Cross-Industry, Cross-Country Allocation

Stefano Cavaglia and Vadim Moroz

Recent empirical evidence has demonstrated that both global industry factors and country factors are important determinants of equity prices. In light of this evidence, we describe a cross-industry, cross-country allocation framework for making active global equity investment decisions. We present a forecasting approach to predicting the relative performance of industries in each of 22 developed country equity markets and demonstrate that a blend of style signals provides an effective way to predict the return performance of these assets. The out-of-sample portfolio performance of investment strategies based on these forecasts for the 1991–2001 period would have provided annual gross returns in excess of the world benchmark return of 400 bps a year with one-way turnover of 50 percent. Conventional global risk models cannot explain this outperformance. Thus, explaining this "anomaly" is a challenge for the investment and academic communities.

Active international equity allocation has traditionally been conducted in two stages. In the first stage, country weights were determined on the basis of the attractiveness of countries in the selection universe. In the second stage, securities were separately selected within each country. This "silo" approach was effective as long as global factors, operating across countries, were relatively unimportant in explaining the cross-section of security price returns. Indeed, ample factor-model-based evidence, as surveyed by Hopkins and Miller (2001), supported this view. Moreover, complementary empirical evidence suggested that country aggregate returns and security returns within countries are predictable. Solnik (1993) found that country returns could be forecasted by using lagged country-level valuation measures and macroeconomic fundamentals; Balvers, Wu, and Gilliland (2000) extended Solnik's work by demonstrating that country returns are mean reverting. The evidence relating to the predictability of security prices within countries is extensive, as surveyed by Cochrane (1999). Whether this predictability reflects time-varying risk factors or market anomalies remains the subject of extensive debate.

The increasing globalization of business enterprise activities presents new challenges and new opportunities for the asset management profession. Diermeier and Solnik (2001) suggested that in a rational asset-pricing world, share price sensitivity to nondomestic factors should be related to the extent of a company's international activities. In an analysis of security prices for seven of the major equity markets, they found empirical support for this hypothesis. In related research, Cavaglia, Brightman, and Aked (2000), Baca, Garbe, and Weiss (2000), and Hopkins and Miller provided strong empirical evidence that the global factors uncovered by Diermeier and Solnik may be reflected in the increasing importance in the performance of global equity portfolios of global industry factors and the declining importance of country factors.[1] The authors concluded that active international equity allocation is now a more complex task than it used to be—a task requiring an assessment of the risk–return trade-offs of global industry factors as well as local factors that are determining security prices.

Although the empirical evidence in support of the increasing importance of global industry factors relative to country factors is now extensive, there is little evidence that asset managers have embraced global industry selection and security selection within industries as the new allocation paradigm. This is hardly surprising, because the empirical evidence in support of the predictability of industry returns and security selection within industries is not as extensive as that which involves the country dimension of the equity allocation decision. Sorensen and Burke (1986) and Beller, Kling, and Levinson (1998) found that U.S. industry returns can be predicted by using either past return

Stefano Cavaglia is head of quantitative strategies at UBS Global Asset Management (Americas) Inc., Chicago. Vadim Moroz is a quantitative strategist at UBS Global Asset Management (Americas) Inc., Chicago.

performance or macroeconomic fundamentals; they cautioned, however, that the extent of asset return predictability may not offset transaction costs sufficiently to maintain the paper profits when their models are implemented.

Capaul (1999) found conflicting evidence about the effectiveness of using traditional style factors for global industries. For instance, he found that low-P/B (price-to-book) industries underperformed high-P/B industries in the 1991–98 period; similarly, buying "large" global industries appeared to be more attractive than buying "small" global industries.[2] Capaul also examined the extent to which traditional patterns of style (value, size, and momentum) returns observed in domestic equity markets (see, for instance, Fama and French 1998 and Rouwenhorst 1998) could be uncovered in security returns within global industries. The evidence he reported is mixed. The observed return patterns were not robust across industries or the various weighting schemes he used to construct self-financing investment strategies. All in all, little published empirical evidence suggests that global industry selection (and security selection within global industries) can be successfully implemented.[3]

How then should asset managers restructure their efforts in light of the increasing importance of global factors? We present an active allocation framework—cross-industry, cross-country allocation (CICCA)—to capture the dynamics of the new global equity environment.

Cavaglia, Brightman, and Aked suggested that global equity investment management must now balance the risk–reward benefits of both country and global industry factors. This goal can be achieved via a first-pass top-down CICCA approach, as illustrated in **Exhibit 1**. This allocation approach calls for the simultaneous selection of "local" industry baskets of securities from around the world. Thus, the asset manager evaluates the relative attractiveness of, for instance, U.S. pharmaceutical stocks relative to other pharmaceutical stocks in non-U.S. markets, relative to other industries in the United States, and relative to other industries in the world. Which relative comparison (within country, within global industry, or across industry/across country) matters most is an empirical question. Ultimately, however, the success of CICCA is determined by the relative ease with which an asset manager can forecast local industry returns and use this information to guide investment decisions. In some instances, the local industry basket of securities comprises only one company; for instance, the Australian Gas Light Company represents the only security in the Australian (local) utility basket. In such instances, distinguishing between security-specific effects and local industry effects is difficult. Recognizing the underlying economic (industrial) activities of companies provides an interesting and economically sensible alternative, however, to style-based grouping of securities. The large dispersion in the performance of industries in the late 1990s to the present suggests that this approach may offer interesting return opportunities.

Some features of CICCA are particularly noteworthy. It provides a means of exploiting top-down and bottom-up opportunities in a consistent framework. That is, country allocations and global

Exhibit 1. Allocation Matrix

	Energy	Materials	Cap Goods	. . .	Utilities
Australia					
Austria					
Belgium					
Canada					
Denmark					
Finland					
.					
.					
.					
Switzerland					
United Kingdom					
United States					

©2002, AIMR®

industry allocations result from local industry selection. The selection of specific stocks can be overlaid on the local industry selection to arrive at the final security holdings for a global equity portfolio; company selection decisions may override or reinforce CICCA decisions. Similarly, style tilts are not imposed from the top down. Rather, they result from local industry tilts. Style tilts at the aggregate level can be monitored for risk-control purposes and can be altered via local industry allocations. We demonstrate how CICCA can be used to construct risk-controlled investment strategies aimed at outperforming global benchmarks.

Industry Valuation Data

Empirical studies addressing the predictability of country and global industry returns have been supported by the availability (through index vendors) of relatively long histories of aggregated valuation measures (most notably, dividend yields, P/B data, and P/E data). The analogous data for local industries have only recently become commercially available; the histories are relatively short, and using some of the data series may result in look-ahead bias because the industry classifications reflect current groupings of securities that were not available to investors before 1999. We circumvented these data limitations by constructing a proprietary history of local industry valuation measures for the period January 1986 through June 2001. We obtained local industry aggregates from two publicly available industry classification schemes—the Financial Times (FT) 36-industry classification (available from December 1985 through May 2000) and the MSCI GICS (Global Industry Classification Standard) 23-industry classification codes (available starting in April 1999). The differences between these two systems are shown in **Exhibit 2**. Using two different classification schemes provided some confirmation of the robustness of our results; in particular, it suggested the extent to which our analysis was sensitive to the granularity of the industry definitions used and to the different groupings of securities.

The data we examined covered the 22 developed country equity markets that comprised the MSCI World Index through 31 May 2001; these markets are listed in Exhibit 2. Our universe of securities was restricted to the constituents of the country-level FT indexes for each of the 22 developed country equity markets, which represents the top 85 percent market capitalization in each country; for the time period we analyzed, this universe comprised 4,135 constituents, of which 1,752 were "alive" on 31 December 2000. Each security was assigned both an FT and an MSCI industry classification as reported by each index vendor (subject to availability). Because the FT definitions that we used were discontinued on 31 May 2000, we used the Barra Global Equity Financial Times model (GEM-FT) data to provide an update through June 2001. When this research was conducted, MSCI industry classifications were not available for securities that were in our universe prior to 1995. Thus, we created a "back history" by mapping pre-1995 FT industry classifications and FactSet industry classifications onto MSCI industry classifications. We then aggregated security-level data on a cap-weighted basis to obtain the valuation and performance characteristics of local industries. We obtained market caps, prices, and dividends from FT and obtained balance sheet and earnings data from Compustat, Worldscope Global, and I/B/E/S International. We exercised particular care to ensure that aggregated local industry data were indeed available to market participants at the time we recorded the information. Because of the inclusion and exclusion effects of the FT security-level index, the number of local industries in our database varies over time. Based on FT industry classifications, the data sample varies from a minimum of 350 to a maximum of 425 local industries; based on the MSCI industry classifications, the sample varies from 267 to 338 local industries.

Forecasting Local Industry Returns

Most empirical studies of asset-pricing anomalies focus on either the cross-sectional or the time-series aspects of generating forecasts that can be used in portfolio construction. The cross-sectional dimension of expected performance (see Capaul, for instance) can be examined by constructing self-financing long–short portfolios designed to buy securities with "attractive" characteristics (for instance, "cheap," low-P/B securities) and to sell those securities with "unattractive" characteristics (for instance, "expensive," high-P/B securities). The researchers use the information ratios of these portfolios to evaluate the merits of alternative predictive variables, which are often associated with particular investment styles. Performance will be largely driven by the magnitude of the dispersion in the predictive variable and the extent to which this dispersion provides information about future returns. Traditional time-series models of asset returns (for instance, that of Beller et al.) generally aim to predict future asset price performance as a function of past explanatory variables. This approach provides a rigorous framework for evaluating alternative predictive variables. Statistical inference can be used to assess the marginal explanatory power of the independent variables. As illustrated in the study of

Exhibit 2. Universe Coverage: Countries and Industries

Countries	Financial Times Industries	MSCI GICS Industries
Australia	Commercial banks	Auto
Austria	Financial institutions	Banks
Belgium	Insurance (life)	Capital goods
Canada	Insurance (property)	Commercial services
Denmark	Real estate	Consumer durables
Finland	Diversified holdings	Diversified financials
France	Oil	Energy
Germany	Nonoil energy	Food and drug retailing
Hong Kong	Utilities	Food, beverages, and tobacco
Ireland	Transportation and storage	Health care
Italy	Automobiles	Hotels
Japan	House durables and appliances	Household
Netherlands	Diversified consumer goods and services	Insurance
New Zealand	Textiles and apparel	Materials
Norway	Beverages and tobacco	Media
Portugal	Health and personal care	Pharmaceuticals
Singapore	Food and grocery products	Real estate
Spain	Entertainment, leisure, and toys	Retailing
Sweden	Media	Software
Switzerland	Business services and computer software	Tech hardware
United Kingdom	Retail trade	Telecom
United States	Wholesale trade	Transport
	Aerospace/defense	Utilities
	Computers, communications, and office equipment	
	Electrical equipment	
	Electronics and instrumentation	
	Machines, engines, and services	
	Auto components	
	Diversified industrials	
	Heavy engineering and shipbuilding	
	Construction and building materials	
	Chemicals	
	Mining, metal, and minerals	
	Precious metals and minerals	
	Forestry and paper products	
	Fabricated metal products	

Sorensen and Burke, statistical measures of goodness of fit need to be interpreted with some caution, however, because some models may result in high-turnover strategies that do not necessarily translate into superior portfolio performance.

Our forecasting model combines the cross-sectional and the time-series properties of the approaches we have reviewed. We used panel regressions to obtain estimates of the expected relative performance of the assets in our study.[4] In this framework, the forecasting equations we estimated took the following form:

$$\begin{aligned}(R_t - \bar{R})_{t \text{ to } t+h} &= \beta_{1t}(x_{1i} - \bar{x}_1) + \beta_{2t}(x_{2i} - \bar{x}_2)_t \\ &\quad + \ldots + \beta_{k,t}(x_{k,i} - \bar{x}_k) + \varepsilon_{i,t}, \\ i &= 1, 2, \ldots n,\end{aligned} \tag{1}$$

where

$R_{i,t \text{ to } t+h}$ = excess return for local industry i from time t to time $t + h$ (where h is the forecast horizon)

$\bar{R}_{t \text{ to } t+h}$ = average excess return (over all local industries $i = 1 \ldots n$) from time t to time $t + h$

$x_{j,i,t}$ = level of jth explanatory variable for local industry i at time t

$\bar{x}_{j,t}$ = average level of the jth explanatory variable at time t (obtained from all local industries $i = 1 \ldots n$)

$\varepsilon_{i,t}$ = residual

In our particular application of panel models, the dependent variable is local industry returns in excess of the local risk-free rate of interest

©2002, AIMR®

(henceforth, local industry "excess returns") relative to the average excess returns. The explanatory variables we considered are style factors and macroeconomic factors that were computed similarly.[5]

Because we used excess returns, the analysis can be viewed as currency hedged from any investor's perspective. This result follows from the arbitrage relationship that interest differentials equal the forward discount, as demonstrated in Singer and Karnovsky (1995).

Consider, for illustrative purposes, a three-month-ahead forecast model with one explanatory variable—dividend yield, *DY*:

$$(R_i - \bar{R})_{t \text{ to } t+3} = \beta_{1t}(DY_i - \overline{DY})_t + \varepsilon_{i,t}. \tag{2}$$

Exhibit 3 outlines the data used in the estimation carried out at a particular point in time. For example, if the dividend yield on the Australian energy sector [DY(AUD i01)] exceeds the dividend yield in all other sectors in all other countries [DY(Avg. world)] and if the response coefficient (beta) is positive, one would expect the returns to the Australian energy sector [Ret(AUD i01)] to outperform the returns to the world index [Ret(Avg. world)]. The outperformance would be determined by the *magnitude* of the responsiveness of future prices to under- or overvaluations (as reflected in the magnitude of the beta coefficient) and by the *extent* of the relative over- or undervaluation (as reflected in the size of the discrepancy between the dividend yield for the Australian energy sector and that for the rest of the world).[6] Our framework provides a means of statistically testing the Graham and Dodd (1962) hypothesis that securities with high dividend yields subsequently outperform; formally, one would expect the beta coefficient to be positive and (statistically) significantly different from zero.

Equation 2 can be estimated via the ordinary least-squares (OLS) method for a single time period (which we denote the "cross-sectional estimation"). At any point in time, the beta obtained from this regression may be positive or negative, reflecting the extent to which market prices subsequently responded to value factors. If relative dividend yields provide a consistently strong indicator of future relative performance, then one would expect the average (over time) of the cross-sectional beta to be positive and significant. In this instance, the time-series/cross-sectional coefficient can be estimated by stacking each of the panel data sets into a single cross-sectional regression that assumes the beta is constant over time.[7]

The panel regression approach has several attractive features. First, it provides a formal framework for combining information signals to obtain a final forecast. One can use standard statistical tests to estimate whether an additional information variable helps the manager predict future performance. For instance, the dividend yield, P/B, and P/E valuation measures are highly collinear and thus provide similar information about future relative price performance; this framework allows the analyst to determine which combination of value signals is the

Exhibit 3. Global-Relative Forecast Model

Panel Data Set		Industry	Dependent Variable: Three-Month-Ahead Excess Returns	Information Signal: Local Sector to World
Australia—AUD				
1	Energy	i01	Ret(AUD i01) – Ret(Avg. world)	DY(AUD i01) – DY(Avg. world)
2	Materials	i02	Ret(AUD i02) – Ret(Avg. world)	DY(AUD i02) – DY(Avg. world)
3	Capital goods	i03	Ret(AUD i03) – Ret(Avg. world)	DY(AUD i03) – DY(Avg. world)
	....	....	....	....
22	Telecom	i22	Ret(AUD i22) – Ret(Avg. world)	DY(AUD i22) – DY(Avg. world)
23	Utilities	i23	Ret(AUD i23) – Ret(Avg. world)	DY(AUD i23) – DY(Avg. world)
	:		:	:
	:		:	:
	:		:	:
United States—USD				
461	Energy	i01	Ret(USD i01) – Ret(Avg. world)	DY(USD i01) – DY(Avg. world)
462	Materials	i02	Ret(USD i02) – Ret(Avg. world)	DY(USD i02) – DY(Avg. world)
463	Capital goods	i03	Ret(USD i03) – Ret(Avg. world)	DY(USD i03) – DY(Avg. world)
	....	....	....	....
482	Telecom	i22	Ret(USD i22) – Ret(Avg. world)	DY(USD i22) – DY(Avg. world)
483	Utilities	i23	Ret(USD i23) – Ret(Avg. world)	DY(USD i23) – DY(Avg. world)

most effective predictor. Second, the regression approach provides an estimate of the projected outperformance of a security relative to its peers or its benchmark.[8] Portfolio optimization can then be used to assess what securities to trade on the basis of their expected outperformance net of transaction costs. Third, the regression approach can be likened to a nested ranking approach. For instance, Chan, Jegadeesh, and Lakonishok (1999) found that a strategy that selects stocks with earnings momentum that have exhibited high recent relative performance dominates strategies that select exclusively momentum stocks; this result can be equivalently obtained from a multiple regression of future returns on earnings momentum and price momentum.

Our approach was to estimate the time-series/cross-sectional version of Equation 1 from monthly data of local industry excess returns for a forecast horizon of three months and to restrict the betas to be constant over the estimation interval. Our choice of forecast horizon is somewhat arbitrary. Our experience has been that three-month estimated coefficients are more stable, however, than for a horizon of one month; moreover, a three-month horizon prevents dependent variables with low persistence from being incorporated, which would result in high-turnover strategies in portfolio construction. Our dependent variable was thus local industry excess returns relative to the world average excess returns (from time t to $t + 3$).

We considered a number of explanatory variables that have been documented to exhibit forecasting power within countries or across countries. The model we finally selected includes the following local industry explanatory variables (expressed in excess of their world mean value):

Momentum: the excess total returns from the previous 12 months (returns from time $t - 12$ to time t) obtained from the FT price appreciation series appropriately adjusted for dividend payments (designated "Lagged return" in the tables).

Value:

- the dividend yield (at time t).
- the forward earnings yield estimate for the second fiscal year made at time t computed from I/B/E/S security-level data; we used a logarithmic transformation of this explanatory variable (designated in the tables "Log($EPS2/P$").

Profitability:

- analyst earnings revisions in fiscal year 1 obtained from I/B/E/S; for this variable, we computed the following ratio, which we denote the "up–down ratio": (Upward earnings revisions—Downward earnings revisions)/Total estimate revisions at time t.
- expected long-term (LT) earnings growth from the I/B/E/S security-level data (at time t).

Macroeconomic variable: yield of U.S. government long bond (with 10-year maturity at time t), which we obtained from MSCI if available and from the Standard and Poor's DRI Money Markets and Fixed-Income database otherwise.

With the exception of the macroeconomic data, we obtained all local industry data series from a cap-weighted aggregation of the relevant underlying security-level information.

Table 1 reports the parameter estimates and their standard errors for the model covering the FT 36-industry classification scheme for various historical estimation intervals; for ease of future reference, we will call this model the "global relative" model. We report a range of historical estimation intervals to suggest that, hypothetically, this model could have been used over the period December 1990 through June 2001. Indeed, in the section "Portfolio Performance of CICCA Strategies," we provide out-of-sample simulated portfolio performance that exploits forecasts computed from the parameter estimates reported here.

As an illustration of how to interpret our results, consider the parameter estimate for the up–down ratio variable obtained for the period December 1985 through December 1990. All else being constant, on 31 December 1990, we would have expected an industry with an up–down ratio of 0.5 relative to a world up–down ratio of 0.1 to outperform the world index by 1.8 percentage points in the three-month period 31 December 1990 through 31 March 1991. The null hypothesis that the parameter is insignificantly different from zero can be rejected at the 10 percent confidence level.

Overall, the results shown in Table 1 confirm past studies of security price behavior—namely, that local industries that have experienced strong past performance (with high lagged-12-month returns), that are attractively valued (with high dividend yields and a low forward P/E), that have strong profitability prospects (with high long-term earnings growth and positive earnings revisions), and that are exposed to low domestic borrowing costs can be expected to outperform their peers globally. Note that our results are consistent and statistically significant over the course of the alternative estimation intervals we examined, which suggests that an investment manager could have used this model to predict industry returns as early as December 1990.

In **Table 2**, we report parameter estimates and their standard errors for the model covering the MSCI 23-industry classification scheme. These estimates are markedly similar, in sign and in

 ©2002, AIMR®

Table 1. Time Series/Cross-Sectional Regression Coefficients: Global-Relative Model, FT Industry Classification
(t-statistics in parentheses)

Independent Variable	31/Dec/85 to 31/Dec/90	31/Dec/85 to 31/Dec/91	31/Dec/85 to 31/Dec/92	31/Dec/85 to 31/Dec/93	31/Dec/85 to 31/Dec/94	31/Dec/85 to 31/Dec/95	31/Dec/85 to 31/Dec/96	31/Dec/85 to 31/Dec/97	31/Dec/85 to 31/Dec/98	31/Dec/85 to 31/Dec/99	31/Dec/85 to 31/Dec/00	31/Dec/85 to 30/Jun/01
Lagged return	0.0270	0.0368	0.0396	0.0295	0.0251	0.0254	0.0263	0.0388	0.0414	0.0413	0.0301	0.0310
	(4.6201)	(6.6903)	(7.6512)	(6.0258)	(5.3900)	(5.6552)	(6.0114)	(9.2584)	(10.2570)	(10.6155)	(8.0608)	(8.4159)
Dividend yield	0.3963	0.4300	0.4598	0.4089	0.3672	0.3878	0.3437	0.3160	0.3187	0.2917	0.3115	0.3159
	(4.6386)	(5.7300)	(6.5160)	(6.0573)	(5.7749)	(6.5269)	(6.1122)	(5.7431)	(5.8123)	(5.4027)	(5.8731)	(5.9927)
Log($EPS2/P$)	0.0069	0.0103	0.0101	0.0089	0.0092	0.0086	0.0111	0.0099	0.0075	0.0063	0.0097	0.0102
	(2.7061)	(4.4805)	(4.5942)	(4.2940)	(4.7921)	(4.8125)	(6.4918)	(5.9208)	(4.5248)	(3.8278)	(5.9118)	(6.2769)
Up–down ratio	0.0368	0.0359	0.0350	0.0340	0.0323	0.0320	0.0329	0.0333	0.0314	0.0257	0.0300	0.0312
	(5.4078)	(5.9784)	(6.2191)	(6.5248)	(6.6898)	(7.1576)	(7.9764)	(8.3510)	(8.0355)	(6.6224)	(7.9013)	(8.3115)
LT earnings growth	0.0022	0.0032	0.0037	0.0031	0.0029	0.0028	0.0022	0.0019	0.0020	0.0017	0.0014	0.0013
	(2.3654)	(4.3132)	(5.3747)	(4.8331)	(5.0664)	(5.1454)	(4.3639)	(3.9252)	(4.1629)	(3.4622)	(2.9193)	(2.7739)
Long-bond yield	–0.0054	–0.0055	–0.0054	–0.0048	–0.0044	–0.0047	–0.0041	–0.0034	–0.0031	–0.0031	–0.0033	–0.0034
	(–9.4574)	(–10.5870)	(–10.9158)	(–10.2670)	(–9.9939)	(–11.3189)	(–10.1458)	(–8.7108)	(–7.8562)	(–7.8642)	(–8.5874)	(–8.7758)

Table 2. Time Series/Cross-Sectional Regression Coefficients: Global-Relative Model, MSCI Industry Classification
(t-statistics in parentheses)

Independent Variable	31/Dec/85 to 31/Dec/90	31/Dec/85 to 31/Dec/91	31/Dec/85 to 31/Dec/92	31/Dec/85 to 31/Dec/93	31/Dec/85 to 31/Dec/94	31/Dec/85 to 31/Dec/95	31/Dec/85 to 31/Dec/96	31/Dec/85 to 31/Dec/97	31/Dec/85 to 31/Dec/98	31/Dec/85 to 31/Dec/99	31/Dec/85 to 31/Dec/00	31/Dec/85 to 30/Jun/01
Lagged return	0.0176	0.0206	0.0294	0.0222	0.0182	0.0187	0.0206	0.0335	0.0385	0.0419	0.0293	0.0316
	(2.3636)	(2.9699)	(4.5911)	(3.7086)	(3.1781)	(3.3952)	(3.8853)	(6.6549)	(7.7977)	(8.8194)	(6.4838)	(7.1814)
Dividend yield	0.3640	0.3529	0.4466	0.3910	0.3833	0.3974	0.3518	0.3411	0.3613	0.3431	0.3852	0.4049
	(3.5146)	(3.8712)	(5.2562)	(4.8765)	(5.0843)	(5.6839)	(5.3508)	(5.3591)	(5.6764)	(5.4689)	(6.2526)	(6.6141)
Log($EPS2/P$)	0.0090	0.0128	0.0109	0.0098	0.0094	0.0089	0.0110	0.0100	0.0081	0.0053	0.0125	0.0131
	(3.0156)	(4.7287)	(4.1603)	(3.9701)	(4.1012)	(4.1383)	(5.3849)	(5.0010)	(4.0772)	(2.6791)	(6.3329)	(6.6999)
Up–down ratio	0.0457	0.0463	0.0486	0.0452	0.0428	0.0403	0.0394	0.0413	0.0377	0.0300	0.0367	0.0364
	(5.6711)	(6.2966)	(7.1072)	(7.1383)	(7.3055)	(7.5013)	(7.9261)	(8.6253)	(7.9888)	(6.3701)	(7.9359)	(7.9245)
LT earnings growth	0.0051	0.0057	0.0060	0.0049	0.0046	0.0041	0.0032	0.0027	0.0029	0.0026	0.0018	0.0016
	(4.6063)	(6.2225)	(7.1725)	(6.5555)	(6.7849)	(6.6482)	(5.6774)	(4.9255)	(5.2237)	(4.6707)	(3.3493)	(2.8553)
Long-bond yield	–0.0058	–0.0029	–0.0055	–0.0050	–0.0048	–0.0049	–0.0042	–0.0036	–0.0033	–0.0032	–0.0037	–0.0038
	(–8.5823)	(–9.6021)	(–9.3425)	(–9.0468)	(–9.1070)	(–10.1744)	(–8.9330)	(–7.8416)	(–7.2230)	(–6.8658)	(–8.1759)	(–8.3799)

magnitude, to those in Table 1. This consistency suggests that our approach is fairly robust to alternative industry aggregation schemes and that response coefficients are somewhat insensitive to the industry granularity of the data.

The forecasts obtained from the regression models reported in Tables 1 and 2 may be viewed as an "optimal" combination of information available to the investment manager at time t. Alternatively, the forecasts may be viewed as a "portfolio" of (information) signals. First principles suggest that this approach should provide an effective way of predicting security price performance; that is, if one signal (e.g., the momentum signal) suggests the wrong future price direction, then other signals (e.g., value and profitability) may compensate and, hopefully, provide a correct (and dominating) contribution to the forecast.

In a sense, our forecasts represent a "style"-diversified prediction. The style diversification captured in the model forecasts can be illustrated by computing the relative importance of the factors that drive projected returns. Formally, for each local industry, we computed the following forecast contribution statistics:

$$FC_{i,j,t} = \frac{\left|\hat{\beta}_{j,t}(x_{j,i} - \bar{x})\right|_t}{\sum_j \left|\hat{\beta}_{j,t}(x_{j,i} - \bar{x})\right|_t}, \tag{3}$$

where $FC_{i,j,t}$ is the forecast contribution of factor j at time t for local industry i and $\hat{\beta}_{j,t}$ is the estimated (rolling) monthly time-series regression coefficient from December 1990 through June 2001, as partially reported in Tables 1 and 2. Note that $\sum_j FC_j = 1.0$ for all industries (for all i) over all time periods (for all t).

One can obtain the forecast contribution for the "average" or representative security by computing the cap-weighted sum of the $FC_{i,j,t}$. In **Figure 1**, we have plotted the forecast decomposition for the average security over time.[9] Several trends are noteworthy. The macroeconomic signals have declined in importance over time—as a result of a decline in the response coefficient and a result of a decline in the dispersion of the long-bond yield across countries. Similarly, momentum terms have risen in importance over time, reflecting the increasing dispersion of past performance (especially among global industries) as well as an increase in the response coefficient. Note, however, that the model is fairly well diversified among the investment style variables. The forecast is not dominated by any one style.

The dispersion of the information signals that we used to predict future asset performance can be further decomposed. Indeed, a security may be attractively valued because its country of domicile is attractive, because the global industry to which it belongs is attractive, or for local industry or stock-specific reasons. We thus conducted a Heston–Rouwenhorst (1994) factor decomposition of each of the independent variables used in the model.[10] This decomposition provides insights into whether

Figure 1. Style-Based Forecast Decomposition: Representative Security, December 1989–June 2001

Note: Based on the MSCI global industry classification as outlined in the text.

©2002, AIMR®

the dispersion in the information signals that enable the asset manager to predict future asset price performance are becoming more "global" and less "local" in nature. It also provides evidence complementary to the findings of Diermeier and Solnik that factors that contemporaneously explain the dispersion in security prices are becoming more global in nature.

Table 3 reports the ratio of the MAD (mean absolute deviation) estimators for the global industry factors to the MAD estimators for the country factors for each of our explanatory variables. The results suggest that global industry factors are now an increasingly important determinant of the information signals that asset managers may wish to use. Having obtained the Heston–Rouwenhorst (1994) factor decomposition for each of the independent variables, we could obtain a graph analogous to Figure 1. For each security, we found the weighted sum of the factor decompositions of all explanatory variables, where the weights were the estimated beta parameters from the regression equation over time; we then computed the factor decomposition for the "average" security by averaging our results over all securities.[11] We present this analysis in **Figure 2** under the assumption that the forecast contribution from the interest rate differentials reflects only country effects.[12] Figure 2 thus provides the country, global industry, and local industry decomposition of the style-based forecast signal decomposed in Figure 1. These results suggest that a greater proportion of the dispersion in the forecast signal is now attributable to dispersion in global factors—in particular, to global industry factors.

Table 3. Information Signal Factor Decomposition: Ratio of Global Industry MAD to Country MAD

	FT Industry Classification		MSCI Industry Classification	
Independent Variable	31/Dec/86 to 31/Dec/95	31/Dec/95 to 30/Jun/01	31/Dec/86 to 31/Dec/95	31/Dec/95 to 30/Jun/01
Lagged return	0.99	1.90	0.92	2.13
Dividend yield	0.52	1.55	0.48	1.56
Log($EPS2/P$)	0.26	1.19	0.26	1.45
Up–down ratio	1.79	2.12	1.64	2.07
LT earnings growth	0.58	0.67	0.57	0.63

Figure 2. Country, Global Industry, and Local Industry Forecast Decomposition: Representative Security, December 1989–June 2001

Note: Based on the MSCI global industry classification as outlined in the text.

Cavaglia, Brightman, and Aked suggested that for security selection, managers would increasingly use relative comparisons of companies within global industries rather than within countries. This conjecture can be examined in the context of our forecasting framework. Our panel regression (see Equation 1) can be modified as follows:

$$\begin{aligned}(R_i - \bar{R})_{t \text{ to } t+h} = {} & \beta^W_{1t}(x_{1i} - \bar{x}_1)_t + \beta^A_{1t}(\bar{x}_1 - \bar{\bar{x}}_1)_t \\ & + \beta^W_{2t}(x_{2i} - \bar{x}_2)_t + \beta^A_{2t}(\bar{x}_2 - \bar{\bar{x}}_2)_t \\ & + \ldots + \beta^W_{k,t}(x_{k,i} - \bar{x}_k)_t \\ & + \beta^A_{k,t}(\bar{x}_k - \bar{\bar{x}}_k)_t + \varepsilon_{i,t}.\end{aligned} \tag{4}$$

where

$\bar{x}_{k,t}$ = mean (at time t) of the particular "group" (e.g., country or industry) in which local industry i belongs.

$\bar{\bar{x}}_{k,t}$ = grand mean of all x_i at time t; equivalently, mean of all group means $\bar{x}_k$

$\beta^W_{k,t}$ = "within"-group response coefficient

$\beta^A_{k,t}$ = "across"-group response coefficient

In Equation 4, which is a generalized version of Equation 1, $\beta^W_{k,t} = \beta^A_{k,t} = \beta_{k,t}$. Differences between $\beta^W_{k,t}$ and $\beta^A_{k,t}$ will largely reflect the appropriateness of the signal decomposition. Thus, if one wishes to highlight relative comparisons within global industries, the relevant group means in Equation 4 are global industry means. We illustrate this approach in **Exhibit 4** with a design matrix (at a point in time) for a model that uses dividend yield as a predictive variable. An economic interpretation of this model is as follows. We might expect Australian banks to outperform all other local industries in the world in either of two cases: (1) Australian banks could be attractively valued relative to all other banks in the world (a within-global-industry effect) or (2) banks in the world could be attractively valued relative to all other global industries (an across-global-industry effect). Differences in the response coefficients would reflect the relative importance of the dispersion of valuations within global industries and across global industries.

Estimates of Equation 4 that use the industry-relative explanatory variables of our global-relative forecast model are in **Table 4** for the particular case of one explanatory variable—the dividend yield; we call this model the "industry-relative model." We provide two snapshots of our estimations—one for the period December 1985 through December 1990, and the other for the period December 1985 through June 2001. As in our discussion of the global-relative model, different estimation windows are provided to demonstrate the potential applicability of this framework for portfolio construction in the 1990–2001 period. The parameters we report are of the right sign; they are generally statistically significant; and they appear fairly stable over time. Using a chi-square test, we examined the hypothesis that within-industry effects are equal to across-industry effects for each explanatory variable jointly.[13] The null hypothesis that the effects are equal was rejected at the 10 percent significance level; thus, we found statistical support for decomposing our information signals into relative comparisons within and across global industries.

The model in Equation 4 provides a fairly general approach to alternative decomposition of predictive variables. A natural alternative to the within-global and across-global industry approach is a within-country and across-country approach. This approach is illustrated in **Exhibit 5** for the dividend yield as the explanatory variable. An economic interpretation of this forecast model follows. We might expect Australian banks to outperform all other industries in the world if (1) Australian banks are attractively valued relative to all other local industries in Australia (a within-country effect) or (2) all Australian industries could be attractively valued relative to industries in all other countries (an across-countries effect). In **Table 5**, we report estimation results for the country-relative model. Overall, these results are similar to those for the industry-relative model. We did find, however, that differences across countries in long-term earnings growth are not significantly related to future local industry performance; thus, we have excluded that explanatory variable from the country-relative model.

In summary, statistical evidence supports the predictability of local industry returns. Different models stress the different comparisons that an asset manager might consider when selecting securities. The economic significance of using forecasts obtained from Equation 4, rather than from Equation 1, for the purpose of constructing optimal global equity allocations can be assessed via strategy backtests that mimic the portfolio construction process over time. These backtests are presented next.

Portfolio Performance of CICCA Strategies

To what extent can the documented predictability of local industry returns be translated into portfolio performance in excess of benchmark returns? We evaluated alternative investment strategies that used out-of-sample forecasts and replicated portfolio construction over the period December 1990

©2002, AIMR®

Exhibit 4. Industry-Relative Forecast Model

Panel Data Set		Industry	Dependent Variable: Three-Month-Ahead Excess Returns	Information Signal: Local Industry to Global Industry	Information Signal: Global Industry to World
Australia—AUD					
1	Energy	i01	Ret(AUD 101)–Ret(Avg. world)	DY(AUD i01)–DY(Avg. global i01)	DY(Avg. global i01)–DY(Avg. world)
2	Materials	i02	Ret(AUD 102)–Ret(Avg. world)	DY(AUD i02)–DY(Avg. global i02)	DY(Avg. global i02)–DY(Avg. world)
3	Capital goods	i03	Ret(AUD 103)–Ret(Avg. world)	DY(AUD i03)–DY(Avg. global i03)	DY(Avg. global i03)–DY(Avg. world)
	. . . .	. . . .	. . . .	. . . .	. . . .
22	Telecom	i22	Ret(AUD 122)–Ret(Avg. world)	DY(AUD i22)–DY(Avg. global i22)	DY(Avg. global i22)–DY(Avg. world)
23	Utilities	i23	Ret(AUD 123)–Ret(Avg. world)	DY(AUD i23)–DY(Avg. global i23)	DY(Avg. global i23)–DY(Avg. world)
	:		:	:	:
	:		:	:	:
	:		:	:	:
United States—USD					
461	Energy	i01	Ret(USD 101)–Ret(Avg. world)	DY(USD i01)–DY(Avg. global i01)	DY(Avg. global i01)–DY(Avg. world)
462	Materials	i02	Ret(USD 102)–Ret(Avg. world)	DY(USD i02)–DY(Avg. global i02)	DY(Avg. global i02)–DY(Avg. world)
463	Capital goods	i03	Ret(USD 103)–Ret(Avg. world)	DY(USD i03)–DY(Avg. global i03)	DY(Avg. global i03)–DY(Avg. world)
	. . . .	. . . .	. . . .	. . . .	. . . .
482	Telecom	i22	Ret(USD 122)–Ret(Avg. world)	DY(USD i22)–DY(Avg. global i22)	DY(Avg. global i22)–DY(Avg. world)
483	Utilities	i23	Ret(USD 123)–Ret(Avg. world)	DY(USD i23)–DY(Avg. global i23)	DY(Avg. global i23)–DY(Avg. world)

Table 4. Model Coefficients: Industry-Relative Forecast Model
(time series/cross-sectional regression parameters; *t*-statistics in parentheses)

	FT Industry Classification				MSCI Industry Classification			
	31/Dec/85 to 31/Dec/90		31/Dec/85 to 30/Jun/01		31/Dec/85 to 31/Dec/90		31/Dec/85 to 30/Jun/01	
Independent Variable	Within-Global-Industry Beta	Across-Global-Industries Beta	Within-Global-Industry Beta	Across-Global-Industries Beta	Within-Global-Industry Beta	Across-Global-Industries Beta	Within-Global-Industry Beta	Across-Global-Industries Beta
Lagged return	0.0252	0.0421	0.0262	0.0535	0.0114	0.0673	0.0261	0.0581
	(4.0908)	(3.0059)	(6.6322)	(6.8606)	(1.4830)	(3.5812)	(5.5256)	(5.9182)
Dividend yield	0.4265	0.2841	0.3101	0.3832	0.4326	0.0740	0.4392	0.2934
	(4.6143)	(1.4965)	(5.4875)	(3.2736)	(3.7585)	(0.3383)	(6.5488)	(2.1736)
Log(*EPS*2/*P*)	0.0081	0.0013	0.0117	0.0061	0.0099	0.0104	0.0117	0.0236
	(2.9510)	(0.2240)	(6.5456)	(1.6444)	(3.0525)	(1.3981)	(5.5152)	(4.9728)
Up–down ratio	0.0373	0.0265	0.0304	0.0324	0.0450	0.0334	0.0365	0.0325
	(5.1538)	(1.3565)	(7.5762)	(2.8394)	(5.3614)	(1.3228)	(7.6247)	(2.1487)
LT earnings growth	0.0013	0.0023	0.0009	0.0019	0.0026	0.0075	0.0012	0.0040
	(1.1114)	(1.4535)	(1.7273)	(1.8557)	(1.9384)	(3.5289)	(2.0586)	(2.9329)
Long-bond yield	–0.0055	–0.0055	–0.0035	–0.0035	–0.0057	–0.0057	–0.0038	–0.0038
	(–9.4195)	(–9.4195)	(–8.9630)	(–8.9630)	(–8.3842)	(–8.3842)	(–8.2290)	(–8.2290)
Joint chi-square test for equality of coefficients								
Chi-square statistic	4.6463		16.9078		19.1471		17.3993	
P-value	0.4605		0.0046		0.0018		0.0038	

through June 2001. This process provided a 10-year assessment of the relative attractiveness of our strategies in several economic cycles and in periods when a variety of styles were in and out of favor.

For all models presented in the previous section, we generated forecasts of three-month excess returns for each month-end over the period 31 December 1990 to 31 May 2001. The betas were reestimated at each month-end from data available only up through the time when forecasts were assumed to be made. For example, forecasts made on 31 December 1990 used betas estimated from data for 31 December 1985 through 30 September 1990 (because of the three-month dependent variable); model parameters were then applied to values of the independent variables on 31 December 1990 to obtain the forecasts made on that date. We applied this procedure for the 126 months of our analysis. We then used the forecasts to evaluate two investment strategies—a self-financing long–short strategy and a fully invested, long-only, risk-controlled investment strategy.

The long–short strategy followed the standard approach used in other studies designed to evaluate the economic content of a predictive relationship (see, for instance, Rouwenhorst or Capaul). We used month-end forecasts to decide allocations among "local" industries. The portfolios were constructed to hold long positions in the 50 assets with the best expected performance and short positions in the 50 assets with the worst expected monthly performance. Portfolio weights were set at ±2 percent for each asset at each month-end rebalancing.

The performance of this investment strategy for each of the forecast models is presented in **Table 6**. The average annual returns range from 17 percent to 24 percent. Formal tests suggest that these returns are statistically significantly different from zero at the 99 percent confidence level.

These results well exceed any of the documented performance of long–short global investment strategies applied at the security level. Furthermore, note that the strategy that used the model emphasizing relative comparisons within and across industries had the best-performing strategy in this period as applied to both the FT and MSCI industry classifications. It provided 220–360 bps of return a year more than the strategy that used the model emphasizing relative comparisons on a bottom-up global basis. Still, readers should interpret these results with some caution. The performance we obtained may be attributable to significant style, country, or industry exposures. Furthermore, our portfolio construction rules did not explicitly control for turnover; thus, the strategies could result in high transaction costs when implemented. These issues are best examined in the context of the long-only, risk-controlled investment strategy.[14]

For the long-only strategy, we assumed that the portfolio was fully invested and that allocations were set at benchmark weights on 31 December 1990. We then used forecasts to solve the standard

©2002, AIMR®

Exhibit 5. Country-Relative Forecast Model

Panel Data Set		Industry	Dependent Variable Three-Month-Ahead Excess Returns	Information Signal: Local Industry to Country	Information Signal: Country to World
Australia—AUD					
1	Energy	i01	Ret(AUD i01)–Ret(Avg. world)	DY(AUD i01)–DY(Avg. country AUD)	DY(Avg. country AUD)–DY (Avg. world)
2	Materials	i02	Ret(AUD i02)–Ret(Avg. world)	DY(AUD i02)–DY(Avg. country AUD)	DY(Avg. country AUD)–DY (Avg. world)
3	Capital goods	i03	Ret(AUD i03)–Ret(Avg. world)	DY(AUD i03)–DY(Avg. country AUD)	DY(Avg. country AUD)–DY (Avg. world)
	. . . .	. . . .	. . . .	. . . .	. . . .
22	Telecom	i22	Ret(AUD i22)–Ret(Avg. world)	DY(AUD i22)–DY(Avg. country AUD)	DY(Avg. country AUD)–DY (Avg. world)
23	Utilities	i23	Ret(AUD i23)–Ret(Avg. world)	DY(AUD i23)–DY(Avg. country AUD)	DY(Avg. country AUD)–DY (Avg. world)
	:		:	:	:
	:		:	:	:
	:		:	:	:
United States—USD					
461	Energy	i01	Ret(USD i01)–Ret(Avg. world)	DY(USD i01)–DY(Avg. country USD)	DY(Avg. country USD)–DY (Avg. world)
462	Materials	i02	Ret(USD i02)–Ret(Avg. world)	DY(USD i02)–DY(Avg. country USD)	DY(Avg. country USD)–DY (Avg. world)
463	Capital goods	i03	Ret(USD i03)–Ret(Avg. world)	DY(USD i03)–DY(Avg. country USD)	DY(Avg. country USD)–DY (Avg. world)
	. . . .	. . . .	. . . .	. . . .	. . . .
482	Telecom	i22	Ret(USD i22)–Ret(Avg. world)	DY(USD i22)–DY(Avg. country USD)	DY(Avg. country USD)–DY (Avg. world)
483	Utilities	i23	Ret(USD i23)–Ret(Avg. world)	DY(USD i23)–DY(Avg. country USD)	DY(Avg. country USD)–DY (Avg. world)

Table 5. Model Parameters: Country-Relative Forecast Model
(time series/cross-sectional regression parameters; *t*-statistics in parentheses)

	FT Industry Classification				MSCI Industry Classification			
	31/Dec/85 to 31/Dec/90		31/Dec/85 to 30/Jun/01		31/Dec/85 to 31/Dec/90		31/Dec/85 to 30/Jun/01	
Independent Variable	Within-Country Beta	Across-Countries Beta	Within-Country Beta	Across-Countries Beta	Within-Country Beta	Across-Countries Beta	Within-Country Beta	Across-Countries Beta
Lagged return	0.0225	0.0351	0.0257	0.0379	0.0225	0.0351	0.0257	0.0379
	(3.2059)	(3.7734)	(5.8521)	(6.3911)	(3.2059)	(3.7734)	(5.8521)	(6.3911)
Dividend yield	0.3507	0.6134	0.2537	0.5372	0.3507	0.6134	0.2537	0.5372
	(3.2779)	(4.2787)	(3.8585)	(6.2652)	(3.2779)	(4.2787)	(3.8585)	(6.2652)
Log(*EPS*2/*P*)	0.0072	0.0061	0.0098	0.0088	0.0072	0.0061	0.0098	0.0088
	(2.1613)	(1.4918)	(4.7007)	(3.3229)	(2.1613)	(1.4918)	(4.7007)	(3.3229)
Up–down ratio	0.0304	0.0441	0.0314	0.0316	0.0304	0.0441	0.0314	0.0316
	(4.1256)	(2.3595)	(7.8772)	(2.7577)	(4.1256)	(2.3595)	(7.8772)	(2.7577)
LT earnings growth	0.0071		0.0038		0.0071		0.0038	
	(4.1419)		4.0670		(4.1419)		(4.0670)	
Long-bond yield	–0.0055	–0.0055	–0.0035	–0.0035	–0.0055	–0.0055	–0.0035	–0.0035
	(–9.1159)	(–9.1159)	(–8.4413)	(–8.4413)	(–9.1159)	(–9.1159)	(–8.4413)	(–8.4413)
Joint chi-square test for equality of coefficients								
Chi-square statistic	3.7903			10.8572	3.7903		10.8572	
P-value	0.4351			0.0282	0.4351		0.0282	

Table 6. Mean Annual Return for Long–Short Investment Strategy
(*t*-statistics in parentheses)

Model	FT Industry Classification	MSCI Industry Classification
Global-relative forecast model	16.72% (10.31)	20.48% (14.30)
Industry-relative forecast model	18.92 (11.13)	24.10 (14.69)
Country-relative forecast model	17.20 (9.92)	21.03 (14.65)

mean–variance portfolio optimization, subject to a number of constraints designed to provide a reasonable representation of an active portfolio manager's strategies: no short sales, a maximum active weight in any local industry of 1 percent, and a maximum active weight in any global industry or country of 10 percent. We imposed position limits because unconstrained mean–variance optimization often results in portfolios with extreme asset weights (Michaud 1998). The limits were designed to be uniform so as to avoid any arbitrariness in our portfolio construction rules.[15] We used the BITA Plus software to carry out the optimizations.[16] We applied the Heston–Rouwenhorst model (1994) that orthogonalizes security returns into global, country, industry, and security-specific factors to measure expected tracking errors; this model is simpler than the Barra GEM (global equity model) because the Heston–Rouwenhorst model abstracts from style risks. Thus, our backtest results can be viewed as conservative because a more sophisticated model should have enhanced performance. The portfolios were rebalanced on a monthly basis. Active positions were altered in response to portfolio weights drifting through time (because of price appreciation) or to provide an improvement in the expected risk–reward trade-offs (net of transaction costs).[17]

The annualized performance of the long-only investment strategy for the two industry classification schemes is in **Table 7**. Returns in excess of the world benchmark are reported. For the period of analysis, our strategy's (gross) outperformance ranged from 363 bps to 400 bps a year. This performance was achieved with fairly reasonable levels of one-way turnover (about 50 percent a year) and reasonable levels of tracking error (about 3 percent), resulting in information ratios in excess of 1.0. The information ratios in our study were obtained from average net returns under the assumption of average one-way transaction costs of 50 bps, but even if we had assumed transaction costs of 2 percent, the net outperformance would remain economically significant. If an investor had exploited global-industry-relative comparisons (see Equation 4 and our illustration in Exhibit 4), outperformance would have been even higher—462–491 bps a year. Country-relative comparisons produced relatively lower outperformance—391–426 bps a year. These results suggest that it behooves active asset managers to organize their analyst teams on a global industry basis.

Table 7. Performance in Excess of Benchmark, 31 December 1990 to 30 June 2001
(in percentage points)

	Global-Relative Forecast Model		Industry-Relative Forecast Model		Country-Relative Forecast Model	
Measure	FT	MSCI	FT	MSCI	FT	MSCI
Gross average annualized returns	3.63	4.00	4.62	4.91	3.91	4.26
Ex post annualized tracking error	2.92	2.87	3.23	3.48	3.07	2.85
Information ratio	1.07	1.22	1.27	1.26	1.11	1.32
Turnover	52.50	50.40	51.9	54.30	51.90	49.00
Best yearly performance	11.51	9.96	11.54	13.18	11.93	10.81
Worst yearly performance	–2.71	–2.98	–2.60	–1.86	–3.53	3.28

As previously stated, we did not explicitly control for style exposures in our portfolio construction. But the reader may be interested in the extent to which the market outperformance of these strategies can be attributed to style exposures that systematically differ from the underlying benchmark. Therefore, for each of our strategies, we computed a Jensen-like alpha. Jensen's (1969) seminal study considered a one-factor model of risk and return. We extended his framework by considering risk factors documented in more-recent asset-pricing studies. In particular, Fama and French (1992) proposed that the risk and return characteristics of U.S. security prices are best characterized by a three-factor model composed of a market factor, a value–growth factor, and a size factor. In their extension of this analysis to international data, Fama and French (1998) demonstrated that a global value–growth factor is an important determinant of the cross-section of international security returns.[18] In his evaluation of U.S. mutual fund performance, Carhart (1997) augmented the Fama–French three-factor model by including a momentum factor. Because Rouwenhorst documented the existence of momentum factor returns for global equities, we considered a four-factor model of international security returns that consisted of a market factor, a value–growth factor, a size factor, and a momentum factor.[19]

Fama and French (1998) obtained their "world" value–growth factor returns by aggregating, on a cap-weighted basis, the national value–growth factor returns. Their national value–growth returns were obtained from self-financing strategies of buying low-P/B stocks and selling high-P/B stocks within each country. They also considered dividend yield and P/E as variables that can characterize value stocks versus growth stocks and found that the value factor returns when these variables are used are highly correlated with those obtained when P/B is used. Unlike our present study, however, they did not consider alternative security weighting schemes (cap weighting versus equal weighting) or alternative ways of stratifying the universe of securities (by country, by global industry, or bottom up).

The sorting variables we used to obtain our factor returns are dividend yield (for value), market cap (for size), and lagged excess returns over the previous 12 months (for momentum).[20] We examined factor return series obtained from equal-weighted and cap-weighted portfolios that spanned the entire universe of securities, and we stratified that universe by country (as in Fama and French 1998), by global industry, or on a bottom-up basis. For example, for value factor returns, the global-industry stratification categorized securities in each global industry as either value or growth. We then aggregated the value–growth return series for each global industry (by market cap or on an equal-weighted basis) to obtain the world value–growth factor return. The bottom-up factor returns were obtained from a single sort of all securities in the world, regardless of country of domicile or industry membership.

We report sample statistics for our factor returns in **Table 8**. As documented in previous studies, we found for our sample period that, on average, value stocks outperformed growth stocks, small caps outperformed large caps, and as for momentum, past "winners" outperformed past "losers." Note that alternative stratification methods significantly affected the properties of the estimated factor returns, which corroborates the need to examine risk-adjusted performance with several models.

For each investment strategy, we estimated a regression of the portfolio monthly returns on a constant and the global market, value, size, and momentum factor returns. Under the joint hypothesis that our factor model is "true" and that markets are efficient, we expected the constant term to be economically small and statistically insignificantly different from zero. In **Table 9**, we report the parameters of the estimated regressions for alternative models based on explanatory factor

Table 8. Factor Returns: Alternative Universe Stratifications, 31 December 1990 to 30 June 2001
(*t*-statistics in parentheses)

	Bottom Up		Industry Relative		Country Relative	
Measure	Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted
Value						
Mean monthly return	0.15%	0.31%	0.36%	0.35%	0.23%	0.31%
	(1.52)	(5.18)	(4.92)	(6.86)	(3.10)	(8.12)
Annualized monthly return	1.84	3.75	4.29	4.18	2.73	3.74
Size						
Mean monthly return	–0.44%	–0.07%	–0.09%	–0.12%	–0.02%	–0.09%
	(–4.04)	(–1.70)	(–2.18)	(–3.42)	(–0.39)	(–2.82)
Annualized monthly return	–5.23	–0.83	–1.06	-1.48	–0.29	–1.12
Momentum						
Mean monthly return	0.77%	0.30%	0.26%	0.20%	0.25%	0.20%
	(4.28)	(5.31)	(4.32)	(4.00)	(3.07)	(4.79)
Annualized monthly return	9.29	3.64	3.10	2.43	3.00	2.36

Notes: Value = long stocks with high dividend yield, short stocks with low dividend yield. Size = long large-cap stocks, short low-cap stocks. Momentum = long stocks with high past-12-month returns, short stocks with low past-12-month returns.

returns that were computed on a cap-weighted basis and with a within-country stratification as in Fama and French (1998). Overall, we found relatively small estimated factor loadings, which may be attributable to the style diversification approach or to the possibility that we were implicitly practicing style rotation across local industries that was not systematically related to style factors as usually defined. More importantly, the constant terms are economically large and statistically significantly different from zero. On a risk-adjusted basis, the global-industry-relative model remained the best-performing model, and this finding held for alternative industry classifications. To assess the robustness of our results, we report the estimated intercept term for alternative methods of constructing the style factors in **Table 10**. Again, we found that the global-industry-relative model dominates all other models on a risk-adjusted basis.

Table 9. Risk-Adjusted Model Performance, 31 December 1990 to 30 June 2001
(*t*-statistics in parentheses)

	FT Industry Classification Models			MSCI Industry Classification Models		
Beta Coefficient	Global-Relative Forecast Model	Industry-Relative Forecast Model	Country-Relative Forecast Model	Global-Relative Forecast Model	Industry-Relative Forecast Model	Country-Relative Forecast Model
Constant	0.0028	0.0034	0.0028	0.0029	0.0038	0.0031
	(4.2647)	(4.6891)	(3.7997)	(4.3543)	(5.0176)	(4.4666)
World	0.9789	0.9982	1.0125	0.9943	0.9751	1.0077
	(50.2312)	(46.7453)	(46.2958)	(50.3808)	(43.2603)	(48.4426)
Value	–0.0312	–0.0197	–0.0066	0.0090	–0.0580	–0.0007
	(–1.6769)	(–0.9671)	(–0.3149)	(0.4714)	(–2.6512)	(–0.0359)
Size	0.0597	0.0626	0.0596	0.0316	0.0286	0.0208
	(2.3078)	(2.2091)	(2.0534)	(1.2041)	(0.9519)	(0.7532)
Momentum	0.0722	0.0891	0.0633	0.0820	0.1143	0.0698
	(3.9738)	(4.4748)	(3.1021)	(4.4456)	(5.4245)	(3.5910)
R^2	0.9632	0.9573	0.9559	0.9629	0.9535	0.9603

©2002, AIMR®

Table 10. Annualized Model Alphas: Risk-Adjusted with Alternative Factor-Return Stratifications, 31 December 1990 to 30 June 2001
(in percentage points)

	Bottom-Up Stratification		Industry-Relative Stratification		Country-Relative Stratification	
Model	Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted	Cap Weighted	Equal Weighted
Forecast model applied to MSCI industry classification						
Global-relative forecast model	3.65	2.90	3.31	2.90	3.48	3.29
Industry-relative forecast model	4.58	4.11	4.65	3.97	4.58	4.47
Country-relative forecast model	3.80	3.27	3.51	3.10	3.76	3.72
Forecast model applied to FT industry classification						
Global-relative forecast model	3.32	2.82	3.25	2.75	3.36	3.41
Industry-relative forecast model	4.00	3.63	4.05	3.58	4.05	3.98
Country-relative forecast model	3.35	2.75	3.00	2.57	3.36	3.42

Note: All reported alphas are statistically significant at the 1 percent level.

However, our findings should be interpreted with some caution. The anomaly we uncovered may be partly attributable to a misspecified risk model. For instance, we may have omitted consideration of regional style risks. Another possibility is that, over time, our strategy may produce style rotations that are not captured by the average or systematic style exposures presented in Table 9. Alternatively, our returns in excess of the market returns may have come from agents adopting local pricing models, so our global approach enabled us to capture the most attractive "local" inefficiencies. Finally, we documented only that relative comparisons within and across global industries were "best" for our predictive models. We did not present evidence that this result is general; indeed, a superior within-countries, across-countries model may exist. We believe our findings present a challenge to the asset management community, which continues to be wedded to the country-based approach to portfolio construction.

Conclusions

The increasing globalization of business activities presents new challenges and new opportunities for the asset management profession. Traditionally, managers carried out active international equity allocations in a two-step process that overlaid security selection within countries on top-down country selection. Diermeier and Solnik found, however, that the sensitivity of individual company returns to nondomestic factors is closely related to the extent of their international activities. Thus, analysis of the individual company and its diversity has become critical and the effectiveness of the traditional allocation approach is outdated.

We consider that global industry factors may account for some of the international effects documented in Diermeier and Solnik. Thus, we believe that the appropriate approach to active equity allocation in the new global environment is a simultaneous assessment of both country and industry factors—that is, a cross-industry, cross-country matrix approach.

CICCA allocations recognize the interaction of country and industry factors in determining security prices. CICCA provides a middle ground between traditional top-down allocation and pure bottom-up security selection in a global equity portfolio. In this framework, country allocations and global industry allocations result from local industry selection. Similarly, global style tilts result from local style tilts. The risks of the resulting country, global industry, and style tilts can be monitored at the aggregate level and can be altered via industry allocations. To obtain final security holdings, security selection decisions can be overlaid on the local industry selection decision. Stock selection may thus override or reinforce CICCA decisions.

We demonstrated how CICCA can be used to construct local industry allocations aimed at outperforming global benchmarks. We presented a forecasting framework to predict the relative performance of local industries and demonstrated that a blend of style signals that includes measures of profitability, value, and price momentum provides an effective means of predicting asset price performance.

We examined the out-of-sample performance of risk-controlled investment strategies based on these forecasts for the 1990–2001 period and found that a CICCA approach would have produced outperformance of the global equity benchmarks by as much as 400 bps a year.

We also examined two alternative models that emphasized either country factors or global industry factors as the principal determinants of the relative attractiveness of a local industry. We found that predictions based on the relative attractiveness of securities within and across global industries dominated those based on the relative attractiveness of securities within and across countries.

In addition, we examined the historical performance of CICCA strategies on a risk-adjusted basis and found that CICCA strategies can deliver an economically and statistically significant outperformance of market returns even after accounting for style factor risk tilts.

Finally, a caveat: The "anomaly" we documented could have various (and conflicting) explanations. On the one hand, although we exercised great care to use only information that was available to market participants at the time we assumed forecasts were made, some look-ahead bias remains in our analysis; namely, our model structure is based on the current knowledge of past factors. On the other hand, because of home-biased investment decisions, large mispricings exist in the global investment universe that can be exploited by a fully integrated global investment platform. A third possibility is that our approach may actually be carrying out style rotation within and across industries, thus providing returns that reflect risks that are not captured by conventional risk models or conventional definitions of style factors. This possibility suggests that further analysis of risk factors is needed in the new global equity landscape. Resolution of these conflicting explanations is an interesting challenge for the investment and academic communities.

We gratefully acknowledge comments from B. Solnik, R. Hodrick, J. Diermeier, B. Singer, K. Terhaar, M. Mednikov, U. Schillhorn, V. Koutsaftis, J. Sefton, and participants at the INQUIRE Europe October 2001 meeting. We are also grateful for the support of M. Aked, who initiated some of the work relating to the proprietary database developed to conduct this study.

Notes

1. Some of the early and related literature stressed the importance of local or national industry factors in determining security returns (Cavaglia, Melas, and Miyashita 1994; Cavaglia Melas, and Tsouderos 2000).
2. In Capaul, global industry "size" was measured as percentage of market capitalization relative to the world index.
3. Other studies that examined the predictability of equity returns across countries and that stressed the industry dimension include Cavaglia, Melas, Tsouderos, and Cuthbertson (1995), Harvey, Solnik, and Zhou (1994), Bauman, Conover, and Miller (1998), and O'Neal (2000).
4. A longitudinal, or panel, data set is one that follows a given example of individuals over time. Panel data sets are an effective means of increasing the size of the data sample (thus increasing the number of degrees of freedom and the resulting efficiency of econometric estimates) at the possible cost of imposing some "pooling" restrictions. A detailed description of the analysis of panel data can be found in the introductory text by Hsiao (1986).
5. To simplify the analysis, we did not consider cross-product terms of the explanatory variables; these variables can be incorporated, however, in the framework we present.
6. We implicitly assumed that the response coefficient is the same for all industries. This assumption can be relaxed via the use of dummy variables, but doing so runs the risk of overparameterizing the model.
7. In the particular case when the forecast horizon is greater than the observational frequency, the OLS estimates of the betas will be unbiased but standard errors for the coefficients will be underestimated because of serial correlation in the residuals. This problem can be remedied by the Newey–West correction to the standard errors. In our correction, we assumed that the variances of the error terms are identical across industries. Hence, our standard errors for the regression parameters are probably understated. Relaxing this assumption would require solving SURE-like systems, which given the size of our data sample, would be computationally demanding.
8. This approach contrasts with rank-based screens of securities. For instance, consider two securities—one with a P/B of 2.00 and the other with a P/B of 2.01. The regression approach will show that the forecasts for these securities are quite close and similar; the rank approach, however, suggests that these securities are markedly different.
9. We plotted the decomposition of the style forecast factor on a cap-weighted basis for the MSCI GICS 23-industry classification scheme; a plot for the average security (in an equal-weighted scheme) would be qualitatively similar. We found similar results for the FT industry classification.
10. Heston and Rouwenhorst (1994) demonstrated how to simultaneously decompose security returns into global factors, country factors, global industry factors, and security-specific factors. Country factors are constructed while controlling for differing industrial structures across countries; global industry factors are constructed while controlling for different country compositions.
11. The following formulas hold at each point in time; for simplicity of exposition, we have omitted time subscripts. Denoting FCST_i to be the forecast for local industry i, then

$$FCST_i = \sum_j \hat{\beta}_j x_{j,i}.$$

Note that for each explanatory variable, we have removed the world mean, as suggested by Equation 1. Using the dummy variable approach of Heston and Rouwenhorst (1994), we can decompose each explanatory variable into a country factor, $x^c_{j,i}$; a global industry factor, $x^{gind}_{j,i}$; and a local industry factor, $x^{lind}_{j,i}$. The local industry factors are analogous to the residuals of the Heston–Rouwenhorst regression, which represented security-specific factors in their particular application. Thus, we note that

$$x_{j,i} = x^c_{j,i} + x^{gind}_{j,i} + x^{lind}_{j,i}.$$

©2002, AIMR®

For each security, we can compute TOT_i as follows:

$$TOT_i = \sum_j \left|\hat{\beta}_j x^c_{j,i}\right| + \sum_j \left|\hat{\beta}_j x^{gind}_{j,i}\right| + \sum_j \left|x^{lind}_j\right|.$$

We can then compute relevant forecast contribution ratios for each security as follows:

$$RATIO^c_i = \sum_j \left|\hat{\beta}_j x^c_{j,i}\right| / TOT_i,$$

$$RATIO^{gind}_i = \sum_j \left|\hat{\beta}_j x^{gind}_{j,i}\right| / TOT_i, \text{ and}$$

$$RATIO^{lind}_i = \sum_j \left|x^{lind}_j\right| / TOT_i.$$

Figure 2 was obtained from a cap-weighted sum of the security-level ratios, in which w_i represents the cap weight of security i as follows:

$$\sum_i w_i RATIO^c_i,$$

$$\sum_i w_i RATIO^{gind}_i, \text{ and}$$

$$\sum_i w_i RATIO^{lind}_i.$$

12. We found that different industries exhibit different contemporaneous interest rate sensitivities but that accounting for country effects (and no differential effects across industries) provided a sufficient and robust specification for the purpose of forecasting future local industry returns.
13. We tested the joint hypothesis that $\beta^W_1 = \beta^A_1$ and $\beta^W_2 = \beta^A_2$ and . . . and $\beta^W_6 = \beta^A_6$. Hence, we tested six parameter restrictions.
14. Our risk-controlled strategy did not explicitly target a specific level of tracking error. Rather, we allowed risk–reward opportunities net of transactions costs (as outlined in Footnote 15) to determine portfolio holdings.
15. When we modified the position limits by a multiplicative constant (e.g., doubled the active country and industry position limits), portfolio performance and tracking errors were accordingly affected while Sharpe ratios remained fairly constant; this result suggests that our findings are insensitive to reasonable alternatives of the simple position constraints we imposed.
16. The utility function we maximized is of the form:

$$U = \frac{\gamma}{1-\gamma}(\alpha w) - (w - wb)^T \mathbf{V}(w - wb) - \frac{\kappa}{1-\kappa} TC,$$

where **V** is the covariance matrix and is equal to $(FL) \times (\mathbf{FC}) \times (FL^T) + SV$; FL, **FC**, and SV are, respectively, the factor loadings, the factor covariance matrix, and the stock-specific variance; and TC stands for estimated transaction costs. The weights of the portfolio and of the benchmark are denoted by, respectively, w and wb. This specification is a fairly standard one (see Sharpe and Alexander 1990) that aims to capture the active risk–return (net of transaction costs) trade-off decisions an investor faces. The parameter γ reflects the investor's degree of risk aversion; that is, a high (low) γ is consistent with low (high) risk aversion and will result in a strategy with high (low) tracking error. The parameter κ reflects the investor's willingness to rebalance the portfolio and incur transaction costs; a high (low) κ will result in a strategy with low (high) turnover. In our optimizations, we used $\gamma = 0.2$ and $\kappa = 0.3$, which resulted in low-turnover and low-tracking-error strategies. We held these parameters constant throughout the simulation period.

17. The use of more-complex portfolio optimizations (relating the amount of trading to volatility in the market or relating the size of active weights to the confidence level of the forecasts) could be beneficial. We plan to evaluate such portfolio construction rules in future research.
18. Fama and French (1998) used the MSCI database, which covers the highest 65 percent market cap of each country in their sample. Thus, they were unable to estimate an international small-cap effect.
19. We are grateful to Bob Hodrick for suggesting this test of investment performance. We also conducted the analysis using the Fama–French two-factor model and found all of our results to be qualitatively similar. We chose to report risk-adjusted alphas generated by a four-factor model to provide the most conservative estimates of risk-adjusted excess performance; indeed, the alpha values reported are uniformly lower than if we had used a two-factor model.
20. We used the dividend yield because this valuation measure is comparable across countries; comparability is particularly important when carrying out global bottom-up sorts or global industry sorts of the investment universe. Nevertheless, we also constructed portfolios that mimicked the value–growth factor by using a P/B sort. The analysis using this definition of value is available from the authors. The qualitative comparison of forecast models remained unchanged when we used the alternative definition, and risk-adjusted performance remained economically and statistically significant.

References

Baca, Sean, Brain Garbe, and Richard Weiss. 2000. "The Rise of Sector Effects in Major Equity Markets." *Financial Analysts Journal*, vol. 56, no 5 (September/October):34–40.

Balvers, Ronald, Yangru Wu, and Erik Gilliland. 2000. "Mean Reversion across National Stock Markets and Parametric Contrarian Investment Strategies." *Journal of Finance*, vol. 55, no. 2 (April):745–772.

Bauman, Scott, Mitchell Conover, and Robert Miller. 1998. "Growth versus Value and Large-Cap versus Small-Cap Stocks in International Markets." *Financial Analysts Journal*, vol. 54, no. 2 (March/April):75–89.

Beller, Kenneth, John Kling, and Michael Levinson. 1998. "Are Industry Stock Returns Predictable?" *Financial Analysts Journal*, vol. 54, no. 5 (September/October):42–57.

Capaul, Carlo. 1999. "Asset-Pricing Anomalies in Global Industry Indexes." *Financial Analysts Journal*, vol. 55, no. 4 (July/August):17–37.

Carhart, Mark. 1997. "On the Persistence of Mutual Fund Performance." *Journal of Finance*, vol. 52, no. 1 (March): 57-82.

Cavaglia, Stefano, Christopher Brightman, and Michael Aked. 2000. "The Increasing Importance of Industry Factors." *Financial Analyst Journal*, vol. 56. no. 5 (September/October 2000):41–54.

Cavaglia, Stefano, Dimitris Melas, and Osamu Miyashita. 1994. "Efficiency Across Frontiers." *Risk*, vol. 7, no. 10 (October):56–61.

Cavaglia, Stefano, Dimitris Melas, and George Tsouderos. 2000. "Have We Underestimated the Gains from International Diversification: Cross-Industry and Cross-Country International Equity Allocation" *Journal of Investing*, vol. 9, no. 1 (Spring):65–71.

Cavaglia, Stefano, Dimitris Melas, George Tsouderos, and Keith Cuthbertson. 1995. "Industrial Action." *Risk*, vol. 8, no. 5 (May):32–36.

Chan, Louis, Narasimhan Jegadeesh, and Joseph Lakonishok. 1999. "The Profitability of Momentum Strategies." *Financial Analysts Journal*, vol. 55, no. 6 (November/December):80–90.

Cochrane, John. 1999. "New Facts in Finance." *Economic Perspectives*, Federal Reserve Bank of Chicago, vol. 23, no. 3 (3rd Quarter):36–58.

Diermeier, Jeff, and Bruno Solnik. 2001. "Global Pricing of Equity." *Financial Analysts Journal*, vol. 57, no. 4 (July/August):37–47

Fama, Eugene, and Ken French. 1992. "The Cross Section of Expected Stock Returns." *Journal of Finance*, vol. 47, no. 2 (June):427–465.

———. 1998. "Value versus Growth: The International Evidence." *Journal of Finance*, vol. 53, no. 6 (December):1975–99.

Graham, B., and D. Dodd. 1962. *Security Analysis*. New York: McGraw Hill.

Harvey, Campbell, Bruno Solnik, and Guofu Zhou. 1994. "What Determines Expected International Asset Returns?" National Bureau of Economic Research Working Paper W4660 (February).

Heston, Steven L., and K. Geert Rouwenhorst. 1994. "Does Industrial Structure Explain the Benefits of Industrial Diversification?" *Journal of Financial Economics*, vol. 36, no. 1 (August):3–27.

———. 1995. "Industry and Country Effects in International Stock Returns." *Journal of Portfolio Management*, vol. 21, no. 3 (Spring):53–58.

Hopkins, Peter, and Hayes Miller. 2001. "Country, Sector, and Company Factors in Global Equity Portfolios." Charlottesville, VA: The Research Foundation of AIMR and Blackwell Series in Finance.

Hsiao, Cheng. 1986. *Analysis of Panel Data*. New York: Cambridge University Press.

Jensen, Michael. 1969. "Risk, the Pricing of Capital Assets, and the Evaluation of Investment Portfolios." *Journal of Business*, vol. 42, no. 2 (April):167–247.

Michaud, Richard. 1998. *Efficient Asset Management*. Boston, MA: Harvard University Press.

O'Neal, Edward. 2000. "Industry Momentum and Sector Mutual Funds." *Financial Analysts Journal*, vol. 56, no. 4 (July/August):37–49.

Rouwenhorst, Geert. 1998. "International Momentum Strategies." *Journal of Finance*, vol. 53, no. 1 (February):267–284.

Sharpe, William, and Gordon Alexander. 1990. *Investments*. Englewood Cliffs, NJ: Prentice Hall.

Singer, Brian, and Denis Karnosky. 1995. "The General Framework for Global Investment Management and Performance Attribution." *Journal of Portfolio Management*, vol. 21, no. 2 (Winter):84–92.

Solnik, Bruno. 1993. "The Performance of International Asset Allocation Strategies Using Conditioning Information." *Journal of Empirical Finance*, vol. 1, no. 1 (June):33–55.

Sorensen, Eric, and Terry Burke. 1986. "Portfolio Returns from Active Industry Group Rotation." *Financial Analysts Journal*, vol. 46, no. 5 (September/October):43–50.

 ©2002, AIMR®