measures. Kaplanis fit time-series models to rolling correlation measures of equities in 15 national markets.[10] Her tests suggested that correlation is not constant. Longin and Solnik estimated a multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model and imposed the null hypothesis that the correlation between equity markets is constant.[11] They rejected this model and concluded that correlation is not constant.

These studies have a number of differences and similarities. Kaplanis used a rolling measure of correlation, an *ex post* measure. For portfolio management over a given horizon, this measure directly relates to portfolio performance. In contrast, the Longin and Solnik GARCH model produces a measure of expected or conditional monthly correlation. Their estimation method imposes the assumption that the conditional monthly correlation is constant. Longin and Solnik also introduced instrumental variables designed to pick up time variation in the expected returns.[12]

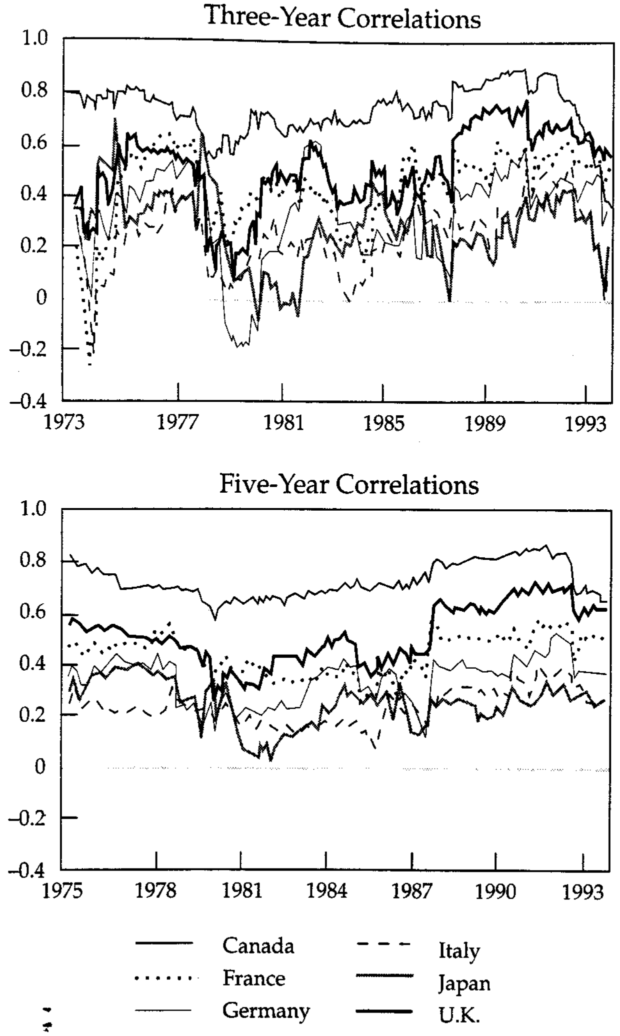
Although the Longin and Solnik model is very useful for testing the hypothesis that the correlations between markets are constant, how it can be used for forecasting correlation is not clear. Even if the model is modified to allow for time-varying conditional correlations, the forecast horizon is one month. Most portfolio managers are evaluated over a longer horizon.

The common feature of the Kaplanis and the Longin and Solnik analyses is that they both test—and reject—the hypothesis that the correlation between markets is constant, but neither investigates the reasons why correlation changes. An exploration of the reasons why correlations change through time is the foundation of our research. We borrowed aspects of both Kaplanis and Longin and Solnik. We retained Kaplanis's idea that the rolling *ex post* correlation is the measure best suited for portfolio management.[13] From Longin and Solnik, we adopted the instrumental variables approach to forecast correlations. That is, in contrast to the univariate time-series models explored by Kaplanis, we used a number of instrumental variables to forecast equity correlations.

As a preliminary analysis of the data, Figure 1 plots the correlation of U.S. equity returns with other G–7 countries' returns for three- and five-year horizons. Obviously, the five-year correlations are the smoothest because the longest moving average is used. Even with a 60-month moving average, however, inspection of these graphs suggests that correlation changes through time. The influence of the October 1987 observation is also obvious (by comparing the results when it enters the correlation calculation and when it is excluded). Furthermore, the correlations appear to be lower in recent years for a number of countries, even ignoring the effect of the crash observation.

Figure 2 graphs the five-year cross-correlations of the six non-U.S. G–7 countries. In each case, the correlations, although reasonably stable, exhibit distinct time variations. Two observations

Figure 1. Three- and Five-Year Rolling Correlations of U.S. with Other G–7 Returns



are noteworthy: (1) the correlation patterns are disrupted from 1979 to 1982, which coincides with the period of a worldwide recession; and (2) over the long term, the correlations appear to have been gradually increasing since 1982. For France, the correlations in 1982 ranged from 30–50 percent but had increased to 30–80 percent by 1993. In 1982, the German correlations ranged from 10–50 percent; by 1993, the correlation ranges had moved to 30–80 percent. The same is true for Italy: In 1982, the range of correlations was between 15 and 40 percent; the range increased to 25–55 percent by 1993. The U.K. correlations exhibited the same pattern as those in the continental European countries: In 1982, the range of correlations was between 30 and 55 percent; by 1993, the correlations were between 40 and 65 percent. Many of the increased correlations are probably the result of closer intra-European ties. For example, the correlation between French and German equities increased from 50 percent in 1982 to almost 80 percent in 1993.

The correlations for Japan with the other G–7 markets had no obvious trends. In 1982, the correlations ranged from 5 percent with the United States to 40 percent with Germany. Those correlations are now 25 percent and 55 percent, respectively. Over the entire sample period from 1975 on, however, the correlations have shown relatively little variation. Compared with the other G–7 countries, Japan has the lowest correlations with the other markets and the smallest range (low to high).

As in Japan, Canada's range of correlations has not moved much during the sample period. The United States–Canada correlation has actually decreased from 80 percent in 1975 to 60 percent in 1993. The Canada correlation with the United Kingdom also has dropped, from 60 percent to 40 percent. Interestingly, during a time of increased trading links with the United States (through the Canada–U.S. Trade Agreement and the North American Free Trade Agreement), the United States–Canada correlation has dropped in recent years—irrespective of the crash observation. This result illustrates the danger of using naive methods to forecast correlations. The decreasing correlation may be a function of the Canadian and U.S. business cycles being out of phase.

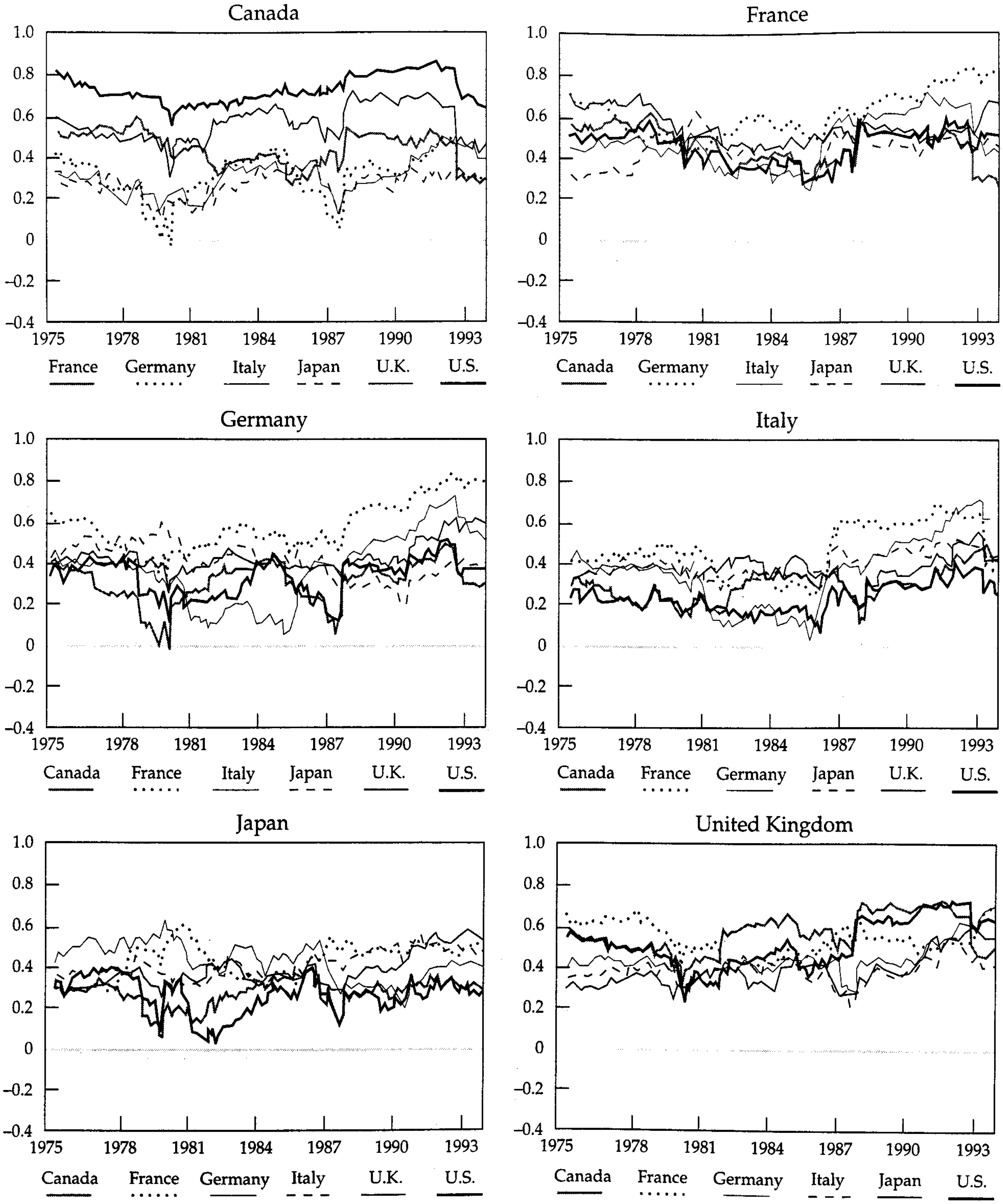
FORECASTING CORRELATIONS

The multivariate forecasting model we studied uses instrumental variables to forecast correlations measured over various horizons. The strategy is to preselect a set of variables designed to reflect persistence in correlation and business-cycle patterns. To minimize any data-snooping problems, we used the same types of variables for each country-pair correlation model; that is, we chose not to maximize the fit for each of the 21 correlation models.

The first instrumental variable is the lagged correlation. The lag length, of course, depends on the forecasting horizon; for example, for five-year correlations, the lag is 60 months. As a result, all of our instruments are strictly predetermined. Lagged correlation was used because of Kaplanis's results showing that correlations have strong mean-reverting behavior.

The next group of variables is linked to mean

Figure 2. Five-Year Rolling Cross-Equity Correlations of the G-7 Countries



reversion in expected returns. Fama and French documented serial correlation in returns over long horizons. The lagged multiperiod returns in both countries were used as regressors.

Fama and French also found that dividend yields can capture some of the time variation in expected returns in U.S. equity markets. Harvey extended this analysis to global equity markets and suggested using both local and U.S. dividend yields to help forecast country returns.[14] We followed this suggestion and added two dividend yields to the forecasting equation. The dividend yields are based on 12-month rolling sums of dividends divided by the most recent price level. These yields are from MSCI and are the same as those used in Harvey and in Ferson and Harvey.[15]

The final set of variables was designed to capture business cycle effects. A measure of the term structure of interest rates for each country was added to the forecasting regressions. Harvey showed that the U.S. term structure moves closely with and forecasts real economic activity.[16] Since 1970, every U.S. recession, including the most recent one, has been preceded by a term structure inversion.[17] Harvey extended this analysis to the G–7 countries.[18] The local term structure is able to forecast economic growth in six of the seven G–7 countries, but not in Japan. Harvey also found that the differences in two countries' term structures have the ability to forecast differences in their economic growth. Harvey's research suggests that term structures are ideal variables to pick up expectations of real economic growth in two countries. The term structures are constructed by taking the difference between long-term government bond yield and short-term bill or equivalent yield.

Before examining the forecasting results, two issues should be highlighted. First, the R^2 of the regressions should increase with the horizon. As the horizon increases, the degree of moving average applied to the data increases, thus reducing the variance. Second, as a result of the overlapping observations, conventional standard errors will be incorrect. All of our regression results have t-statistics that are robust to the serial correlation in the errors induced by the overlap and by any conditional heteroscedasticity that might exist in the data.[19]

FORECASTING RESULTS

Table 4 presents the regression results for the U.S. equity correlations for one-, three- and five-year horizons. The discussion will focus on the five-year correlations. The first insight is that a univariate model—correlation as a function of its own lagged value—is misspecified. In all of the regressions, variables other than the lagged correlation help predict future correlation. For some countries (United States–United Kingdom and United States–Germany), the lagged correlation does not enter the regression with a significant coefficient when the other variables are included. The lagged correlation, however, is an important predictor variable for the correlations of the United States with the other four countries. Lagged correlation is the most important predictor in Japan. This finding is not unexpected given the persistence and stability evident in Figure 2.

We also estimated univariate models that included only the lagged correlation measure. These models were most successful for Japan (R^2 = 34 percent), France (R^2 = 19 percent), Canada (R^2 = 12 percent), and Italy (R^2 = 12 percent). Nevertheless, the multivariate model, for which results are presented in Table 4, explains much more of the variation than do the univariate models. For the above four countries, the R^2s from the multivariate regressions are 72 percent, 78 percent, 88 percent, and 78 percent, respectively. Obviously, additional variables are needed to forecast correlation successfully.

Lagged returns are almost always important in predicting correlations. Both lagged returns enter the regressions significantly in three countries (United Kingdom, Italy, and Canada) and the lagged U.S. return enters the regressions of all other countries except Italy. The average t-ratio on the lagged U.S. return is higher than 6.0 in these regressions.

The inclusion of the term structure variables adds to the explanatory power of the regressions. The lagged U.S. term structure is significantly different from zero in all countries except the United Kingdom and Canada. The U.S. term structure enters the regressions for Germany, Japan, and France with coefficients more than four standard errors from zero. The local term structure is somewhat less successful. This country-specific term structure measure is important for Japan, Germany, and Canada.

Another way to gauge the importance of the term structure variables is to reestimate the regressions and include only the term structure variables. Under these circumstances, the explanatory power (R^2) of these variables is impressive in many countries: United Kingdom, 53 percent; Japan, 19 percent; Italy, 24 percent; Germany, 2 percent; France, 33 percent; and Canada, 20 percent.

The final variables examined are the dividend yields. These variables are designed to proxy for expected returns in the two countries. The dividend yield has been identified as a predictor of asset returns. In the regression results in Table 4, the dividend yields are an important explanatory variable. The local yield is important in predicting correlations in the United Kingdom and Germany. The U.S. dividend yield is important in France, Germany, and Italy.

No attempt has been made to maximize the fit

Table 4. Forecasting Multiperiod Correlations: U.S. Returns versus Other G-7 Countries

Country Pair		Intercept	Lagged Correlation	Lagged Foreign Return	Lagged U.S. Return	Lagged Foreign Dividend Yield	Lagged U.S. Dividend Yield	Lagged Foreign Term Spread	Lagged U.S. Term Spread	Adjusted R^2
One-year correlations										
United States	Canada	0.588	0.259	0.011	−0.234	−0.068	0.049	−0.011	−0.015	0.127
		[1.18]	[0.88]	[0.05]	[−0.99]	[−0.87]	[0.93]	[−0.56]	[0.50]	
	France	0.885	−0.354	−0.090	−0.061	−0.107	0.062	0.017	−0.025	0.338
		[5.23]	[−3.37]	[0.93]	[−0.41]	[−0.414]	[1.26]	[0.81]	[−1.19]	
	Germany	0.820	−0.032	−0.122	0.394	0.107	−0.207	0.013	−0.094	0.253
		[3.24]	[−0.20]	[−0.89]	[1.21]	[0.98]	[−1.98]	[0.61]	[−3.95]	
	Italy	0.850	−0.161	0.005	−0.285	−0.023	−0.095	0.002	−0.058	0.086
		[2.21]	[0.90]	[0.10]	[−1.43]	[−0.41]	[−1.52]	[0.05]	[−1.55]	
	Japan	0.911	−0.194	−0.102	0.121	0.129	−0.173	0.041	−0.062	0.183
		[2.65]	[−1.03]	[−0.57]	[0.38]	[1.13]	[−1.87]	[0.90]	[−1.79]	
	United Kingdom	1.193	−0.170	0.133	−0.036	−0.054	−0.066	−0.035	−0.050	0.359
		[3.90]	[−1.36]	[1.17]	[−0.19]	[−0.97]	[−1.48]	[−3.22]	[−2.79]	
Three-year correlations										
United States	Canada	0.689	−0.107	0.043	0.646	−0.018	0.017	0.004	0.011	0.448
		[3.31]	[−0.57]	[0.19]	[3.89]	[−0.67]	[0.99]	[0.39]	[1.70]	
	France	0.700	−0.192	−0.167	0.338	−0.038	0.000	−0.017	0.017	0.607
		[5.37]	[−1.49]	[−1.83]	[2.38]	[−2.80]	[0.01]	[−1.68]	[2.79]	
	Germany	0.647	−0.496	0.265	0.171	−0.029	−0.013	−0.051	0.004	0.503
		[3.09]	[−3.43]	[2.16]	[0.77]	[−0.74]	[−0.27]	[−2.10]	[0.41]	
	Italy	0.626	−0.468	−0.054	0.558	−0.024	−0.063	0.013	0.016	0.442
		[3.14]	[−3.68]	[−0.89]	[1.99]	[−1.44]	[−2.15]	[1.63]	[1.47]	
	Japan	0.542	−0.692	0.086	−0.655	−0.044	−0.009	−0.019	0.022	0.492
		[6.51]	[−8.25]	[0.68]	[−2.50]	[−1.37]	[−0.44]	[−0.78]	[2.97]	
	United Kingdom	0.712	−0.176	0.332	0.339	−0.025	−0.019	−0.023	0.014	0.692
		[2.97]	[−1.94]	[2.05]	[1.24]	[−0.49]	[0.94]	[−4.15]	[1.90]	
Five-year correlations										
United States	Canada	1.211	−0.758	−0.393	0.884	0.003	−0.005	0.007	0.004	0.875
		[5.84]	[−3.03]	[−4.93]	[13.13]	[0.65]	[−0.65]	[2.30]	[1.30]	
	France	0.613	−0.275	−0.024	0.417	−0.011	−0.016	0.005	0.013	0.781
		[9.82]	[−4.19]	[−0.54]	[3.24]	[−1.98]	[−2.66]	[1.03]	[6.34]	
	Germany	−0.034	0.062	0.235	1.337	−0.025	0.057	0.023	−0.015	0.719
		[−0.32]	[0.83]	[1.92]	[16.72]	[−3.14]	[2.71]	[7.55]	[−4.27]	
	Italy	0.424	−0.505	0.184	0.242	0.003	−0.029	0.003	0.006	0.775
		[6.90]	[−6.28]	[2.80]	[1.83]	[−0.23]	[−4.50]	[0.95]	[2.01]	
	Japan	0.386	−0.324	−0.000	0.314	−0.018	−0.009	−0.020	−0.018	0.719
		[4.47]	[−4.78]	[−0.00]	[3.02]	[−1.80]	[−0.68]	[−2.30]	[−6.04]	
	United Kingdom	0.337	0.134	−0.408	1.681	−0.039	0.045	−0.006	0.004	0.817
		[1.33]	[0.85]	[−3.32]	[3.36]	[−2.17]	[1.82]	[−0.85]	[0.91]	

Notes: Rolling multiperiod correlations are based on annualized U.S. dollar returns on the MSCI total return indexes over three different time horizons. The predictor variables are the lagged correlation, the lagged returns, dividend yields, and term structures (long government yield minus short-term Treasury bill or equivalent) in each country. The predictor variables are lagged by the forecast horizon. That is, the 60th lag is used to forecast the five-year correlations. The sample is for January 1970–December 1993.

of the individual models. One concern in doing so was that the number of variables (eight) in each regression is high compared with the number of nonoverlapping correlations. We pursued (but do not report) a more parsimonious specification that uses the lagged correlations and the difference between the local and U.S. returns, dividend yields, and term structures. This model has few parameters and also reduces the multicollinearity between predictor variables. The R^2s, however, are lower because the local and U.S. parameters were restricted. For the five-year regressions, the restricted (unrestricted, from Table 4) R^2s are: Canada, 62 percent (88 percent); France, 54 percent (78 percent); Germany, 16 percent (72 percent); Italy, 65 percent (78 percent); Japan, 38 percent (72 percent); and the United Kingdom, 62 percent (82 percent).

Table 5 summarizes the predictive regressions for the other cross-equity correlations for the one-,

Table 5. Summary of Cross-Equity Correlations Forecast Precision

Country	United States	Canada	France	Germany	Italy	Japan
One-year correlations						
Canada	0.127					
France	0.338	0.218				
Germany	0.253	0.290	0.504			
Italy	0.085	0.321	0.181	0.224		
Japan	0.183	0.213	0.219	0.213	0.112	
United Kingdom	0.358	0.233	0.251	0.335	0.110	0.154
Three-year correlations						
Canada	0.449					
France	0.606	0.443				
Germany	0.503	0.675	0.658			
Italy	0.441	0.656	0.416	0.646		
Japan	0.492	0.497	0.555	0.485	0.594	
United Kingdom	0.692	0.654	0.691	0.509	0.344	0.494
Five-year correlations						
Canada	0.875					
France	0.781	0.486				
Germany	0.719	0.772	0.703			
Italy	0.775	0.803	0.730	0.897		
Japan	0.719	0.705	0.692	0.757	0.752	
United Kingdom	0.817	0.434	0.470	0.625	0.693	0.718

Notes: R^2s are adjusted for degrees of freedom. Rolling multiperiod correlations are based on annualized U.S. dollar returns on the MSCI total return indexes during three different time horizons. The predictor variables are the lagged correlation, the lagged returns, dividend yields, and term structures (long government yield minus short-term Treasury bill or equivalent) in each country. The predictor variables are lagged by the forecast horizon. That is, the 60th lag is used to forecast the five-year correlations. The sample is for January 1970–December 1993.

three- and five-year horizons. The same sets of variables are able to capture much of the variation in the cross-equity correlations. Only two of the adjusted R^2s are lower than 50 percent (United Kingdom–Canada and United Kingdom–France) in the five-year horizon.

DIAGNOSTICS AND OUT-OF-SAMPLE ANALYSIS

Correlations must always fall within the range of -1 to 1, but the regression does not force the fitted values to lie within this range. One obvious diagnostic is to see if any of the forecasts fall outside the required range. Figure 3 presents the in-sample fitted values, as well as the out-of-sample fitted values, through 1998 for the five-year correlation regression models.

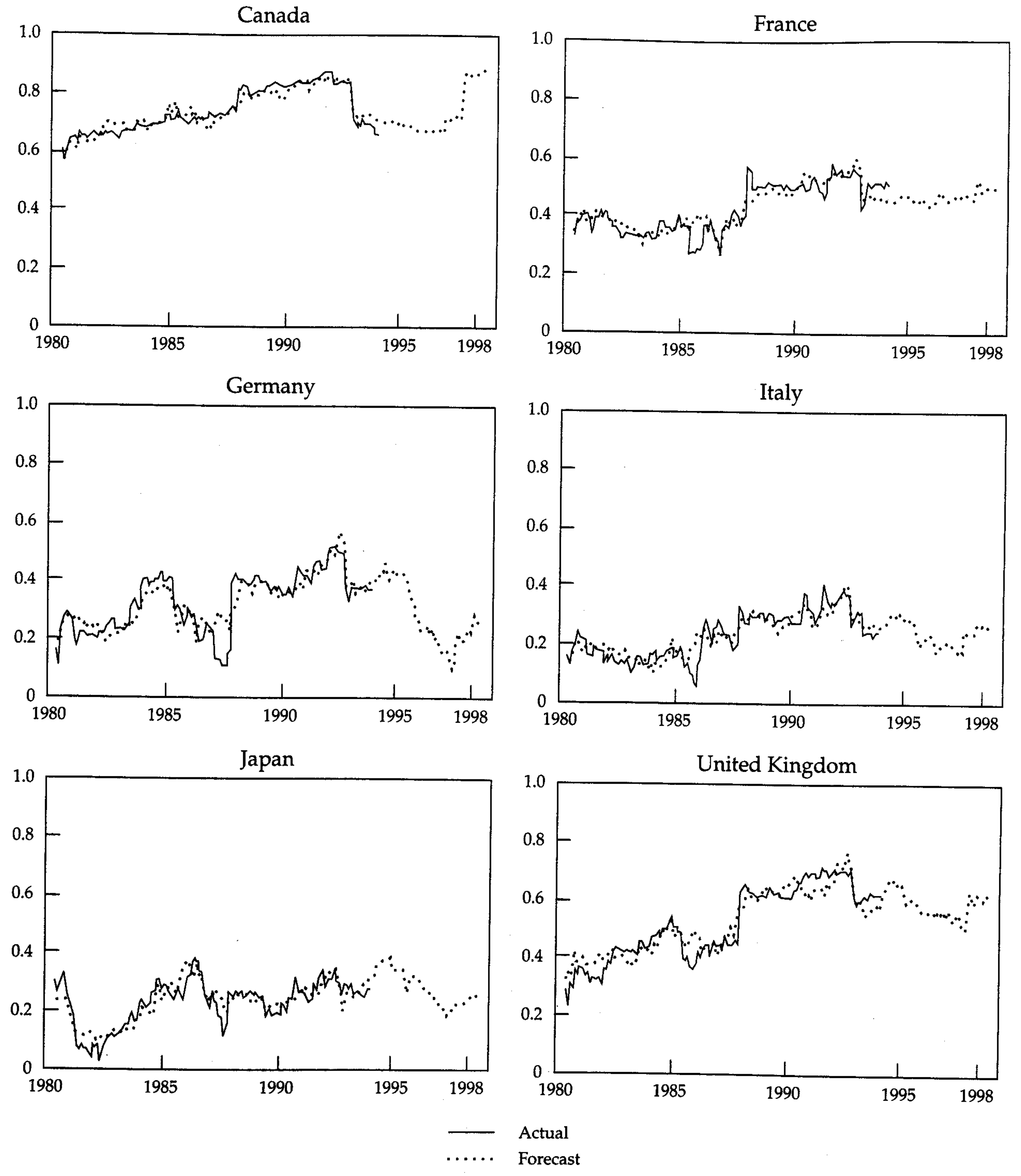
The models appear to capture the time variation in correlation, even though the models' output is forecasts. The correlation between 1980 and 1984, for example, is forecast with data from 1979. Although there are a number of misses, the fitted values closely track the realized correlations.

What about the future? The regressions, combined with data available in December 1993, provide forecasts of correlations for the period from January 1994 through December 1998. These forecasts are summarized in Table 6. For comparison, the table also reports correlation forecasts based on the previous five-year correlations and a first-order autoregressive model.[20] For France, the U.S. return correlation is forecasted to remain stable at the present level of about 50 percent. The German–United States correlation is expected to decline from the present level of 36 percent to 25 percent. The United States–Italy equity correlation is forecasted to increase from 24 percent to 27 percent over the time period. The Japanese–United States correlation will decrease slightly from 26 percent to 23 percent. The United Kingdom–United States correlation will remain steady at 60 percent. The Canada–United States correlation, which sharply declined during 1992 and 1993, will increase from the present level of 64 percent to 86 percent, according to the forecasting model.

CONDITIONAL CORRELATIONS IN QUANTITATIVE INVESTMENT MANAGEMENT

The most important input for quantitative asset management programs is expected return. Asset weights are less sensitive to volatilities and correlation than they are to expected returns. Neverthe-

Figure 3. Fitted and Out-of-Sample Five-year Forecasts of G-7 versus U.S. Equity Returns Correlations



less, differences in correlation will influence the calculation of the optimal portfolio weights.

Tactical Asset Allocation

To focus on the impact of the correlation forecasts, we compared asset allocation weights for the various correlation-forecasting models detailed in Table 6 when the global minimum-variance portfolio is chosen. The global minimum-variance portfolio weights do not depend on expected return. Out-of-sample forecasts for the volatilities and correlations were calculated for the

Table 6. Out-of-Sample Equity Correlation Forecasts, January 1994–December 1998

Country	United States	Canada	France	Germany	Italy	Japan
Regression model forecasts						
Canada	86%					
France	49	49%				
Germany	25	46	69%			
Italy	27	34	47	18%		
Japan	23	41	31	28	49%	
United Kingdom	60	64	44	44	49	27%
Five-year historical correlation forecasts						
Canada	64					
France	50	28				
Germany	36	29	80			
Italy	24	40	45	53		
Japan	26	29	47	38	44	
United Kingdom	60	47	67	61	38	60
Autoregressive forecasts						
Canada	79					
France	38	49				
Germany	30	32	63			
Italy	22	26	48	28		
Japan	22	26	40	37	41	
United Kingdom	49	60	47	30	40	31

Notes: Correlations are based on five-year U.S. dollar returns on the MSCI total return indexes. The predictor variables in the regression model are the lagged correlation, the lagged returns, dividend yields, and term structures (long government yield minus short-term Treasury bill or equivalent) in each country. The predictor variables are lagged by the forecast horizon. That is, the 60th lag is used to forecast the five-year correlations. The historical correlation forecast is the previous five-year correlation. The autoregressive model uses the 60th lag of the correlation to forecast the next five-year correlation. The sample is for January 1970–December 1993.

period from January 1994 to December 1998. Volatility-forecasting models use basically the same set of instrumental variables as the correlation models.

Volatility-prediction models use a country's lagged volatility plus lagged five-year returns, dividend yield, and the local term structure of interest rates. Because returns are calculated in U.S. dollars, the model also uses lagged U.S. returns, dividend yield, and a term structure measure.

Table 7 presents the allocation weights of the global minimum-variance portfolios based on the different correlation forecasts. Each column lists the optimal weights according to which forecasting model was used (the historical model, the autoregression model, or the regression model). Because the historical average is commonly used in portfolio selection, the discussion will focus on comparison of the historical average with the full-regression model forecasts.

The regression forecasts suggest a dramatic reallocation for Canada. The historical model places a 19.6 percent weight on Canada, whereas the regression model places no investment in Canada. The historical result reflects the recent decrease in the Canadian correlations (see Figure 2), while the regression model forecasts that the Canadian correlations will rise to normal levels over the next five years. The German portfolio weight almost doubles from the historical to the regression model because the regression forecasts are lower than the recent historical correlation. Italy's regression-based weight is higher by 4 percentage points, increasing to 13.7 percent, and the U.S. allocation increases by 8 percentage points, to 53.7 percent. The global minimum-variance weights for France, Japan and the United Kingdom remain almost unchanged.

The forecasting model was also applied to a purely domestic (U.S.) asset allocation between equities and long-term government bonds. As expected, the minimum-variance portfolio places most weight in the bonds, although the weights assigned by the historical and regression models differ sharply. The historical correlation forecast indicates that only 3 percent of wealth be placed in equities; the regression forecasts suggest that stock–bond correlations will decrease, so 16 per-

Table 7. Sensitivity of Portfolio Weights to Different Correlation Forecasts

Asset	Weight (historical)	Weight (autoregression)	Weight (full regression)
Global asset allocation: 1994–1998			
United States	46.09%	49.79%	53.67%
Canada	19.61	3.82	0.00
France	0.00	0.00	0.00
Germany	12.08	15.52	21.44
Italy	9.36	14.24	13.67
Japan	12.84	11.50	12.20
United Kingdom	0.00	5.10	0.00
Domestic (U.S.) asset allocation: 1994–1998			
U.S. stocks	3.30	15.00	16.10
U.S. bonds	96.70	85.00	83.90

Notes: Weights are for the global minimum-variance portfolio, which is not necessarily optimal for all investors. Correlation forecasts are based on the following three models: the previous five-year correlation (historical) ending December 1993, an autoregressive forecast, and the full regression model forecast detailed in Table 5. Correlations are based on U.S. dollar returns on the MSCI total return indexes. The U.S. bond return is based on the Ibbotson Associates U.S. government bond return series. The sample is for January 1970–December 1993.

cent, rather than 3 percent, of wealth should be placed in equities.

Derivative Securities

Correlation forecasts are useful in a number of applications in derivative securities. These applications must involve at least two assets and fall into the category of exchange options.[21] For example, the outperformance call option applied to domestic stocks and bonds pays off the difference between the returns on stocks and bonds. The implied volatility of this option is a function of the expected volatility of stocks, the expected volatility of bonds, and the expected correlation between stock and bond returns.

The outperformance option is a growing over-the-counter product for domestic asset management and for global allocation. To measure the sensitivity of the value of this option to the correlation inputs, we modeled an outperformance option (stocks versus bonds) with five years to maturity. The difference between option values' historical correlation and full-regression model correlation forecasts was 17 percent.

Another popular over-the-counter option is the foreign exchange cross-rate option. The expected volatility of an option on the deutschemark–yen rate is a function of the expected volatility of the U.S. dollar–deutschemark rate, the expected volatility of the U.S. dollar–yen rate, and the expected correlation between the two rates. This over-the-counter market is liquid enough that reliable implied correlations can be calculated. The implied correlation is the market's best guess about the correlation between the two assets over the life of the option, given that the option model is correctly specified.[22] These implied correlations might also be predicted using variables similar to those analyzed in our equity correlation analysis.

CONCLUSIONS

Correlation is an important input for portfolio management, but little is known about the behavior of correlation through time and the ability to predict correlation. We found that cross-equity correlations in the G–7 countries are affected by the business cycle. Correlations are highest when any two countries are in a common recession, and they are lower during recoveries and when the business cycles in the two countries are out of phase. We also found that correlations are not symmetric in up and down markets. They are much higher in down markets—what we call negative semicorrelation. This higher correlation is not just a function of the influential October 1987 observation. When we recalculated the correlations without the Crash observation, we got similar results.

The asymmetric behavior of correlations during the business cycle and in different return states motivated our correlation-forecasting model. This model tests the hypothesis that correlation can be forecasted with variables that measure the persistence of returns and volatility, the expected business cycle in two countries, and the differential in expected returns in those two countries. Our estimates suggest that much of the variability in the correlations through time is predictable.

These findings have implications for asset management. We found that our correlation forecasts lead to substantially different portfolio weights in both global asset allocation and the domestic (U.S.) portfolio choice between stocks and bonds. Correlation forecasts are also critical in the valuation of derivative securities that involve the exchange of two or more assets.[23]

FOOTNOTES

1. Semicorrelation is a measure of the degree of comovement of two assets measured separately in bull markets and in bear markets.
2. W.F. Sharpe, *Investments*, 2nd ed. (Englewood Cliffs, N.J.: Prentice-Hall, 1981).
3. See E.F. Fama, "The Behavior of Stock Market Prices," *Journal of Business*, vol. 38, no. 1 (January 1965):34–105; M. Richardson and T. Smith, "A Test for Multivariate Normality in Stock Returns," *Journal of Business*, vol. 66, no. 2 (April 1993):295–321; C.R. Harvey and G. Zhou, "International Asset Pricing with Alternative Distributional Specifications," *Journal of Empirical Finance*, vol. 1, no. 1 (1993): 107–31; and C.R. Harvey, "Predictable Risk and Returns in Emerging Markets," working paper, Duke University, 1994.
4. W.V. Harlow III and R.K.S. Rao, "Asset Pricing in a Generalized Mean–Lower Partial Moment Framework," *Journal of Financial and Quantitative Analysis*, vol. 24, no. 3 (September 1989):285–311; and W.V. Harlow III, "Asset Allocation in a Downside Risk Framework," *Financial Analysts Journal*, vol. 47, no. 5 (September/October 1991):28–40.
5. R. Bookstaber and R. Clarke, "Problems in Evaluating the Performance of Portfolios with Options," *Financial Analysts Journal*, vol. 41, no. 1 (January/February 1985):48–62; A. Lewis, "Semivariance and the Performance of Portfolios with Options," *Financial Analysts Journal*, vol. 46, no. 4 (July/August 1990):67–76; N.H. Josephy and A.D. Aczel, "A Statistically Optimal Estimator of Semivariance," *European Journal of Operational Research*, vol. 67 (1993):267–71; Harlow and Rao, "Asset Pricing in a Generalized Mean–Lower Partial Moment Framework," and Harlow, "Asset Allocation in a Downside Risk Framework."
6. Notice that the total correlation for the U.S. equities and U.S. bonds is greater than the three state-based classifications. This result is attributable to the fact that the total correlation calculation uses the overall mean, whereas the state-based correlations use means that depend on the state.
7. R. Roll, "The International Crash of October 1987," *Financial Analysts Journal*, vol. 44, no. 5 (September/October 1988):19–35.
8. D.B. Keim and R.F. Stambaugh, "Predicting Returns in the Bond and Stock Market," *Journal of Financial Economics*, vol. 17, no. 2 (December 1986):357–90; J.Y. Campbell, "Stock Returns and the Term Structure," *Journal of Financial Economics*, vol. 18, no. 2 (June 1987):373–400; E.F. Fama and K.R. French, "Dividend Yields and Expected Stock Returns," *Journal of Financial Economics*, vol. 22, no. 1 (October 1988):3–26; and E.F. Fama and K.R. French, "Business Conditions and Expected Returns on Stocks and Bonds," *Journal of Financial Economics*, vol. 25, no. 1 (November 1989):23–50.
9. F. Black, "Studies of Stock Market Volatility Changes," *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economics Statistics Section* (1976): 177–81; D.B. Nelson, "Conditional Heteroskedasticity in Asset Returns: A New Approach," *Econometrica*, vol. 59, no. 2 (March 1991):347–70; G.W. Schwert, "Why Does Stock Market Volatility Change over Time?" *Journal of Finance*, vol. 44, no. 5 (December 1989):1115–54; and G.W. Schwert, "Business Cycles, Financial Crises and Stock Volatility," *Carnegie-Rochester Conference Series on Public Policy*, vol. 31 (1989):83–126.
10. E.C. Kaplanis, "Stability and Forecasting of the Comovement Measures of International Stock Market Return," *Journal of International Money and Finance*, vol. 7, no. 1 (March 1988):63–76.
11. F. Longin and B. Solnik, "Is the Correlation in International Equity Returns Constant: 1960–1990?" working paper, Groupe HEC, 1993.
12. Instrumental variables are variables that are known today that can be used to predict correlations in the future. They are also known as predictor variables.
13. This approach is consistent with the analysis of C.B. Wainscott, "The Stock–Bond Correlation and Its Implications for Asset Allocation," *Financial Analysts Journal*, vol. 46, no. 4 (July/August 1990):55–60.
14. C.R. Harvey, "The World Price of Covariance Risk," *Journal of Finance*, vol. 46, no. 1 (March 1991):111–57.
15. Harvey, "The World Price of Covariance Risk"; and W.E. Ferson and C.R. Harvey, "The Risk and Predictability of International Equity Returns," *Review of Financial Studies*, vol. 6, no. 3 (1993):527–66.
16. C.R. Harvey, "Forecasting Economic Growth with the Bond and Stock Markets," *Financial Analysts Journal*, vol. 45, no. 5 (September/October 1989):38–45.
17. See C.R. Harvey, "The Term Structure Forecasts Economic Growth," *Financial Analysts Journal*, vol. 49, no. 3 (May/June 1993):6–8.
18. Harvey, "Forecasts of Economic Growth"; C.R. Harvey, "The Term Structure and World Economic Growth," *Journal of Fixed Income*, vol. 1, no. 1 (June 1991):4–17; and Harvey, "Term Structure Forecasts Economic Growth."
19. See W.K. Newey and K.D. West, "A Simple, Positive Semi-Definite, Heteroskedasticity-Consistent Covariance Matrix," *Econometrica*, vol. 55, no. 3 (May 1987):703–708.
20. The first-order autoregressive model is a simple forecasting model that uses only one predictor variable—the historical correlation.
21. See W. Margrabe, "The Value of an Option to Exchange One Asset for Another," *Journal of Finance*, vol. 33, no. 1 (March 1978):177–86.
22. The ability of the implied correlation to forecast future correlation is analyzed in C. Erb, C.R. Harvey, and T. Viskanta, "Implied Foreign Currency Correlations for Asset Management," working paper, First National Bank of Chicago, Chicago, IL, 1994.
23. Harvey's research was supported by the Batterymarch Fellowship. We appreciate the constructive comments of the *FAJ*'s editor, W. Van Harlow III. Bruno Solnik's presentation at the 1993 CEPR Conference on International Finance in Maastrich provided the inspiration for this paper.