Internet Appendix of "International Stock Return Comovements"*

Table IA.I

Match Between SIC and FTSE Industry Classifications

DataStream provides FTSE level 4 industries, and French's website provides SIC 30 industries.

merged	FTSE level 4 industries		SIC 30 industries		
1	1	mining	17	Mines	Precious Metals, Non-Metallic, and Industrial Metal
2	2	oil and gas	19	Oil	Petroleum and Natural Gas
			18	Coal	Coal
3	3	chemicals	9	Chems	Chemicals
4	4	construction	11	Cnstr	Construction and Construction Materials
5	5	forestry and paper	24	Paper	Business Supplies and Shipping Containers
6	6	steel and other metals	12	Steel	Steel Works Etc
7	9	electronics and electrical equipments	14	ElcEq	Electrical Equipment
8	10	engineering and machinery	13	FabPr	Fabricated Products and Machinery
9	11	automobiles	15	Autos	Automobiles and Trucks
10	12	household goods and textiles	6	Hshld	Consumer Goods
			7	Clths	Apparel
11	13	beverages	2	Beer	Beer & Liquor
	14	food producers and processors	1	Food	Food Products
	27	food and drug			
12	15	health	8	Hlth	Healthcare, Medical Equipment, Pharmaceutical Products
	17	personal care			
	18	pharmaceuticals			
13	19	tobacco	3	Smoke	Tobacco Products
14	20	distributors	26	Whlsl	Wholesale
15	21	retailers	27	Rtail	Retail
16	22	leisure, entertainment and hotesl	4	Games	Recreation
	24	restaurants, pubs and breweries	28	Meals	Restaraunts, Hotels, Motels
17	23	media and photography	5	Books	Printing and Publishing
18	26	transport	25	Trans	Transportation
19	28	telecom services	21	Telcm	Communication
20	29	electricity	20	Util	Utilities
	30	gas distribution			
	31	water			
21	34	banks	29	Fin	Banking, Insurance, Real Estate, Trading
	35	insurance			
	36	life assurance			
	37	investment companies			
	38	real estate			
	39	specialty and other finance			
22	7	aerospace and defence	16	Carry	Aircraft, ships, and railroad equipment
23	8	diversified industrials	10	Txtls	Textiles
24	16	packaging	22	Servs	Personal and Business Services
	25	support services			
	33	software and computer services			

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25	32	information technology hardware	23	BusEq	Business Equipment
26	40	ineligible	30	Other	Everything Else

Table IA.II
Model fit for subsets of portfolios

To mitigate the degrees of freedom problem, we choose subsets of the industry-country (or country-style) space to examine whether we obtain the same inference. We report the rank over all models for the WLFF and WLAPT models, with 1 meaning the lowest possible RMSE or the best model, etc. An asterisk next to 1 means that the best model is significantly better than the other models. We consider five cases, described in the first column. The sample period is January 1980 to December 2005. The first and second subsets examine industry-country portfolios, within the G5 countries, using either the most volatile and least volatile industries or the largest and smallest industries in terms of market capitalization. This gives us at most 20 portfolios per six-month period. The WLFF and WLAPT models remain best with the WLFF model becoming significantly better than any other model in the second case. This pattern persists for the third case, where our industry-country portfolios are the TMT industries in the G5 countries. Brooks and Del Negro (2004) show that the TMT industries are important in explaining the increase in world market volatility at the end of 1990s.

We also conduct the subset experiment for the country-style portfolios. Our fourth case looks at the G5 countries, and four extreme portfolios (small growth, small value, big growth, and big value). WLAPT has a significantly smaller RMSE than all the other models. Finally, we use the Far East countries (Australia, Hong Kong, New Zealand, and Singapore), and four extreme portfolios (small growth, small value, big growth, and big value). This sample contains mostly smaller countries that are possibly less well integrated with the world capital market. There are two interesting findings. First, the WLAPT remains the best model, and the difference between WLAPT and WLFF remains significant. This indicates that the WLAPT better captures relevant (global/regional) market-wide forces than the WLFF for less integrated markets. The second interesting finding is that the DCI model beats, although in a non-significant way, the other models except for the APT-type models. When markets are possibly segmented, the dummy variable approach manages to capture country-specific or style-specific factors relatively well.

For U.S. firms, return and accounting data are obtained from CRSP and CompuStat; for other countries, return and accounting data are obtained from DataStream. All the returns are denominated in U.S. dollars. There are a total of eight models. Model WCAPM is the global CAPM, in which the only factor is the global market portfolio return. Model WFF is the global Fama-French three-factor model, in which the factors are the global market portfolio return, the global SMB portfolio, and the global HML portfolio. The model WAPT is the global APT model with three factors. The models WLCAPM, WLFF, and WLAPT include both local factors and global factors, with the local factors constructed over regional markets and orthogonalized to the relevant global factors. Model DCI/DCS uses the dummy variable approach from Heston and Rouwenhorst (1994).

	Rank of WLFF	Rank of WLAPT
Case I: G5 countries, least volatile industries (food and utility) and most volatile industries (info tech and electronics)	2	1
Case II: G5 countries, smallest industries (household and recreation) and biggest industries (finance and oil and gas)	1*	2
Case III: G5 countries, TMT industries (Telecom, Media and Info Tech)	1*	2
Case IV: G5 countries, small growth, small value, big growth, and big value portfolios	2	1*
Case V: Far East countries (Australia, Hong Kong, New Zealand, Singapore), small growth, small value, big growth, and big value portfolios	4	1*

Table IA.III
Firm level comovements

Our model has been applied and tested for industry-country and country-style portfolios. Here we test whether the WLFF and WLAPT models also outperform the Heston-Rouwenhorst type models for individual firm returns. We choose four firms as examples: Novartis (a large phamaceutical firm headquartered in Switzerland), Merck (a large phamaceutical firm headquartered in the U.S.), IBM (a large info tech firm headquartered in the U.S.), and Nihon Unisys (a mid-size info tech firm headquartered in Japan). We select the four firms from different countries, different industries, and different styles to emphasize the country and industry effects. To calculate the WLAPT and WLFF model-implied correlations for every six-month period, we first estimate the factor loadings for the four firms. The implied correlations then follow from equation (3). To calculate the correlations implied by the dummy variable models for every six-month period, we first identify each firm's country, industry, and style, and the model-implied covariance is calculated as in equation (9). Consequently, we are applying a model that was derived for industry-country portfolios or country-style portfolios in an "out-of-sample" experiment with firm-level data.

Table 3 reports some properties of the sample correlations of the firm returns and the implied correlations from the WLFF and WLAPT models and from the dummy variable models DCI and DCS. We also report the time-series correlation between the correlation in the data and the one implied by the models. The sample period is January 1980 to December 2005. All the returns are denominated in U.S. dollars. The model WLFF is a Fama-French type model with factors from both the global and regional markets. The model WLAPT is an APT model with three factors from both the global and regional markets. The model DCI/DCS is the dummy variable model from Heston and Rouwenhorst (1994).

The first pair is Novartis and Merck, which are from the same industry/style but from different countries. The average correlations generated by the WLFF/WLAPT models are much closer to the sample correlations than the other models are, and the correlations are close to the sample correlations than the correlations produced by the DCI and DCS models. Hence, the WLFF/WLAPT models better match comovement dynamics between Novartis and Merck.

We also examine another five pairs, Novartis and Nihon Unisys, Novartis and IBM, Merck and Nihon Unisys, Merck and IBM, and Nihon Unisys and IBM. The advantage of the WLFF/WLAPT models over the DCI/DCS models remains, and it is even more dramatic in terms of matching the time-series dynamics of comovements. The correlation between the model and sample comovements is at least 65% for the WLFF/WLAPT models, but it can drop to as low as 20% for the dummy variable models. The dummy variable approach appears not flexible enough to capture firm-level comovements, while the WLFF/WLAPT models perform well for this set of firm returns.

	correlation	Correl (sample correl, model correl)
Novartis and Merck		
data	25%	
WLFF	31%	70%
WLAPT	31%	66%
DCI	54%	65%
DCS	45%	51%
Novartis and Nihon Unisys		
data	7%	
WLFF	10%	69%
WLAPT	9%	85%
DCI	15%	62%
DCS	28%	48%
Novartis and IBM		
data	12%	
WLFF	24%	70%
WLAPT	22%	82%
DCI	21%	42%
DCS	44%	32%
Merck and Nihon Unisys		
data	5%	
WLFF	9%	73%
WLAPT	12%	76%
DCI	22%	25%
DCS	23%	36%
Merck and IBM		
data	22%	
WLFF	53%	76%
WLAPT	49%	86%
DCI	66%	58%
DCS	98%	20%
Nihon Unisys and IBM		
data	7%	
WLFF	13%	80%
WLAPT	14%	65%
DCI	51%	44%
DCS	21%	50%

Table IA.IV
Out-of-sample performance using global minimum variance portfolios

For each half year, we compute the candidate variance-covariance matrices based on each model and we compute the corresponding global minimum variance portfolio. We use the sample variances along the diagonal for the covariance matrix. We hold this portfolio during the next six months and compute its volatility using weekly returns. We repeat these steps for each six-month period and average the computed volatilities over the full sample. In addition to all portfolios, we consider five cases of portfolios subgroups (see Table II for full descriptions). The sample period is January 1980 to December 2005. For U.S. firms, return and accounting data are obtained from CRSP and CompuStat; for other countries, return and accounting data are obtained from DataStream. All the returns are denominated in U.S. dollars. The model WCAPM is the global CAPM, in which the only factor is the global market portfolio return. The model WFF is the global Fama-French three factor model, in which the factors are the global market portfolio return, the global SMB portfolio, and the global HML portfolio. The model WAPT is the global APT model with three factors. The models WLCAPM, WLFF, and WLAPT include both local factors and global factors, with the local factors constructed over regional markets and orthogonalized to the relevant global factors. The model DCI/DCS uses the dummy variable approach from Heston and Rouwenhorst (1994). The model DI (DS) is the restricted dummy variable model with only industry (style) dummies. The model DC is the restricted dummy variable model with only country dummies.

	Case I: G5 volatility industry portfolios	Case II: G5 size industry portfolios	Case III: G5 TMT portfolios	Case IV: G5 style portfolios	Case V: Far East style portfolios
WCAPM	**0.0954**	0.1130	0.1263	0.1079	0.1486
WLCAPM	0.0961	0.1139	0.1233	0.1034	0.1476
WFF	0.0965	**0.1125**	0.1252	0.1071	0.1476
WLFF	0.0981	0.1153	0.1235	0.1048	0.1475
WAPT	0.0998	0.1132	0.1246	0.1050	**0.1461**
WLAPT	0.0991	0.1150	**0.1232**	**0.1028**	0.1477
DCI	0.1246	0.1227	0.1345	0.1186	0.1565

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