CROSS COUNTRY INDUSTRY BETAS

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Abstract

We study the differences in the industrial composition between two stock market indices, the Italian FTSE MIB and the Chinese Shanghai Composite Stock Exchange. We argue that differences in the set of industry weights, measured through market capitalization, on different stock markets carry valuable information required for adjusting industry betas in an emerging market context. On the basis of 256 weekly observations of 1,020 companies belonging to 10 industrial sectors on the Italian and Chinese stock markets, we test the hypotheses that statistically significant cross-country differences in industry betas and industry weights exist and that cross-country differences in industry betas are linearly related to cross-country differences in industry weights. The empirical evidence gathered confirms the existence of cross-country structural differences in industry betas and industry weights, but confutes the hypothesis of a linear relationship between the two.

Keywords: Industry Betas, Emerging Markets, CAPM

JEL Classification: G30, G10, G12

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1 Introduction

Investment analysts face several conceptual and practical challenges when applying traditional enterprise valuation techniques, conceived in and for the developed markets (DMs), to the peculiar economic context of the emerging markets (EMs).

This paper explores the applicability of the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965) in emerging capital markets, and specifically the effects of the industrial structure of a stock market on industry betas. Research has provided mixed evidence that the industrial composition of a stock market can explain the magnitude of industry betas (Roll, 1992; Heston and Rutheworst, 1994; Lally, 2004). Because of the backwardness of the information infrastructure further challenges arise when applying the model in the EMs. Evidence has been found of a statistically significant difference between median EM- and U.S.-derived industry betas (Pereiro, 2010), which confirms the need to tailor traditional valuation models to the peculiar economic context of emerging markets.

The focus of this paper is to expand the research on industry betas by verifying whether the explanatory power of industry characteristics holds in an Italian/Chinese scenario. Our goal is to test the statistical significance of the difference in mean industry betas between Italy and China, and whether differences in industry weights can offer a satisfactory explanation for such difference. Identifying the link between cross-country differences in the industrial composition of stock markets and cross-country differences in industry betas would provide a way to easily adapt the information available on the developed markets to the peculiar economic context of the emerging markets. Data involve returns on equity from the main stock markets in Italy and China for 10 broad industrial sectors. On the basis of a database of 256 weekly observations of 980 companies belonging to the Chinese Shanghai Composite Stock Market Index and 40 companies belonging to the Italian FTSE MIB, we found that cross-country differences in both mean industry weights and mean industry betas exist, but that there is no linear relationship between these two variables. The paper is structured as follows. Next section discusses relevant literature about enterprise evaluation and CAPM in Emerging Markets, while section 3 addresses the discussion on the importance of industry factors over country factors. Section 4 details data and methodology used in this paper, while section 5 presents the empirical findings. A last section concludes the work and indicates limitations and avenue for future research on the matter.

2 Enterprise evaluation and the CAPM in the Emerging Markets

When assessing the value of an enterprise in the emerging markets, analysts face several theoretical and practical challenges due to the peculiarities of the economic context. For valuation techniques based on discounted cash flows (as the DCF, whose the CAPM



is instrumental for the computation of the opportunity cost of risk capital), the additional risk of emerging markets must be accounted for in the estimation of both the cash flows and the opportunity cost of capital (James and Koller, 2000). Some of the factors differentiating developed and emerging markets are widespread corruption, poor governance mechanisms, and the inefficient information infrastructure (Bruner et al., 2002; Teti et al., 2012). Financial assets in emerging markets are priced at a discount because of the weak corporate governance mechanisms and the highest level of corruption of the environment. The discount on prices for financial securities is also negatively affected by the degree of diffusion of the press, rate of tax compliance, and level of competition on product markets (Dyck and Zingales, 2004). From a macroeconomic point of view, relevant barriers to investments in emerging markets are represented by poor credit ratings, high inflation, governmental control over exchange rates, and poor quality of regulatory and accounting frameworks (Bekaert, 1995).

Since the meaningfulness of the evaluation process relies on the availability of quality information, efficient information infrastructures play a crucial role in the applicability of enterprise valuation techniques in emerging markets. Corporate management is a primary source of information for the market about the assets and securities of a firm. The legal mechanisms and regulatory bodies affecting the quality and timeliness of management's reporting have therefore a crucial role in lower transparent environments as the emerging markets (Leuz et al., 2003).

In the light of the peculiar characteristics of the economic context in emerging markets, some authors have tried to provide alternative models to the CAPM, while other have focused on adapting the traditional valuation techniques to the characteristics of the emerging markets. Research has focused on testing whether the variables that affect risk and return measures in the developed markets hold their explanatory power also in emerging markets. Returns on equity in emerging markets appear to be affected by the same variables as the developed markets, such as momentum, market-to-book value, and company size. Country-specific sources of political, financial, and economic risk are particularly relevant in emerging markets, and strongly correlated to equity returns (Jeanne and Rancière, 2011). Country-specific risk has therefore been traditionally important for international diversification purposes.

Although economic intuition suggests that emerging markets are riskier than developed markets, finding a measure of risk that satisfactorily explain expected returns has proven to be a challenge for both academics and practitioners. Initial research has shown that in emerging markets betas fail to explain expected returns (Rouwenhorst, 1999). Furthermore, very few emerging markets showed betas (calculated against the world stock market) higher than 1, a result that counters the intuition that emerging markets are riskier than developed markets, and supports the idea that emerging markets are little integrated with global capital markets (Harvey, 1995). Further research has shown that many country betas for emerging markets have substantially increased above 1, but their relation with expected returns is still weak (Estrada, 2001). These findings are consistent with the hypothesis of a progressive integration of capital markets over time (Bekaert and Harvey, 1995).

However, since local betas mostly fail in capturing the riskiness of emerging markets, academics and practitioners have tried to find measures of risk significantly correlated with expected returns, and that overcome the practical challenges due to the lack of data and the little transparency in the emerging markets. For instance, publicly-available country credit ratings have proven to be a successful predictor of returns by transmitting meaningful country-specific information to investors (Erb et al., 1995). Other authors suggest that the semistandard deviation of returns with respect to the mean is able to fully capture the downside risk of doing business in emerging markets, and provides an objective, easy-to-compute alternative to betas and country credit ratings. The semi-standard deviation of returns has been proven to effectively explain also the cross-section of industry returns in the emerging markets (Estrada, 2001).

Although both theoretical and practical adaptations of the CAPM have been proposed, the backwardness of emerging markets in terms of information infrastructure and governance mechanisms greatly challenge the applicability of the CAPM. The lack of integration in capital markets constitutes the main barrier, as it magnifies countryspecific risk and challenges one of the assumptions of the model - the perfect efficiency of capital markets. In addition, the lack of data appears to reduce the ability of calculating betas so to capture all the relevant facets of risk. Notwithstanding the effort made by academics and practitioners to tailor the CAPM to the specificities of the emerging markets, best practices have yet to emerge, and a universally accepted model to be identified.

3 The increasing importance of industry factors over country factors

The academic debate over the relative importance of country vs. industry factors has been raging since the inception of the notion of international diversification. To be efficiently applicable, the CAPM would require a single, perfectly efficient capital market that reflects the systematic risk embedded in human economic activity. A single international portfolio has proven to be a better proxy of such ideal market than a single national stock market (Solnik, 1974). Early research about international diversification of risk concluded



that the benefits greatly outweigh the costs in terms of higher trading costs, regulatory and cultural differences, and currency and political risk (Grubel, 1968; Levy and Sarnat, 1970). International diversification owes its potential to the low correlation among the returns of different national stock indexes. Investors can therefore reduce the overall risk they bear by allocating their capital in different economic contexts: the more different these economic contexts are, the less the returns on equity are correlated with each other, and the less a loss on some of them is likely to spread to the others.

Although the benefits of international diversification are clear, the question is where such benefits come from: whether the low correlation among different national stock indexes is due to country-specific factors or to the different industrial composition of the national stock markets. Early research on this topic found conflicting evidence. Roll (1992) found industrial composition to prevail over country specificities; Heston and Rouwenhorst (1994) found country factors to be more important. Further empirical studies confirmed the prevalence of country-specific factors, but acknowledged that in internationally integrated industries (i.e., traded goods) industry factors are stronger than in geographically limited industries (non-traded goods) (Griffin and Karolyi, 1998). As a consequence of the progressive international integration of capital markets, industry factors are to become increasingly important in investment strategies (Weiss, 1998).

Indeed, since the beginning of the new millennium, industry factors appear to dominate over country factors. However, the debate is still open depending on the countries considered, the classification of industries used, and the time period analyzed (Cavaglia et al., 2000). Although countryspecific factors have historically played a prominent role, their importance appears to be fading because of increased economic integration among countries (Solnik and Roulet, 1999). The determinants of such economic integration are multiple, ranging from lower trade barriers to the removal of restrictions to foreign investments in national capital markets. Some authors hold that the increased importance of industry factors is just temporary, and caused by a bubble in the IT, media and telecommunications industry (Brooks and Del Negro, 2004). The same authors also argue that what was previously the diversification power of single countries can be found today in different geographic regions, defined as clusters of geographically and culturally close countries (Brooks and Del Negro, 2005).

Emerging markets offer a clear example of this reasoning. Although industry factors appear to prevail in developed markets, country-related differences remain important between developed and emerging capital markets, and across emerging markets. Crosscountry diversification seems to yield more benefits than cross-industry diversification in emerging markets, although taking into account the industrial composition of stock indexes holds relevant explanatory potential (Serra, 2003). Investors are therefore advised to pay attention first to the set of countries represented in their portfolios, and then decide the weight to give to each industry (Devereux and Sutherland, 2010).

Although the debate about the relative importance of industry vs. country-specific factors and its determinants is far from the conclusion, especially in the context of emerging markets, researchers appear to agree on a point: the more countries are economically integrated (in terms of trade barriers and capital markets), the lower the importance of country-specific factors is. This allows analysts and investors to focus their attention on cross-industry diversification, and in particular on the industrial structure of national stock markets. This finding also affects the valuation of non-publicly traded equities in the emerging markets. The question here is how to adapt the information from developed capital markets (i.e., the industry beta) to the single emerging market. If country-specific factors are becoming negligible because of higher economic integration, adapting industry beta will mean to take into account just the differences in the industrial composition of the stock market.

4 Data and Methodology

4.1 Dataset and Research Hypotheses

The empirical test contained in this paper is based on data from the major stock markets of Italy and of The People's Republic of China. For Italy, data come from the FTSE MIB index computed by Borsa Italiana S.p.a. (Milan, Italy), while for China data are gathered from the SHANGHAI COMPOSITE Stock Exchange. Data of all the companies already active or started their operations during the period of observation are considered. On average, the Italian FTSE MIB active companies, comprises 40 while the SHANGHAI COMPOSITE counts on average 980 active firms, for a total number of 1,020 companies. Observations are taken weekly over a 5-year period ranging from January 5th, 2007 to December 30th, 2011, for a total of 256 weeks. The weekly frequency has been judged a satisfactory trade-off between need to maximize the number of observations and need to avoid unnecessary volatility which distinguishes daily observations. Observations include 3 types of original data across 10 different industrial sectors. Original data are then recombined to construct 4 derived variables, and then used in the statistical testing. Original variables include:

• Applied Beta (APPLIED_BETA): the ratio of the covariance of the equity returns of the company and of the market over the variance of returns of the market;

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• Market Capitalization (CURR_MKT_CAP): the value of equity of the company at the market price at the moment of observation;

• Financial Leverage (TOT_DEBT_OVER_TOT_EQUITY): the ratio of the value of a company's total debt over that company's total equity.

These three original variables have been used to calculate 4 derived variables, which have then been the object of statistical testing:

• W_{i,t}, the total weight (in terms of market capitalization) of industry "i" against the relative stock market at the period of observation "t";

• $\Delta W_{i,t}$, the difference of the total weight of industry "i" at the period of observation "t". Since industry weights are expressed in percentage points, differences are expressed into basis points (for instance, a difference of 1% corresponds to a difference of 100 basis points). This variable is used has the explanatory variable of differences in industry betas;

• $B_{u,t}$, the unlevered beta, calculated by applying the Hamada formula of each company in period "t"; For calculation purposes, we used a corporate tax rate of 27.5% for Italian companies, and 25% for Chinese companies.

• $B_{i,t}$, the beta of industry "i" at moment "t", defined as the average (weighted by market capitalization) of the unlevered betas of the companies operating in a country in industry ""i" at moment "t".

Industries are selected according to the classification followed by the database of origin, and span 10 different industrial sectors, described as follows.

• Consumer Discretionary (CD), includes goods and services that are bought at discretion of consumers (among the others: fashion, entertainment, automotive);

• Consumer Staples (CS), comprehends goods and services indispensable to consumers (for instance, food and beverages);

• Energy (EN), includes firms active in the production of energy;

• Financials (FI), includes firms active in banking and insurance;

• Health Care (HC), production of medical devices, drugs, or biotechnologies;

• Industrials (IN), manufacturing of large machineries (i.e., defense systems, aircrafts, ships, and trains);

• Information Technology (IT), production of computer hardware and software;

• Materials (MA), production and transportation of basic materials;

• Telecommunications (TC), devices and infrastructures for circulating information;

• Utilities (UT), transportation of primary resources (energy, water, sewing).

Based on the most important insights drawn from the background literature analyzed in previous

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sections, three different hypotheses are empirically tested:

H1 – There is a statistically significant difference in average industry betas between Italy and China.

H2 – There is a statistically significant difference in average industry weights (in terms of market capitalization) between Italy and China.

H3 – There is a linear relationship between cross-country differences in industry weights and cross-country differences in industry betas.

4.2 Statistical Testing

In this section we identify the appropriate technique to translate the hypotheses of the empirical research into statistical terms. HP 1 and 2 are tested by conducting a T-test for the difference of the mean, by computing a T-statistic and then calculating the corresponding p-value. These tests are conducted on the data series of $B_{i,t}$, and $W_{i,t}$, which are weighed means of the corresponding values of unlevered betas and market capitalization for individual companies. This allows us to assume the normality of the distribution of the means, and conduct the T-test for the sample of means. One T-test for each variable is conducted for each industrial sector by comparing the data from Italy and from China.

HP 3 is tested through a linear regression according to the ordinary least square (OLS) method. The goal here is to find at least one significant coefficient for a linear equation linking changes in industry betas to changes in industry weights. Both dependent and independent variables are expressed in basis points and in absolute terms. The regression equation is the following:

$$\Delta \mathbf{B}_{i,t} = \sigma + \sum_{i=1}^{10} \gamma_i \Delta \mathbf{W}_{i,t} + v_t \quad \text{with } i=1,\dots 10 \quad (1)$$

Where: $\Delta B_{i,t}$ is the difference in the beta of industry "i" between Italy and China at time "t"; σ is the constant; $W_{i,t}$, is the difference of the weight of industry "i" between Italy and China at time "t"; γ_i is the coefficient of the difference of the weight of industry "i"; v_t is the disturbance term.

A regression equation is calculated for each of the ten industrial sectors. For each regression equation, the following checks are conducted to check the validity of the assumptions at the basis of the OLS method. According to the OLS method, the coefficients in the equation are the best linear unbiased estimators of the coefficient of the actual population under a few assumptions: the relationship between the dependent and the independent variables is linear; the disturbance term is normally distributed with mean zero and fixed variance; the disturbance term is not correlated to the independent variables. In addition, since the linear regression has multiple independent variables, the independence of such variables from each other must be checked to avoid multicollinearity. To check multicollinearity, the first step is to calculate the covariance matrix of all the independent variables. Further confirmation is provided by the Variance Inflation Factor (VIF), and explored through an F-Test in the Analysis of Variance (ANOVA) of each equation. In our set of independent variables, the Health Care (HC), and the Energy (EN) sectors show high correlations in several pairs of variables. Moreover, also the Utilities (UT)-Information Technology couple (IT) are highly correlated to each other. The sign and magnitude of the correlation ratios involving EN is probably attributable to the strong weight that the EN sector has in both indexes, being therefore negatively affected by changes in the weights of any other industrial sector. The high correlation among other sectors is likely to be explained by an economic rationale. The threshold value of confidence selected for decision making is $\alpha = 5$.

4.3 Italian and Chinese markets analysis

Over the period of analysis, the SHCOMP had an average weekly return of -0.03%, with a standard deviation of 0.0411, while the MIB index showed an

average weekly return of 0.01% and a standard deviation of 0.0406. The surprisingly similar evolution pattern of average returns and standard deviation in the two markets appears to provide further evidence of the progressive integration of capital markets, strengthening the hypothesis that country specificities are progressively fading in favor of industry factors. Thus, differences in industrial composition are set to become the main explanatory variable of the differences between national economies. Further economic integration appears also to transcend capital markets, towards the real economy. In 2008, when the sub-prime mortgages bubble exploded unleashing a severe financial crisis, volatility on the developed market (Italy) soared. while returns on the SHCOMP seemed to remain stable on their previous path. However, at the beginning of 2009 the SHCOMP experienced its worst week, and volatility suddenly raised to a level similar to the Italian stock market. Further data allow a more in-depth comparison of the performances of the stock markets that will be the object of empirical testing.

	CI)	С	S	El	N	F	ŦI	Н	С
	CHI	ITA	CHI	ITA	CHI	ITA	CHI	ITA	CHI	ITA
						25,22	41,73			
Industry Weight	4,45%	9,03%	2,79%	1,39%	20,35%	%	%	35,61%	1,91%	0,29%
Applied Beta*	0,759	0,892	0,734	0,657	0,762	1,045	0,774	1,034	0,672	0,521
Industry Beta*	0,559	0,499	0,612	0,528	0,603	0,739	0,418	0,333	0,509	0,432
Financial										
Leverage*	79,702	118,15	38,86	42,50	35,256	65,773	122,19	367,49	81,327	19,754
	IN	1	ľ	Г	Μ	A	Т	Ċ	U	Т
	CHI	ITA	CHI	ITA	CHI	ITA	CHI	ITA	CHI	ITA
Industry Weight	13,82%	5,65%	1,62%	1,64%	9,12%	0,55%	0,78%	5,50%	3,43%	35,62%
Applied Beta*	0,800	0,867	0,734	1,045	0,878	1,044	0,699	0,881	0,781	0,691
Industry Beta*	0,534	0,189	0,584	0,890	0,582	0,741	0,595	0,418	0,405	0,356
Financial	118,72	150,28	48,86	23,56	187,09			153,11	139,37	142,53
Lavaraga*		0	•	0	7	5000	02 177	~	1	5
Leverage	9	8	2	2	/	30,809	23,177	3	1	5

Table 1. Cross-Industry comparison (average statistics)

Table 1 shows that more than 60% of the total market capitalization of the stock markets of both Italy and China is represented by the financial and the energy sector, which are the industrial sectors powering and financing a country's economy. Although limited to a small fraction of the total market capitalization, also the information technology sector has similar weights in both markets (1.6%). The most striking differences come from the industrial, the materials and the utilities sectors. In the SHCOMP, industrial goods, heavy machinery, and basic materials show much higher average weights, while Italy exhibits higher weights in value added

sectors, such as telecommunications and discretionary goods, including luxury goods and automotive. In addition, the Italian stock exchange shows an overdeveloped utilities sector.

Average applied betas once again reflect the importance of particular industrial sectors relatively to the whole stock market. In Italy, the EN and FI sectors, which account for a large portion of the total capitalization, are almost perfectly correlated with the market, exhibiting betas close to 1. In addition, the relatively small number of companies included in the FTSE MIB makes the market particularly sensitive to changes in the share price of firms in the financial,



and energy sector. On the SHCOMP, the highest values of applied beta correspond to manufacturing oriented sectors, such as industrial goods and basic materials. However, volatility of stock returns is enhanced by the financial leverage of a company.

Average financial leverage appears to be higher in Italy than in China, with a few noticeable exceptions for the MA, HC, and IT sectors. An interesting difference in average leverage is also represented by the FI sector, which in China exhibits a significantly lower level as compared to Italy. Such characteristic of the Chinese financial sector is likely to be at the foundation of the resilience of China to the financial side of the global crisis of 2008, and is probably due to the strong presence of the State in such strategic sector. Industry betas, which are by construction the weighted average of individual unlevered company betas, follow a pattern similar to applied betas without including the enhancement generated by the financial leverage. To appreciate the magnitude of such enhancement, it is worth noticing the differences between industry and average applied betas in the Chinese MA sector, and in Italy's IN, and in the FI sector of both countries. In such sectors, the high level of leverage is responsible for a large difference between applied and industry betas.

5 Empirical Findings

Tables 2 to 11 summarize the results for the ten analyzed sectors.

Table 2	. Univariate	Statistics -	Consumer	Discretionary	(CD)
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CD University statistics	Industry We	eight	Industry Beta	
CD - Univariate statistics	CHI	ITA	СНІ	ITA
Mean	4.45%	9.03%	0.5589	0.4991
Standard deviation	0.0092	0.0100	0.2394	0.0382
Standard error of the mean	0.0006	0.0006	0.0150	0.0024
Minimum	0.10%	6.73%	0.0758	0.4467
Median	4.76%	8.97%	0.6971	0.4975
Maximum	6.58%	11.50%	1.1223	0.5819
Range	6.48%	4.77%	1.0465	0.1351
Skewness	-0.0472	0.0116	-0.7577	0.4413
Kurtosis	0.7971	-0.7007	-0.9360	-0.8925
Number of observations	256			
T-Tests for mean difference (P-Value)				
1-tailed	8.1E-212		4.96E-05	
2-tailed	1.6E-211		9.92E-05	

Table 3.	Univariate	Statistics -	Consumer	Staples ((CS)
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CS. University statistics	Industry We	Industry Beta		
CS - Univariate statistics	СНІ	ITA	СНІ	ITA
Mean	2.788%	1.387%	0.6122	0.5275
Standard deviation	0.0052	0.0030	0.1440	0.1084
Standard error of the mean	0.0003	0.0001	0.0090	0.0067
Minimum	0.00%	0.90%	0.2555	0.0921
Median	2.72%	1.33%	0.6854	0.5596
Maximum	3.97%	2.22%	0.8490	0.6857
Range	0.0397	0.0131	0.5934	0.5936
Skewness	-0.234	0.633	-0.887	-2.601
Kurtosis	2.277	-0.353	-0.335	8.433
Number of observations	256		256	
t-statistic for computing				
95%-confidence intervals	1.9693		1.9693	
T-Tests for mean difference (P-Value)				
1-tailed	2.96E-132		1.39E-13	
2-tailed	5.92E-132		2.77E-13	



	Industry Weig	ght	Industry Beta	
EN - Univariate statistics	CHI	ITA	CHI	ITA
Mean standard deviation standard error of the mean	20.35% 0.0602 0.0037	25.22% 0.0217 0.0013	0.6026 0.1156 0.0072	0.7385 0.0810 0.0050
Minimum Median Maximum Range	0.00% 20.22% 33.41% 0.3341	20.66% 25.82% 30.83% 0.1016	0.1808 0.6112 0.7964 0.6155	0.5531 0.7767 0.8732 0.3201
Skewness Kurtosis	-0.656 0.063	-0.179 -0.525	-1.014 2.428	-0.494 -0.692
number of observations	256		256	
t-statistic for computing 95%-confidence intervals	1.9693		1.9693	
T-Tests for mean difference (P-Value) 1-tailed 2-tailed	1.676E-28 3.352E-28		1.03E-43 2.05E-43	

Table 4. Univariate Statistics – Energy (EN)

Table 5. Univariate Statistics – Financials (FI)

FI - Universite statistics	Industry Weig	Industry Beta		
FI - Onivariate statistics	CHI	ITA	CHI	ITA
Mean	41.73%	35.61%	0.5087	0.4315
Standard deviation	0.0364	0.0506	0.1594	0.1550
Standard error of the mean	0.0022	0.0031	0.0099	0.0096
Minimum	36.21%	24.15%	0.1287	0.0000
Median	40.81%	36.46%	0.5626	0.4050
Maximum	74.40%	42.41%	0.7560	0.7793
Range	0.3818	0.1826	0.6272	0.7793
Skewness	3.430	-0.483	-0.996	0.062
Kurtosis	24.735	-0.912	-0.122	2.029
Number of observations	256		256	
t-statistic for computing 95%-confidence intervals	1.9693		1.9693	
T-Tests for mean difference (P-Value) 1-tailed	3.545E-45		2.16E-08	
2-tailed	7.091E-45		4.32E-08	

Table 6. Univariate Statistics – Health Care (HC)

UC University statistics	Industry Weig	Industry Beta		
HC - Univariate statistics	CHI	ITA	СНІ	ITA
Mean	1.91%	0.29%	0.5087	0.4315
Standard deviation	0.0051	0.0016	0.1594	0.1550
Standard error of the mean	0.0003	0.0001	0.0099	0.0096
Minimum	0.10%	0.00%	0.1280	0.0000
Median	1.85%	0.32%	0.5626	0.4050
Maximum	2.85%	0.58%	0.7560	0.7793
Range	0.0275	0.0058	0.6272	0.7793
Skewness	-0.105	-0.243	-0.996	0.062
Kurtosis	-0.721	-1.163	-0.122	2.029
Number of observations	256		256	
t-statistic for computing 95%-confidence intervals	1.9693		1.9693	
T-Tests for mean difference (P-Value)				
1-tailed	9.3E-146		2.16E-08	
2-tailed	1.9E-145		4.32E-08	
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IN University statistics	Industry Weig	Industry Beta		
In - Univariate statistics	CHI	ITA	CHI	ITA
Mean	13.82%	5.65%	0.5337	0.1887
Standard deviation	0.0143	0.0103	0.0815	0.0442
Standard error of the mean	0.0008	0.0006	0.0050	0.0027
Minimum	9.41%	4.10%	0.3122	0.1286
Median	14.02%	5.31%	0.5687	0.1671
Maximum	16.62%	8.33%	0.6382	0.2774
Range	0.0721	0.0423	0.3260	0.1487
Skewness	-0.464	1.260	-1.272	0.674
Kurtosis	-0.204	0.456	0.711	-1.058
Number of observations	256		256	
t-statistic for computing 95%-confidence intervals	1.9693		1.9693	
T-Tests for mean difference (P-Value)				
1-tailed	2.8E-259		6.5E-199	
2-tailed	5.5E-259		1.3E-198	

Table 7. Univariate Statistics – Industrials (IN)

Table 8. Univariate Statistics – Information Technology (IT)

IT - Univariate statistics	Industry Weig	Industry Beta		
	CHI	ГГА	CHI	ІТА
Mean	1.62%	1.64%	0.5839	0.8900
Standard deviation	0.0038	0.0028	0.2468	0.1548
Standard error of the mean	0.0002	0.0001	0.0154	0.0096
Minimum	0.04%	1.18%	0.0288	0.6641
Median	1.66%	1.56%	0.7381	0.9000
Maximum	2.25%	2.32%	0.8119	1.1428
Range	0.0220	0.0114	0.7830	0.4786
Skewness	-0.372	0.723	-0.951	0.033
Kurtosis	-0.510	-0.451	-0.603	-1.513
Number of observations	256		256	
t-statistic for computing 95%-confidence intervals	1.9693		1.9693	
T-Tests for mean difference (P-Value) 1-tailed 2-tailed	0.283214 0.566429		2.31E-49 4.62E-49	

Table 9. Univariate Statistics – Materials (MA)

MA - Univariate statistics	Industry Wei	Industry Beta		
WIA - Univariate statistics	CHI	ITA	CHI	ITA
Mean	9.12%	0.55%	0.5823	0.7407
Standard deviation	0.0122	0.0012	0.1262	0.0953
Standard error of the mean	0.0007	7.65E-05	0.0078	0.0059
Minimum	6 21%	0 33%	0 3323	0.6219
Median	8 97%	0.55%	0.5525	0.0217
Maximum	12 5004	0.5770	0.0034	0.7231
Disast	15.59%	0.03%	0.7399	0.9260
Range	0.0737	0.0049	0.4075	0.3061
Skewness	0.832	0.082	-0.815	0.521
Kurtosis	1.608	-0.862	-1.051	-1.026
	254		0.5.6	
Number of observations	256		256	
t-statistic for computing				
95%-confidence intervals	1,9693		1.9693	
T Tests for mean difference (D Value)	10000		117 070	
1 toiled	2 66E 222		954E 47	
1-tailed	5.00E-222		0.34E-4/	
2-tailed	7.32E-222		1./1E-46	



TC University statistics	Industry Weight		Industry Beta	
IC - Univariate statistics	CHI	ITA	CHI	ITA
Mean	0.78%	5.50%	0.5954	0.4176
Standard deviation	0.0016	0.008	0.1689	0.0346
Standard error of the mean	0.0001	0.000	0.0105	0.0021
Minimum	0.00%	4.21%	0.1599	0.3301
Median	0.78%	5.22%	0.6740	0.4179
Maximum	1.27%	7.49%	0.7904	0.4738
Range	0.0127	0.0328	0.6305	0.1437
Skewness Kurtosis	-0.133 0.873	0.758 -0.600	-1.026 0.171	-1.061 0.953
Number of observations	256		256	
t-statistic for computing 95%-confidence intervals	1.9693		1.9693	
T-Tests for mean difference (P-Value) 1-tailed 2-tailed	7.7724E-210 1.5545E-209		2.369E-43 4.737E-43	

Table 10. Univariate Statistics – Telecommunication Services (TC)

 Table 11. Univariate Statistics – Utilities

UT - Univariate statistics	Industry Weight		Industry Beta	
	CHI	ITA	CHI	ITA
Mean	3.43%	15.13%	0.4046	0.3562
Standard deviation	0.0078	0.0278	0.0802	0.0402
Standard error of the mean	0.0004	0.0017	0.0050	0.0025
Minimum	2.34%	10.72%	0.1367	0.2781
Median	3.17%	15.46%	0.4337	0.3446
Maximum	5.77%	21.00%	0.5125	0.4202
Range	0.0343	0.1027	0.3758	0.1421
Skewness	1.700	0.255	-1.591	-0.194
kurtosis	1.789	-0.944	2.168	-0.889
Number of observations	256		256	
t-statistic for computing 95%-confidence intervals	1.9693		1.9693	
T-Tests for mean difference (P-Value) 1-tailed 2-tailed	1.1E-176 2.2E-176		9.04E-17 1.81E-16	

From the general cross-country comparison of the data from the Italian and Chinese stock market indexes it is possible to strengthen the intuition that structural differences in the industrial composition and the inherent riskiness of the two countries exist.

The first finding of our statistical analysis is that the industrial composition of a stock market yields valuable information about a country's economy. economy relies heavily China's on basic manufacturing, and industrial goods, while the Italian stock exchange is characterized by firms active in the industrial sectors of consumer discretionary, and developing economy, utilities. China, as is characterized by sectors that can leverage on the country's wide pool of cheap labor force and lenient governmental control, while Italy, as developed economy, is focused on higher value added sectors, which can build on a relatively more educated workforce. Moreover, in both countries, the energy and the financial sectors hold significant weights. The production and provision of energy and financial services can be interpreted as the engine and the accelerator of each country's economy. Financial leverage is used to boost growth on strategically important industrial sectors. This is particularly evident on the Chinese SHCOMP, where strategically

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important sectors show higher leverage as compared to the Italian FTSE MIB. This is the case not only of the aforementioned MA and IN sectors, but also of the Health Care and Information Technology, set to become the backbone of China's economy according to the 12th 5-Year Development Plan issued in 2012.

The second finding is that a statistically significant cross-country difference in average industry betas in all the 10 industrial sectors analyzed is identified. The significance of both 2-tail and 1-tail T-Tests makes it possible to conclude not only that industry betas between Italy and China are significantly different, but also that they are appreciably higher in the country that exhibits the highest average value. The IT sector provides an interesting observation. Although the cross-country difference in average industry weight was not confirmed for this sector, a statistically significant difference in industry betas was found. This finding confirms that differences in industry weights are not sufficient in explaining differences in industry betas, especially in the case of an emerging market. Crosscountry differences in returns and betas between developed and developing markets are also attributable to differences in the broader political, economic, and social environment, and to the degree of State intervention in a country's economy.

The third finding relates the existence of a statistically significant cross-country difference in average industry weights in all the industrial sectors analyzed, with the exception of the IT sector. In general, the significance of 2-tail T-Tests implies that industry weights are significantly different, while 1-tail T-Tests confirmed that they are significantly higher in the country that exhibits the highest average value. In the IT sector, industry weights in Italy and

China exhibited not only similar average values (1.62% and 1.64% respectively) but also similar volatility.

The fourth finding is that the assumed linear relationship between cross country differences in industry betas and cross-country differences in industry weights cannot be identified. All of the 10 regression models performed suffered from overwhelming flaws that undermined their explanatory power: the evidence gathered is that for all but one industrial sectors the Breusch-Pagan heteroscedasticity test and the Jarque-Bera nonnormality test have not been successful, confirming the possible presence of homoscedasticity and nonnormal distribution of residuals, which undermine the ability of the regression coefficients to reliably approximate the population coefficients. Furthermore, the values of the VIF measure detect potential multicollinearity issues. The result is that even though most of the coefficients of the explanatory variables are significant and the R^2 values satisfactorily high for all the 10 regressions run, their significance and predicting power of the whole model are limited. Some of these problems were tackled with an ANOVA and the use of logarithmic and semilogarithmic transformations, but none of these remedies was successful. The conudrum is therefore threefold. Either there is no relationship between industry weights and industry betas, or such relationship is not linear. It can also be the case that such relationship exists and is linear, but the regression model (in terms of dependent and explanatory variables) was wrongly articulated. Figures 1 to 10 shows the graph abut residuals vs. fitted values for the ten examined sectors.

Figure 1. Residuals vs Fitted Values – Consumer Discretionary



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Figure 2. Residuals vs Fitted Values – Consumer Staples

Figure 3. Residuals vs Fitted Values – Energy



Figure 4. Residuals vs Fitted Values – Financials







Figure 5. Residuals vs Fitted Values – Health Care

Figure 6. Residuals vs Fitted Values – Industrials



Figure 7. Residuals vs Fitted Values – Information Technology



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Figure 8. Residuals vs Fitted Values – Materials





Figure 10. Residuals vs Fitted Values – Utilities



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6 Conclusions, limitations and avenue for future research

This paper finds its place in the ongoing debate over the relative importance of industry- vs. countryspecific factors in explaining cross-country differences in the volatility of returns. The results of the analysis conducted counter the economic intuition that returns in emerging markets are riskier due to the unstable economic and political environment, and should therefore be associated with higher betas. Such finding strengthens the idea that relevant information is distorted and poorly reflected by returns on emerging capital markets. Such peculiarities also confirm the poor integration of emerging markets with the international capital markets due to the dominant presence of local investors, inefficient circulation information, and barriers to foreign investments (Bekaert and Harvey, 1995). Industry betas have therefore been found to be significantly different between the developed and the emerging capital market object of analysis. Consistently with findings from previous studies, we also observed instability in the evolution of unlevered betas between 2007 and 2011, and lower volatility in industry betas than in the unlevered betas of individual firms (Wiggenhorn, Payne and Daghestani, 2008).

Cross-country differences in average industry weights proved to be statistically significant for 9 industrial sectors out of 10. The differences found in average industry weights between Italy and China are consistent with the expectation that the specificities of a country's economy are reflected in the industrial composition of its most representative stock market. However, it is important to remember that in case of emerging markets, country-specific risk factors are still more relevant than industry-specific risk factors for international diversification purposes (Eun et al., 2010). Such findings would imply that countryspecific factors still carry a larger amount of information than industry factors. When adapting the CAPM to the emerging markets, equity analysts should then pay higher attention to country-related than to industry-related specificities. However, differences in the industrial composition of stock markets are not irrelevant, especially as sudden changes in industry weights are particularly frequent and violent in emerging markets, and greatly affect volatility of returns (Hameed and Ashraf, 2009).

Exploring the relationship between industry weights and industry betas was the purpose of our ordinary-least-square linear regression model, although the presence of a relationship is theoretically sound, the assumption of a linear relationship between the two factors has been rejected for all 10 industrial sectors. If differences in industry weights were found to explain most of the difference in cross-country industry betas, then analysts would have to take into account just cross-country differences in the industrial composition when applying the CAPM from a country to another. To conclude, although differences in industry betas are reasonably to expect in the light of the theory of the CAPM, and although such differences have been confirmed by empirical evidence in the Italy-China comparative study conducted in this paper, the nature and the strength of the relationship between industry beta and industry weights are yet to be found.

One possible limitation of this study is represented by potential distortive effects of the global financial crisis derived from the explosion of the USdriven sub-prime mortgages speculative bubble. Volatility of returns (betas) and industry weights might have changed during the years after the beginning of the financial crisis as a consequence of unique events, and therefore represent a biased sample of observations (Dell'Acqua et al., 2012). The study should be reproduced when the effects of the financial crisis will be over, in order to verify that the results do not depend on unrepeatable circumstances. A second possible limitation is represented by the potential limited representativeness of the Shanghai Composite Stock Exchange and of the FTSE MIB to represent their respective national economies, so that findings of this research could be extended only to a limited extent to investments in non-publicly listed equity. In the case of the SHCOMP, the effects of the presence of the State in China's economy must also be to taken into account, while in the case of the FTSE MIB the problem is the exiguous number of companies in some industrial sectors, and in the stock market as a whole, which account for just 4% of the firms active on the SHCOMP. Moreover, the definition of the industrial sectors influences cross-country industry comparisons. For these reasons future research on this matter could be conducted by including other developed capital markets (for instance, the whole European Union), and by using alternative industry classifications.

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