AN EMPIRICAL MODEL OF THE INTERNATIONAL COST OF EQUITY*

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The aim of the study is to propose an empirical model of the international cost of equity by investigating and analyzing the long-run relation between disaggregated country risk ratings and country stock market index returns for a large panel of countries. The study tests the hypothesis that, given the available theoretical and empirical evidence, country risk ratings and country stock market index returns should move together in the long-run and there should be a long-run equilibrium between them; thus country risk ratings, with their forward-looking nature about the political, macroeconomic and financial fundamentals of a large number of countries, may behave as long-run state variables for stock returns to the extent they are undiversifiable internationally. The results of the analysis provide evidence in favor of the argument that disaggregated country risk ratings, in particular the political and economic risk ratings, are related to stock market returns in the long-run. Using this relation, an empirical model of the international cost of equity is proposed. The model takes country risk ratings as inputs and finds the international cost of equity for a specific country of known risk ratings.

Keywords: International Cost of Capital, International Cost of Equity, Country Risk, International Asset Pricing

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1. Introduction

As Harvey points out in his 2005 paper, the calculation of the cost of (equity) capital in international capital markets is a long-standing problem in finance. The Capital Asset Pricing Model (CAPM) and its multifactor versions are dominantly used in countries like the US, where 73.5% of respondents use CAPM to calculate the cost of equity according to Graham and Harvey (2001) survey of US CFOs. However, outside the US the results of those methods show considerable variation and there is no consensus as to how international cost of equity needs to be calculated.

The available international asset pricing models, such as that of Solnik (1974), generally require the assumption of world market integration and that investors hold a diversified world market portfolio. Such assumptions are hardly realistic even in developed countries, where well-functioning equity markets exist. Furthermore, for those developing and under-developed countries with no equity markets, asset pricing models are inapplicable. Therefore, it still is a challenging task for international investors to find the cost of equity in a given country.

Here, we develop an empirical model of the international cost of equity by examining potential relations between disaggregated country risk ratings and respective country stock market index returns for a large panel of countries. We hypothesize that country risk ratings and country stock market index returns should covary in the long-run (they should be cointegrated); thus country risk ratings could behave as long-run state variables for stock returns. Since country risk ratings are determined by careful examination of country specific variables that reflect macroeconomic, financial and political fundamentals, it is plausible to think of short and long-run relations between such variables and stock markets. Indeed, "Asset prices are commonly believed to react sensitively to economic news" (Chen, Roll and Ross, 1986; p383) and "The comovements of asset prices suggest the presence of underlying exogenous influences…" (Chen, Roll and Ross, 1986; p384) .

As measures of disaggregated country risk ratings, we used Political Risk Services' International Country Risk Guide (ICRG) economic, financial and political risk ratings. These risk ratings assess a variety of country-specific variables from economic, financial and political perspectives. Taken together, these variables are good candidates for pervasive state variables. In fact, "*Macroeconomic variables are excellent candidates for these extramarket risk factors, because macro changes simultaneously affect many firms' cash flows and may influence the risk adjusted discount rate" (Flannery and Protopapadakis, 2002, p751).* The justification for this statement can be set forth using a simple theoretical framework, which was also employed by Chen, Roll and Ross (1986) (CRR) in their influential work.

Following discounted cashflow calculations and CRR, stock prices can be written as the value of expected discounted dividends:

$$p = \frac{E(c)}{k}$$

where *E(c)* is the dividend stream and *k* is the discount rate. Thus actual return in any period is given by:

$$\frac{dp}{p} + \frac{c}{p} = \frac{d\left[E(c)\right]}{E(c)} - \frac{dk}{k} + \frac{c}{p}$$

It follows that stock prices should be affected from systematic forces that influence expected cash flows and the discount rate.

An intuitive examination of the country risk components used reveals that economic, financial and political risk ratings include variables that are potentially relevant in systematically affecting the determinants of the discount rate, and the economic component of country risk ratings is relevant in determining expected cash flows through the inflation and real production channels.

The hypothesized relation between country risk ratings and country stock market index returns is also consistent with Ross's (1976) Arbitrage Pricing Theory (APT)[1]. The APT states that expected returns are based on the systematic exposure of a security to risk factors that cannot be diversified away. As opposed to the widely used CAPM, which assumes that all investors hold the market portfolio as the only risky asset, APT recognizes that investors take into account multiple sources of macroeconomic risk factors and their expected return depends on the respective sensitivities to these factors. To the extent that the components of country risk ratings are non-diversifiable, variation in country risk should be associated with changes in expected returns. Given that global financial markets are at least partially integrated, it is possible that country risk may not be diversified away.

To this end, country risk rating components (economic, financial and political) can be considered as potential candidates, systematically relating to country stock market index returns. However, given the number of variables within each risk rating component and their complex interrelations, this influence can be expected to be more prevalent in the long-run. That is, a long-run cointegrating relation between disaggregated country risk ratings and stock market index returns can be expected.

There is evience in the literature that there exist relationships among country risk ratings, national stock markets and expected returns. Following this path, we propose testing whether there is a long-run equilibrium relation between disaggregated country risk ratings and country stock market index returns for a large panel of countries. In other words, we hypothesize that since country risk ratings reflect financial, economic and political fundamentals of a country, from which stock prices are known to be affected, disaggregated country risk ratings can act as long-run state variables for predicting country stock market movements, thus there should be a long-run equilibrium relation between disaggregated country risk ratings and country stock market index returns. If such a relationship can be shown, the implications can provide useful insights with regard to expected returns and cost of equity capital for direct investment in a country with available country risk ratings. This relation constitutes the basis for the proposed model that is used in calculating the international cost of equity.

Contributions of the study are summarized as follows:

a. The study develops an empirical model that calculates the international cost of equity for an average-risk investment in a given country of known political and

[1] We believe that CRR model is a multi-factor model, but not necessarily an APT model as it may not fulfill all the assumptions of APT.

economic risk ratings. The model can be used to find the cost of equity for any country as long as the political and economic risk ratings are available. Since country risk ratings are reported for a large number of countries, the model has wide international applicability.

b. The study investigates both short- and long-run relations between country risk ratings and stock market movements in the international setting. The fundamental idea of the study that stock market index returns and country risk ratings should co-move implies an equilibrium in the long-run and adjustment dynamics in the short-run. Therefore, in addition to the long-run relations, the study also provides insights with respect to the short-run dynamics, in particular the speeds of adjustment, once the system is shocked.

c. It discerns the relative effects of political, financial and economic risk variables on international expected equity returns. The panel cointegration tests show that disaggregated risk ratings and country stock market index returns are cointegrated and disaggregated risk ratings are the forcing variables in the relation where country stock market index returns are the dependent variable. The long-run coefficients of the cointegration relation provides useful insights regarding the separate effects of political, financial and economic risk ratings on expected returns.

d. The study utilizes relatively rigorous and recent panel time series methods to deal with three important empirical issues: dynamic relations between country risk ratings and stock market movements, heterogeneity of this relation across countries, and cross-sectional error dependence due to unobserved common factors and spillover effects.

The structure of the paper is as follows: In the second part, the relevant literature is reviewed. The third part includes empirical analysis; the fourth part interprets the results. The fifth part concludes.

2. Related Literature

In examining the relation between international cost of equity and country risk ratings, two lines of literature are relevant. The first is of the well-known asset pricing models used as the fundamental theoretical base in calculating the cost of equity in a given country. The second is of the relation between stock markets and components of country risk ratings. Alternative ways that are used in practice in calculating the international cost of equity are also of interest. Most of these methods are based on different variations of the fundamental asset pricing models augmented with adjustments to reflect international risk factors.

Although the two fundamental asset pricing theories, the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT) were developed in a single country (the US) context with the assumption of market segmentation, they form the basis for all alternative methods used in calculating the international cost of equity. CAPM's strong assumptions limit its empirical strength, but it is still the most widely used model in the finance industry. Indeed, Graham and Harvey (2001) find in a survey of US CFOs that 73.5% of respondents use CAPM to calculate the cost of equity.

As opposed to its theoretical perfection, the CAPM has little empirical strength. Since it requires many unrealistic assumptions, this is somewhat expected. The Arbitrage Pricing Theory, developed by Ross (1976) is an alternative way to calculate expected returns with much less assumptions.

Given this framework, there are diverse ways to calculate the international cost of equity in practice (Harvey, 2005). Harvey (2005) documents twelve alternative waysto calculate the international cost of equity.[2]

2.1. Relation Between Country Risk Components and Stock Returns

Many of the components of country risk ratings mentioned above have been found in the literature to associate with stock market movements.

The leading works are those of Fama (1981, 1990), Chen, Roll and Ross (1986) and Schwert (1990), who find that corporate cash flows are related to macroeconomic variables in the US. Similarly, Hardouvelis (1987) finds that US stock prices respond to announcements of trade deficit, the unemployment rate and personal income. Flannery and Protopapadakis (2002) demonstrate that two inflation measures (the CPI and the PPI) affect only the level of the market portfolio's returns; three real factors (Balance of Trade, Employment/Unemployment and Housing Starts) affect only the returns' conditional volatility, while a Monetary Aggregate (generally M1) affects returns and conditional volatility. Graham, Nikkinen and Sahlström (2003) find that employment report, NAPM manufacturing, producer price index, import and export price indices and employment cost index announcements have significant influence on stock valuation in the US. Finally, Chen (2009) demonstrates that term spreads and inflation rates are the most useful predictors of stock market recessions in the US stock market.

The relationship between macro variables and stock markets is observed outside the US as well. For instance, Bilson, Brailsford and Hooper (2001) find that money supply, good prices, real activity and exchange rates are significant in their association with emerging market equity returns above that explained by the world factor. Other studies such as Humpe and Macmillan (2007), Kwon and Shin (1999), Mukherjee and Naka (1995) investigate stock indices and macroeconomic variables using cointegration.

Cheung and Ng (1998) and Wongbangpo and Sharma (2002) investigate the cointegrating relationship in a multi-country context. Cheung and Ng (1998)'s tests indicate that real stock market indices of five countries (Canada, Germany, Italy, Japan and the US) cointegrate with measures of the countries' aggregate real activity, such as real oil price, real consumption, real money stock and real output. Wongbangpo and Sharma (2002) observe long and short-term relationships between stock prices and GNP, the CPI, the money supply, the interest rate and the exchange rate for Indonesia, Malaysia, Philippines, Singapore and Thailand.

The relation between stock returns and inflation is also extensively studied (Fama and Schwert, 1977; Fama, 1981; Geske and Roll, 1983; Solnik, 1983; Gultekin, 1983; Brandt and Wang, 2003; Hess and Lee, 1999; Lee, 1992; Boudoukh et. al., 1994). Fama and Schwert's (1977) study find a negative relation between expected inflation (and to a lesser extent unexpected inflation) and common stock returns. This puzzling result was later explained by Fama (1981) with the proxy hypothesis. Fama (1981) argues that the negative relation between stock returns and inflation is induced

[2] They are The World CAPM, The World Multifactor CAPM, The Bekaert and Hervey Mixture Model, The Sovereign Spread Model (Goldman Model), The Implied Sovereign Spread Model, The Sovereign Spread Volatility Ratio Model, Damodaran Model, The Ibbotson Bayesian Model, The Implied Cost of Capital Model, The CSFB Model, Globally Same Expected Returns and The Erb-Harvey-Viskanta Model. For details, please see Harvey(2005).

by negative relations between inflation and real activity. Geske and Roll (1983) argue that this could be an empirical illusion because a spurious causality is induced due to the following mechanism: A random real shock that affects stock returns signals changes in unemployment and corporate earnings, which in turn induce changes in tax revenues, in Treasury borrowing and thus Federal Reserve "monetization" of the increased debt. Realizing this mechanism, rational investors adjust prices accordingly. Geske and Roll's (1983) model was further supported by Solnik (1983) and by Gultekin (1983) both being unable to find a positive relation between stock returns and inflation.

To explain the stock returns-inflation puzzle, Brandt and Wang (2003) propose the "time-varying risk aversion" approach, which argues that inflation increases investors' degree of risk aversion, thereby increasing the risk premiums and discount rates, thus resulting in undervaluation of stocks. Hess and Lee (1999) argue in their "two-regime" hypothesis that supply shocks induce a negative relation between stock returns and inflation, while demand shocks cause a positive relation, because supply shocks reflect real output disturbances while demand shocks are mainly due to monetary disturbances.

Lee (1992) uses VAR analysis to investigate the interactions among stock returns, interest rates, real activity and inflation, and demonstrates that little variation in inflation is explained by stock returns, while stock returns help explain a substantial fraction of the variance in real activity. Boudoukh et. al. (1994), on the other hand, show that there is a positive relationship between stock returns and inflation for non-cyclical industries, while the opposite holds for cyclic industries. They also find that the negative relationship between stock returns and inflation turns to positive in the long horizon.

Theoretical and empirical studies also show that political risk influences stock market movements, especially in emerging markets. First, Agmon and Findlay (1982) argue that domestic political risk may either reduce cash flows to the firm or increase investment risk and thus reduce asset value. Bailey and Chung (1995) find some evidence of equity market premiums for exposure to exchange rate and political risk in Mexico. Kim and Mei (2001) investigate the possible market impact of political risk in Hong Kong and find that political developments have a significant impact on the market volatility and returns. Similarly, Chan and Wei (1999) demonstrate that favorable (unfavorable) political news is correlated to positive (negative) returns for the Hong Kong Hang Seng index. Regarding the relative influence of political risk in developed and developing countries, Bilson, Brailsford and Hooper (2002)'s results indicate that political risk is more important in explaining return variation in emerging markets than in a comparative sample of developed markets.

Harvey (2004)'s results also point out to the same disuse: Using International Country Risk Guide's political, financial and economic risk measures, he examines the importance of these risk components in portfolio and direct investment decisions. While his tests show little evidence that country risk measures are priced in developed countries, the composite, financial and economic risk ratings produce large average hedge portfolio returns in emerging markets. Specifically, the hedge portfolios formed on the financial and economic risk yield average annual returns of more than 13% in emerging markets. Portfolios formed on the composite rating yield an annual return of

9%. Thus, he concludes that country risk is priced in emerging markets but not in developed countries.

2.2. Risk Ratings and Stock Markets

Empirically, the effects of corporate credit ratings on individual stock prices are extensively studied; however, the literature is slant in investigating the effects of sovereign credit ratings on national stock markets. On the other hand, the predictive power of country credit ratings in explaining expected returns is mainly and extensively studied by Erb, Harvey and Viskanta (1995, 1996a, 1996b). Their first study in 1995 suggests that the country credit ratings can help discriminate between the high-expected return and the low-expected return countries. They find a 12 percentage point difference between the highest- and lowest-credit risk portfolios.

The relationship between expected returns and country credit ratings was formally tested by Erb, Harvey and Viscanta (1996a). They hypothesize that since country credit ratings are survey-based, they can be used as ex-ante measures of fundamental risks. They use Institutional Investor's semiannual country risk ratings and estimate a time-series cross sectional regression of MSCI return index on country risk by combining all the countries and ratings into one large model. They find an empirical relationship between country credit ratings and expected returns and use this relation to establish hurdle rates for projects of average risk in emerging country investments. However, their model includes only one risk measure, a composite country credit rating to explain expected returns.

A disaggregated investigation was later performed by Erb, Harvey and Viskanta (1996b), who examine the relationship between political, financial and economic risks on expected fixed-income returns. They employ a cross-sectional time-series approach and regress a vector of quarterly returns on each of the lagged risk attributes. They find that the International Country Risk Guide's (ICRG) financial risk component is negatively related with returns, indicating that increased financial risk (or reduced financial risk rating) is associated with higher returns. When the lagged logarithmic changes of the risk attributes are used in the regressions, they find positive and significant signs on financial and economic variables for un-hedged and foreign exchange portfolios. For the ICRG economic variable, they find positive and significant signs in un-hedged, local and foreign exchange portfolio returns. They also show that the country risk attributes are significantly related to real yields of fixed income securities.

There are relatively few studies that investigate the effects of sovereign credit ratings on national stock markets. Kaminsky and Schmukler (2001) examine the effects of sovereign ratings and outlook changes on the instability of emerging markets financial markets. They find that sovereign ratings and outlook changes have significant effects on both stock and bond markets. Brooks, Faff, Hillier and Hillier (2004) investigate the aggregate stock market impact of sovereign rating changes and find that while rating upgrades show little evidence of abnormal return behavior, rating downgrades have a significant and negative impact on domestic stock markets. Subaşı (2008), on the other hand, finds that sovereign rating downgrades have little negative effects on stock and exchange rate returns and volatility, probably because rating changes might be anticipated by the markets and therefore prices already discounted the information.

Sovereign debt rating changes are also found to have spillover effects on international debt and stock markets (Gande and Parsley, 2005; Ferreira and Gama, 2007; Li, Jeon, Cho, and Chiang, 2008). These studies generally use Standard &Poor's sovereign credit ratings.

Hail and Leuz (2006) examine cross-country differences in the cost of equity capital on the basis of differences in countries' disclosure and securities regulation. Following Erb, Harvey and Viskanta (1996a), they use the annualized fitted values of the regression of semiannual stock returns on Institutional Investor's semiannual country credit-risk ratings as a proxy for future expected returns and compare these values with their implied cost of capital estimates. They find that these two measures are highly and significantly correlated, although they are calculated using different methods and variables.

Chen, Roll and Ross (1986) test whether innovations in macroeconomic variables are priced in the stock market. They propose a set of relevant variables and obtain the time-series of unanticipated movements. They find that industrial production, changes in risk premium, twists in the yield curve, measures of unanticipated inflation and changes in expected inflation systematically affect stock market returns. Relating to the present study, it is conceivable to think that these factors are more or less embedded in the political, financial and economic risk components, therefore it is plausible to expect significant relationships between stock market index movements and these risk attributes.

There are also studies investigating the association between political risk and foreign direct investment (FDI) (e.g. Clare and Gang, 2010; Jimenez, 2011). Clare and Gang (2010) find that exchange rate risk and political risk have negative effects on FDI from US multinationals to developing countries. On the other hand, Jimenez (2011)'s results indicate that higher political risk attract more FDI in the case of FDI from Spain, France and Italy to Central and Eastern European countries as well as North Africa, because of the firms that search niche markets "where they can take advantage of their political capabilities".

Sari, Uzunkaya and Hammoudeh (2013) examine the relationships between disaggregated country risk ratings and stock market movements in Turkey, using the autoregressive distributed lag approach, which was developed by Pesaran and Pesaran (2009) and Pesaran, Shin and Smith (2001). Using International Country Risk Guide's (ICRG) financial, economic and political risk ratings, they find that there is a long-run relationship between Turkey's disaggregated country risk ratings and its stock market index movements. In the long-run, Turkey's economic, financial and political risk rating components are the forcing variables of stock market movements. However, in the short-run, only the political and financial risk rating components have positive and significant impact on the market movements.

Hammoudeh, Sari, Uzunkaya and Liu, (2013) extend Sari, Uzunkaya and Hammoudeh (2013)'s work to BRICS (Brazil, Russia, India, China and South Africa) countries. They examine the relationships among the economic, financial and political risk ratings of the BRICS countries and relate those risk ratings to their respective national stock markets in the presence of representatives of the world's major stock markets and oil market. In other words, adding two more variables (namely the US stock market index and oil price) to Sari, Uzunkaya and Hammoudeh (2013)'s work, they investigate the dynamic relations between BRICS's disaggregated country risk ratings, respective country stock markets, US stock market and oil price. They also examine the interrelationships among the national country financial risk ratings factors to discern transmission of the risk spectrum among the BRICS. They find that only the Chinese stock market is sensitive to all the factors. Financial risk ratings generally demonstrate more sensitivity than economic and political risk ratings, and political risk is sensitive to both financial and economic risk ratings. Among the five BRICS, Brazil shows special sensitivity to economic and financial risks, while Russia and China hold strong sensitivity to political risk and India demonstrates special sensitivity to higher oil prices.

In the context of the consumption based CAPM, Bansal and Kiku (2011) show that when cash flows and consumption are cointegrated, temporary deviations between their levels forecast long-horizon dividend growth rates and returns. This is possible by modeling dividend growth rates, price-dividend ratios and returns by means of the error-correction specification of the cointegrating relation.

The foregoing discussion shows that there exists a relationship between macroeconomic variables and stock returns. Either leading or lagging, stock returns and macro variables are related. There is also evidence that political risk influences stock prices. Therefore, it is conceivable to think that country risk ratings, which are made up of macroeconomic, financial and political risk variables, should also be related to stock markets.

However, given the number of variables within each risk rating component and their complex interrelations with stock market returns, it is plausible to expect that the co-movement of country risk ratings and stock market returns would be more apparent in a long-run perspective. In other words, these variables should move together in the long-run and there should be a long-run equilibrium relation between them. This is analogous to argue that stock market returns and disaggregated country risk ratings should be cointegrated.

3. The Hypotheses

Based on the discussion above, our study is primarily interested in testing this cointegration hypothesis, which will be done in a panel time series setting[3]. If the null of no cointegration is rejected, statistically significant coefficients (if any) of the long-run cointegrating relation between the involved variables will provide cross-sectional expected return relations with respect to risk ratings. In other words, statistically significant coefficients of the long-run cointegrating relation will represent the "international reward for risk" for the respective rating component. Any statistically significant coefficient will also imply that the respective risk factor cannot be diversified away internationally and thus they are priced, consistent with the well-known asset pricing theories.

An advantage and a useful characteristic of cointegrated relations is that the variables in the relation respond to any deviation from long-run equilibrium. This feature implies an error-correction mechanism, from which short-run dynamics can be assessed. If the hypothesized cointegration relation between disaggregated risk ratings and stock market returns is supported by the data, the short-run dynamics, especially the speed of adjustment to equilibrium, will be of particular interest.

[3] The justification of using panel time series methods is given in section 3.3.

Consistent with the asset pricing traditions, there should be a positive relation between stock market expected returns and country risk. In other words, higher country risk should be associated with higher expected returns if country risk is a proxy for systematic risk factors. Since higher (lower) ratings correspond to lower (higher) risk, negative signs are expected on the long-run coefficients of the political, financial and economic risk ratings in all specifications that are discussed in detail in Section 3.3.

4. Data and Variables

As measures of disaggregated country risk ratings, Political Risk Services' International Country Risk Guide (ICRG) economic, financial and political risk ratings are used. ICRG provides these ratings on a monthly basis with numerical scales, higher numbers indicating lower risk and lower numbers higher risk. The Political Risk component is based on 100 points, while both Financial and Economic Risk components are based on 50 points. Dividing the total of Political, Financial and Economic risk components by two yields the Composite Risk Rating. The data is available on a monthly basis between January 1984 and May 2016. The starting date of the data differs from country to country, earliest starting from Jan 1984. Thus the time dimension (T) of the panel becomes as large as 389 for some countries.

The ICRG ratings differ from the ratings of other global credit rating agencies in several aspects. First, among other ratings agencies such as Moody's, Euromoney, S&P's, Institutional Investor and Economic Intelligence Unit (EIU), ICRG is the only one providing ratings on a monthly basis (Hoti, unpublished working paper), which increases the frequency of time-series data. Second, in addition to a composite index, the ICRG provides political, financial and economic risk ratings separately, which can facilitate the practical assessments done by international investors regarding the respective fundamentals of a country that is of interest. Furthermore, if some specific risk factors have greater bearing on investments, customized composite ratings can be calculated by changing the weights of the disaggregated factors.

The ICRG Economic Risk Rating *(E)* includes the following sub-components with their respective weights in parenthesis: GDP per head (10%), real GDP growth (20%), annual inflation rate (20%), budget balance as a percentage of GDP (20%) and current account as a percent of GDP (30%). The Financial Risk Rating (*F*) sub-components are, foreign debt as a percent of GDP (20%), foreign debt service as a percentage of exports of goods and services (20%), current account as a percent of exports of goods and services(30%), net international liquidity as months of import cover (10%) and exchange rate stability (20%). Finally, the Political Risk Rating (*P*) sub-components are as follows: Government stability (12%), socioeconomic conditions (12%), investment profile (12%), internal conflict (12%), external conflict (12%), corruption (6%), military in politics (6%), religion in politics (6%), law and order (6%), ethnic tension (6%), democratic accountability(6%), and bureaucratic quality (6%). For the same period and frequency, I will use Morgan Stanley Capital International's (MSCI) total dollar-denominated equity return index for the sample countries.

An important consideration about the ICRG data is that it might have measurement errors in measuring country risk. In other words, the reliability of the ICRG country risk data in predicting risk realizations is in question and should be assessed. Howell and Chaddick (1994) and Bekaert, et. al. (2014) are good examples in this respect. The former compares the predicting ability of political risk ratings provided by three different methods: that of *The Economist, of the* Political Risk Services (PRS) and of the Business Environment Risk Infirmation (BERI). They compare the projections of the three methods with realized lossess and assess their prediction ability. Their results suggest that the PRS political risk predictions are the most reliable among the three methods assessed. Similarly, Bekaert, et. al. (2014) find that "*ICRG political risk ratings represent meaningful differences in the probability of future political risk realizations*" (p.477).

Another consideration about disaggregated risk ratings would be their correlations among each other and the extent of multicollinearity. Correlations between the changes of the variables given in Appendix-G show that multicollinearity is not a significant concern.

To measure country stock market index returns, Morgan Stanley Capital International's (MSCI) Country Stock Market USD Price Index data is used. Data was obtained from Datastream. The first difference of the natural logarithm of MSCI price indices gives the continuously compounded return on the respective stock market index.

The (monthly) data covers the period Jan-1984 and May-2016. The intersection of the cross-sectional and time dimension of the available data results in a cross-sectional dimension of 45 and an unbalanced time dimension; earliest starting from Jan 1984, latest from Jan 1995. Of the total 45 countries, 24 are developed and 21 are emerging economies (The list of countries in each sample is given in Appendix C).

5. Methodology

As justified in the foregoing parts, this paper is particularly interested in the potential long-run relations between disaggregated country risk ratings and stock market returns. To investigate such a relation, we assume based on the relevant literature, that stock market returns and disaggregated risk ratings are jointly determined by a vector autoregression (VAR) process. This assumption is particularly appropriate for two reasons: first, the effect of risk ratings on stock market returns may occur over time rather than all at once. Second, stock markets can be influenced from their past performance due to the well-known momentum effect of Jegadeesh and Titman (1993).

Chudik, Pesaran, Mohaddes and Raissi (2015) show that when a dependent variable y_t and a regressor x_t are jointly determined by a vector autoregression process of order 1, the conditional model for y_t is an ARDL(1,1) specification of y_t on x_t. Then, they assert that the general form of this process in a panel data setting is an ARDL(p_y,p_x,p_x,...) model:

$$y_{it} = \sum_{l=1}^{p_{yi}} \varphi_{il} y_{i,t-l} + \sum_{l=0}^{p_{xi}} \beta'_{il} x_{i,t-l} + u_{it} \qquad (1)$$

$i = 1,2,....N$

$t = 1,2,.....T$

$$u_{it} = \gamma_t' f_t + \varepsilon_{it}$$

where $\boldsymbol{f}$ is an $m \times 1$ vector of unobserved common factors; p_{yi} and p_{xi} are lag orders of the dependent and independent variables, respectively. The lag orders are selected sufficiently long to make u_{it} a serially uncorrelated process across all i. Then the long-run coefficient vector becomes:

$$\theta_i = \frac{\sum_{l=0}^{p_x} \beta_{il}}{1 - \sum_{l=1}^{p_y} \hat{\varphi}_{il}} \tag{2}$$

There are mainly two approaches in the literature to estimate θ (Chudik, Pesaran, Mohaddes and Raissi, 2013). The first is to estimate the short-run coefficients (β and φ) as an initial step and then to substitute these estimates in Eq(2) to calculate the long-run coefficient(s). This method uses the ARDL approach to estimate long-run relations.

The second approach, developed by Chudik, Pesaran, Mohaddes and Raissi (2013) and Chudik, Pesaran, Mohaddes and Raissi (2015), estimates the long-run coefficients directly without estimating short-run coefficients first. This is done by reparametrizing the ARDL model (1) as follows[4]:

$$y_{it} = \theta_i' x_{it} + \alpha_i'(L)\Delta x_{i,t-l} + u_{it} \tag{3}$$

where, $u_{it} = \varphi(L)^{-1}$, $u_{it} = \varphi(L) = 1 - \sum_{l=1}^{p_{yi}} \varphi_{il} L^l$, $\theta_i = \delta_i(1)$,

$\delta_i(L) = \varphi^{-1}(L)\beta_i(L) = \sum_{l=0}^{\infty} \delta_{il} L^l$, $\beta_i(L) = \sum_{l=0}^{p_{xi}} \beta_{il} L^l$, and $\alpha_i(L) = \sum_{l=0}^{\infty} \sum_{s=l+1}^{\infty} \delta_s L^l$

Note that Eq(3) does not include a lagged dependent variable, so it is a distributed lag (DL) representation. Chudik, Pesaran, Mohaddes and Raissi (2015) demonstrate that least squares can be used to obtain consistent estimates of the long-run coefficient θ directly by regressing y_{it} on x_{it} and $\{\Delta x_{it-l}\}_{l=0}^{p}$ in the absence of feedback effects from lagged values of y_{it} onto x_{it}. The truncation lag order p is chosen as an increasing function of the sample size (specifically, p is selected as the integer part of $T^{1/3}$, where T is the length of the time dimension). If there exist feedback effects from lagged values of y_{it} onto x_{it}, however, this approach becomes inconsistent, as in this case u_{it} will be correlated with x_{it}. On the other hand, strict exogeneity is not required for consistency in this approach. For more details please refer to Chudik, Pesaran, Mohaddes and Raissi (2015).

In this framework, the hypothesized long-run relation is examined basically by the Autoregressive Distributed Lag (ARDL) method of Pesaran and Shin (1998) and the Distributed Lag (DL) method of Chudik, Pesaran, Mohaddes and Raissi (2015) on a panel data setting.

To estimate the ARDL specification, Mean Group (MG) Estimator of Pesaran and Smith (1995) and Pooled Mean Group (PMG) estimator of Pesaran, Shin and Smith (1999) are used that accommodate cross-country slope heterogeneity. The Dynamic Fixed Effect (DFE) estimator is also used for comparison purposes. To deal with cross-sectional error dependence, the Cross-Sectionally Augmented ARDL (CS-ARDL) approach of Chudik and Pesaran (2015) and Cross-Sectionally Augmented

[4] For the proof, please see Chudik, Pesaran, Mohaddes and Raissi (2015).

Distributed Lag (CS-DL) approach developed by Chudik, Pesaran, Mohaddes and Raissi (2013) and Chudik, Pesaran, Mohaddes and Raissi (2015) are used. The CS-DL method also deals with some of the shortcomings of the ARDL specification, while it has also its own drawbacks. The relative merits of these ARDL and DL methods are discussed below.

The basic ARDL specification is as follows:

$$\Delta y_{it} = c_i + \sum_{l=1}^{p_y} \varphi_{il} \Delta y_{i,t-l} + \sum_{l=0}^{p_x} \beta'_{il} x_{i,t-l} + \gamma_i Dummy_{it} + \eta_i Trend + u_{it} \tag{4}$$

where,

$$\hat{\lambda}_i = 1 - \sum_{l=1}^{p_y} \hat{\varphi}_{il} \tag{5}$$

and

$$\hat{\theta}_i = \lambda_i^{-1} \sum_{l=0}^{p_x} \hat{\beta}_{il} \tag{6}$$

and y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, $x_{it} =(lnP_{it}, lnF_{it}, lnE_{it})'$, lnP_{it} is the natural logarithm of Political Risk Rating, lnF_{it} is the natural logarithm of Financial Risk Rating, lnE_{it} is the natural logarithm of Economic Risk Rating provided by International Country Risk Guide(ICRG), *Dummy* is a dummy variable marking the beginning of the recent global financial crisis as December 2007, *Trend* is a linear time trend and p_x and p_y are respective lag orders. Note that the left hand side of the equation is a return expression as the first difference of the natural log of the MSCI country stock market index gives the continuously compounded monthly return for the relevant stock market index. The maximum lag order is taken as six, which is supposed to be long enough for a stock market to react changes in country risk ratings.

Even though the alternative commonly used cointegration approach developed by Johansen (1988, 1991) and Johansen and Juselius (1990) is more efficient in multivariate systems, the ARDL approach has three basic advantages over these two approaches: First, ARDL is valid irrespective of whether the series are *I(0)* or *I(1)* and whether the regressors are exogenous or endogenous (Chudik, Pesaran, Mohaddes and Raissi, 2013). The former characteristic is attractive because the data used in this study represent a mix of *I(0)* and *I(1)* series[5]. This feature of ARDL also avoids the pre-testing problems involved in standard cointegration methods. The previously adopted methods in Johansen (1988, 1991) and Johansen and Juselius (1990) and Engle and Granger (1987) are valid in cases where the underlying variables are integrated of the same order (Pesaran, Shin and Smith, 2001). The latter advantage is also appealing, because reverse causality can be important in the relation where disaggregated country risk ratings are the independent variables and stock market return is the dependent variable. By employing this method, we are able to account for possible feedback among the variables.Related literature indicates that the political, financial and economic risk ratings

[5] The unit root tests of the series are not reported, but available from the author upon request.

Another advantage of ARDL approach is obtaining more efficient cointegration relationships with small samples (Ghatak and Siddiki, 2001; Narayan, 2005). And last but not the least, ARDL overcomes the problems resulting from non-stationary time series data (Laurenceson and Chai, 2003). Stock and Watson (2003) report that if a regressor has a unit root, then the OLS estimator of its coefficient and the corresponding t-statistic from OLS estimation can have non-normal distributions. This problem may lead to spurious regression and autoregressive coefficients that are biased towards zero.

The ARDL approach has also its limitations. Due to the inclusion of lagged dependent variables in the regressions, if the time dimension is not sufficiently long and the speed of convergence towards long-run equilibrium is slow, the ARDL can be subject to large sampling uncertainty (Chudik, Mohaddes, Pesaran and Raissi, 2015). Because of these reasons, lag order selection is critical in ARDL applications as underestimating the correct lag order may result in inconsistent estimates while overestimating may lead to inefficiency and low power (ibid). In relation to our case, neither of these limitations seem to be crucial because, first, the time dimension is quite large (T_{max}=358) and second, the empirical results show that the speed of adjustment of the system is rather high.

Another drawback of the classical ARDL approach, which is applicable to and important for our case is that it assumes cross-sectional independence of errors. This assumption is problematic because numerous unobserved global factors may simultaneously affect all cross-sectional units and can lead to biased estimates if these unobserved common factors are correlated with the regressors (Chudik, Pesaran, Mohaddes and Raissi, 2013). Indeed the Cross-Sectional Dependence Test of Pesaran (2004, 2013) shows in our case that there is considerable dependence of errors across countries. This needs to be carefully taken into account.

To deal with cross-sectional error dependence, two methods will be used. The first is the Cross-Sectionally Augmented ARDL (CS-ARDL) approach of Chudik and Pesaran (2015) and the second is the Cross-Sectionally Augmented Distributed Lag (CS-DL) approach of Chudik, Pesaran, Mohaddes and Raissi (2013) and Chudik, Pesaran, Mohaddes and Raissi (2015).

The Cross-Sectionally Augmented ARDL (CS-ARDL) approach of Chudik and Pesaran (2015) augments the ARDL regression given in Eq(7) with cross-sectional averages of the dependent variable, regressors and a sufficient number of their lags as follows:

$$\Delta y_{it} = c_i + \sum_{l=1}^{p_y} \varphi_{il} \Delta y_{i,t-l} + \sum_{l=0}^{p_x} \beta'_{il} x_{i,t-l} + \sum_{l=0}^{p_{\bar{z}}} \psi'_{il} \bar{z}_{t-l} + \gamma_i Dummy_{it} + \eta_i Trend + u_{it} \qquad (7)$$

where,

$$\hat{\lambda}_i = 1 - \sum_{l=1}^{p_y} \hat{\varphi}_{il} \qquad (8)$$

and

$$\hat{\theta}_i = \lambda_i^{-1} \sum_{l=0}^{p_x} \hat{\beta}_{il} \tag{9}$$

and y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, x_{it} =(lnP_{it}, lnF_{it}, lnE_{it})', $\bar{z}_t$ =($\bar{y}_t, \bar{x}'_t$)', $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, lnP_{it} is the natural logarithm of Political Risk Rating, lnF_{it} is the natural logarithm of Financial Risk Rating, lnE_{it} is the natural logarithm of Economic Risk Rating provided by International Country Risk Guide(ICRG), *Dummy* is a dummy variable marking the beginning of the recent global financial crisis as December 2007, *Trend* is a linear time trend term and p_x=p_y=1,2; p_z=3.

The CS-ARDL approach has the advantages of the classical ARDL approach and additionally it allows for cross-sectional dependence of errors. However, it is applicable only to stationary panels[6] and still subject to the small *T* bias of the classical ARDL approach (Chudik, Pesaran, Mohaddes and Raissi, 2015).

Finally, Cross-Sectionally Augmented Distributed Lag (CS-DL) approach of Chudik, Pesaran, Mohaddes and Raissi (2013) and Chudik, Pesaran, Mohaddes and Raissi (2015) augments the DL regression given in Eq(10) with cross-sectional averages of the dependent variable, regressors a sufficient number of their lags as follows:

$$\Delta y_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1} \delta_{il} \Delta x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \omega_{y,il} \Delta \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \omega'_{x,il}\, \bar{x}_{t-l} + \gamma_i Dummy_{it} + \eta_i Trend + u_{it} \tag{10}$$

where y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, x_{it} =(lnP_{it}, lnF_{it}, lnE_{it})', $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, lnP_{it} is the natural logarithm of Political Risk Rating, lnF_{it} is the natural logarithm of Financial Risk Rating, lnE_{it} is the natural logarithm of Economic Risk Rating provided by International Country Risk Guide(ICRG), Dummy is a dummy variable as defined before and *Trend* is a linear time trend term, and p=1,2,3,…7; p_y=0, p_x=7.[7] The time trend is included in all specifications to account for any possible trending behavior that could result in spurious regressions.

The main advantage of the CS-DL method over the panel ARDL approach is that it is robust to important specification issues and its small sample performance is better as compared to the ARDL approach when *T* is not large (Chudik, Pesaran, Mohaddes and Raissi, 2015). Its advantages stem from:

(a) its robustness to the possible inclusion of nonstationary regressors and/or factors,

[6] Various panel unit roots were conducted to see whether the panels are stationary or not. Im, Pesaran, Shin, Fisher Type Dickey-Fuller and Fisher Type Phillips-Pherron panel unit root tests all reject the null that "all panels contain unit roots", concluding that "some panels are stationary".

[7] The truncation lag order *p* is selected as the integer part of $T^{1/3}$, where *T* is the time dimension of the series.

(b) its applicability to both heterogeneous and homogenous coefficient cases across panel units,
(c) its robustness to an arbitrary degree of serial correlation in the error terms ε_{it} and f_t,
(d) the fact that, under certain conditions, there is no need to know the number of unobserved common factors,
(e) its allowance for weak cross-sectional dependence in the idiosyncratic errors ε_{it},
(f) its independence from the lag order selection p_{yi} and p_{xi}; only a truncation lag order selection is selected,
(g) its robustness to possible breaks in the idiosyncratic errors ε_{it}.

The CS-DL approach has also an important disadvantage: In the presence of feedback effects (reverse causality) from lagged values of the dependent variable onto the regressors, the CS-DL estimation of the long-run coefficients will be inconsistent; since when there is feedback effects, u_{it} will be correlated with the regressors, which creates a bias even when N and T are sufficiently large.

Comparing the relative advantages and disadvantages of the CS-ARDL and CS-DL approach, it should be emphasized that they are not substitutes; they are rather complementary methods, because they have their own merits and drawbacks, which cannot be fully compensated by the other.

5.1. Estimation Methods

When N is large and T is long enough to run separate time series regressions for each group, four procedures are traditionally used to estimate the average effect of some exogenous variable on a dependent variable (Pesaran and Smith, 1995):

1. Estimating separate regressions for each group and averaging the coefficients over groups (the mean group estimator-MG).
2. Combining the data by imposing common slopes, allowing for fixed or random intercepts, and estimating pooled regressions (classical fixed and random-effect estimators).
3. Averaging the data over groups and estimating average time-series regressions.
4. Averaging the data over time and estimating cross-section regressions on group means.

In the static case, where the regressors are strictly exogenous and the coefficients differ randomly and are distributed independently of the regressors across groups, all four procedures provide consistent (and unbiased) estimates of the coefficient means (Pesaran and Smith, 1995, *p80*). For dynamic heterogeneous models, however, Pesaran and Smith (1995) show that this is not the case.

They demonstrate that the pooled and aggregate estimators (the second and third options given above) are not consistent in dynamic heterogeneous models, even for large N and T, and the biases can be "very substantial". They argue that unless the slope coefficients are in fact identical, traditional pooled estimation methods can produce misleading parameter estimates in dynamic panels. Because, incorrectly ignoring coefficient heterogeneity induces serial correlation in the disturbance when the regressors are serially correlated, and this generates inconsistent estimates (even as $T \rightarrow \infty$) in dynamic models. (For more details please see Pesaran and Smith, 1995):

A similar approach can be advanced for the aggregate time-series estimator case (i.e., averaging the data over groups and estimating average time-series regressions) (Pesaran and Smith, (1995).

Averaging the data over time and estimating cross-section regressions on group means (the fourth alternative in the list above), produce consistent estimates of the average long-run coefficients (Pesaran and Smith (1995). However, they also warn that running cross-section regressions based on a single or a few years of observations is not likely to yield unbiased or consistent estimates.

For estimation of dynamic random coefficient models, Pesaran and Smith (1995) proposed the Mean Group Estimator (MG), which can obtain consistent estimates of coefficients in large dynamic heterogeneous panels. The MG Estimator is based on estimating separate regressions for each group and averaging the coefficients over groups. Pesaran, Smith and Im (1996) use Monte Carlo experiments to investigate the small sample properties of various dynamic heterogeneous panel data model estimators and find that even for quite small panels ($N=T=20$) the MG Estimator performs well in estimating the long run effects. Their Monte Carlo experiments also clearly show that the traditional pooled estimators can be quite misleading for dynamic heterogeneous panels and can regularly lead to incorrect inferences.

As an alternative to the traditional pooled fixed and random effect approaches in dynamic heterogeneous panels, Pesaran, Shin and Smith (1999) propose an intermediate model, in which intercepts, short-run coefficients and error variances are allowed to differ freely across groups, while long-run coefficients are restricted to be the same across groups. They call this the Pooled Mean Group Estimator (PMG). They argue that budget or solvency constraints, arbitrage conditions, or common technologies influencing all groups in a similar way make it quite reasonable to expect the long-run equilibrium relationships between variables to be similar across groups, but it is not the case for short-run dynamics and error variances, which could be different due to group specific factors.

In the classical panel ARDL case, in addition to the PMG and MG estimators, dynamic fixed effect (DFE) estimator is also used for comparison purposes. As mentioned earlier, the DFE estimator is inconsistent unless slope parameters are homogenous across cross sections. The PMG estimator is consistent and efficient under parameter homogeneity, but inconsistent if the true model is heterogeneous. The MG estimator is consistent in either case as long as the errors are cross-sectionally independent.

In the CS-ARDL case, PMG and MG estimators, in the CS-DL case only MG estimator is used.

6. Empirical Application and Results

Considering that the hypothesized relations may vary depending on the degree of market integration, the methodology described above is applied to 3 different samples; developed countries, emerging countries, and the full sample.

The empirical application starts with panel unit root tests, since the CS-ARDL approach is applicable only to stationary panels. In addition, the estimation methods discussed in the previous section (PMG, MD and DFE) assume that a long-run relation exists between the included variables. Therefore, panel cointegration tests were conducted for each sample. Panel cointegration tests serve also to one of the main purposes of this study: to test whether there is a long-run relation between disaggregated country risk ratings and stock market index returns.

6.1. Panel Unit Root Tests

Three different unit root tests are applied to the series for each sample: i) Im, Pesaran, Shin panel unit root test, ii) Fisher Type Dickey-Fuller panel unit root test and iii) Fisher Type Phillips-Pherron panel unit root test. The null hypothesis of the Im, Pesaran, Shin panel unit root test is that "all panels contain unit roots" against the alternative "some panels are stationary". The remaining two tests are based on the same null hypothesis against "at least one panel is stationary". Levin-Lin-Chiu, Harris-Tzavalis and Breitung tests could not be applied because all of them require strongly balanced data.

Panel unit root tests applied to developed, emerging countries and full sample all strongly reject the null hypothesis that all panels contain unit roots. In the frontier countries sample there is evidence of unit root in the political risk rating and some tests (not all) fail to reject the null in composite and financial risk ratings. All tests strongly reject the null in MSCI index and economic risk rating series for the frontier countries sample. From the panel unit root tests, we can only conclude that at least one or some of the panels are stationary. This is consistent with the unit root tests applied to individual series, which yielded *I(0)-I(1)* mixed results. The results of the panel unit root tests are given in Appendix-A.

6.2. Panel Cointegration Tests

Pedroni's (1999) panel cointegration tests are used to test whether the series in the panels have long-run equilibrium relationships (cointegrated). The advantage of the Pedroni's cointegration test is that it is applicable to heterogoneous panels with medium to large N and large T, and with one or more nonstationary regressors. It provides seven statistics under a null of no cointegration: panel-*v*, *rho*, group-*rho*, panel-*t* (non-parametric), group-*t* (non-parametric), panel-*adf* (parametric *t*), and group-*adf* (parametric *t*).

Panel cointegration tests all strongly reject the null of no-cointegration for all the sub-samples (developed, emerging and frontier) and for the full sample when both disaggregated and composite risk ratings are used as independent variables. This provides strong evidence in favor of the main hypothesis in this study that there should be a long run relation between disaggregated (and composite) risk ratings and stock market index returns. The cointegration test results are given in Appendix-B.

6.3. Cross-Sectional Dependence Tests

For each of the methods (DFE, PMG, MG) to estimate the ARDL, CS-ARDL and CS-DL regressions, cross-sectional dependence test statistics are calculated to check whether there is significant dependence of errors across cross-sectional units. As discussed before, unobserved global factors may simultaneously affect all cross-sectional units, creating a cross-sectional dependence of errors, which can lead to biased estimates if these unobserved common factors are correlated with the regressors (Chudik, Pesaran, Mohaddes and Raissi, 2013). The results of the cross-sectional dependence tests for different samples, estimation methods and lags are discussed and interpreted in the Empirical Results section.

6.4. Hausman Tests

As discussed earlier, the DFE estimation method assumes homogeneity in cross-sectional coefficients for both short- and long-run relations; PMG assumes heterogeneity in short-run coefficients while assuming homogeneity in the long-run coefficients. The MG estimator allows heterogeneity in both short- and long-run coefficients. If the long-run coefficients are actually heterogeneous across cross-sectional units, then the DFE method may produce biased results, while the MG method is consistent in any case. However, the PMG estimator is efficient (and consistent) if parameter homogeneity holds. To test parameter homogeneity, Hausman test is used in this study. The Hausman test compares an estimator θ_1 (known to be consistent under both the null and alternative hypothesis) with θ_2 (known to be efficient and consistent under the null, but inconsistent otherwise). The null hypothesis is that θ_2 is efficient and consistent, in which case there should be no systematic difference between θ_1 and θ_2. If the null is rejected, which is an indication of systematic difference between θ_1 and θ_2, there is evidence that the assumptions on which the efficient estimator is based are doubtful. Therefore, the consistent estimator (θ_1) is selected in this case. If the test fails to reject the null hypothesis, the efficient (and consistent) estimator (θ_2) is selected. In our case, the MG estimator is the consistent estimator under both the null and the alternative hypothesis, while the PMG and DFE estimators are efficient (and consistent) under the null, but inconsistent otherwise. The results of the Hausman tests for different samples, estimation methods and lags are discussed and interpreted in the Empirical Results section.

6.5. Empirical Results

The results of the empirical tests are presented in 3 different samples (developed countries, emerging countries, the full sample). For each sample, two different sets of independent variables are considered: disaggregated risk ratings and composite risk ratings. Furthermore, for each sample and different set of independents, three different specifications are used to estimate the long-run coefficients: classical ARDL, Cross-Sectionally Augmented ARDL (CS-ARDL) and Cross-Sectionally Augmented DL (CS-DL). For the classical ARDL, three different estimation methods (Dynamic Fixed Effects (DFE), Pooled Mean Group (PMG) and Mean Group (MG)) are used. For the CS-ARDL specification, only PMG and MG estimators, and finally, for the CS-DL specification only MG estimator is employed.

The empirical model proposed in this study is based on the CS-DL results due to the following reasons: for all estimation alternatives in the classical ARDL approach (DFE, PMG and MG) and lag specifications (from 1 to 6), there is strong evidence of cross-sectional error dependence between cross-sectional units. According to Chudik, Pesaran, Mohaddes and Raissi (2013), cross-sectional dependence of errors in panel time series may lead to biased estimates if unobserved global factors that simultaneously affect all cross-sectional units are also correlated with the regressors. The cross-sectional dependence (CD) test of Pesaran (2004, 2013) yields very large statistics for all estimation alternatives and lag specifications, thus they might be misleading. To deal with the cross-sectional error dependence, CS-ARDL and CS-DL methods are employed. The CS-ARDL approach yields substantial decrease, as compared to the classical ARDL, in the cross-sectional dependence test statistics. However, this statistics is still statistically significant, indicating that there is still dependence of errors in the cross-sectional units. In addition, the long time dimension requirement of the ARDL approach becomes even longer in the CS-ARDL method, when the cross sectional averages are added to the specification. When cross-sectional averages and lags of the three independent variables (political, financial and economic risk ratings) and of the dependent variable are added to the specification, obtaining coefficient estimates becomes even more difficult. Indeed, CS-ARDL approach was not able to obtain coefficient estimates for lags greater than two and this limited our ability to examine the robustness of coefficients to higher lag orders. The CS-DL approach, on the other hand, computes the long-run coefficients directly without calculating the short-run coefficients first; therefore it can accommodate longer lag orders and was able to calculate long-run coefficient estimates for lag orders as long as 7 months. This enabled us to examine the robustness of the estimates to increasing lag orders, observe the pattern that coefficient estimates follow when higher lag orders are imposed and judge whether estimates converge. In addition, the CS-DL approach is robust to many of the problems that other approaches (classical ARDL and CS-ARDL) have and it fits better to the conditions of the data and variables used in this study. Therefore, only the results tables of the CS-DL approach are reported in the study[8].

In the classical ARDL specification, the coefficient of the dummy variable that marks the beginning of the 2008 global crisis is always statistically significant for all lag orders and estimation alternatives, indicating that the 2008 crisis indeed affected countries globally. Thus, to investigate whether there is any structural break due to the 2008 global crisis (i.e. whether there is a change in the long-run coefficients after the crisis), the sample was also divided into two time periods (before the 2008 crisis and afterwards) and the same procedure was applied to each time period. The results of this analysis are discussed in Section-6.5.3.

6.5.1. Composite Risk Ratings and Stock Market Index Returns

6.5.1.1. Developed Countries

Table-1 shows the long-run coefficient estimates of the CS-DL approach. Since the maximum length of the time dimension is 389 for the developed country sample, p_x is set equal to 7, which is the integer part of $T^{1/3}$. Coefficient estimates for different lag orders (1 to 7) are also obtained and shown in Table-1.

Table-1 indicates strong evidence of a long-run relation between composite risk ratings and stock market index returns. The coefficients of the composite risk rating are statistically significant for all lag orders 1 to 7. The coefficients are significant at 1% level for all lags, except for the lag 1, for which the significance level is 5%. The sign of the coefficients are all negative as expected; indicating a negative long-run relation between composite risk rating and stock market index returns (lower returns for higher ratings (lower risk) and higher returns for lower ratings (higher risk)). The magnitude of the coefficients for lag orders 1 to 7 falls into the range (-0.054, -0.095). The robustness of the coefficients to lag orders becomes apparent for higher lag orders (3 to 7). In other words, starting from the third lag order, the range that the long-run coefficients fall into becomes narrower and they tend to converge to a value between -0.085 and -0.090. This is an indication that the long-run equilibrium is reached in around 3 months once the system is shocked, which is consistent with the speed of adjustment coefficients suggested by the classical ARDL approach.[9]

[8] The results of the other approaches (Classical ARDL and CS-ARDL) are available from the authors upon request.

[9] Classical ARDL results are not reported but available upon request.

Thus, the long-run coefficient is taken as the average of estimated coefficients for lags 3 to 7, which is -0.088. This implies that a permanent increase in the composite risk rating is associated with 8.8 basis points decrease in monthly stock market index returns, which makes 1.051 percentage points annually. Therefore, since increased composite risk rating means lower risk, a one percent permanent increase in country (composite) risk is associated with an average 1.051 percentage points increase in annual return. The sign of the coefficient is negative as expected, meaning that higher rating (lower risk) is associated with lower return and vice versa.

This result is consistent with the main hypothesis of the paper that country risk may have bearings on stock market returns and that higher risk should be associated with higher returns.[10]

The coefficient of the dummy variable loses its significance for all lag specifications, which is somewhat expected because of the inclusion of cross-sectional averages of the regressors, dependent variable and a sufficient number of their lags in the specification, which already accounts for spillover effects and common global factors, possibly including the 2008 global crisis.

[Insert Table-1 About Here]

6.5.1.2. Emerging Countries

Table-2 shows the long-run coefficient estimates of the CS-DL approach for the Emerging Countries sample. Since the maximum length of the time dimension is 341 for the emerging country sample, p_x is set equal to 7[11]. Coefficient estimates for different lag orders (1 to 7) are also obtained and shown in the Table. For all lag orders, the coefficients are statistically significant (at 10% for lag 1, at 5% for lags 2 to 5 and at 1% for lags 6 and 7). The sign of the coefficients are all negative as expected; indicating a negative long-run relation between composite risk rating and stock market index returns (lower returns for higher ratings (lower risk) and higher returns for lower ratings (higher risk)). From lag 1 to lag 7, long-run coefficient estimates fall into a range (-0.063; -0.104). This range gets narrower starting from lag 4, and the long-run coefficient seems to converge to a range between -0.090 and -0.100. This is an indication that the long-run equilibrium is reached in around 4 months once the system is shocked.

Thus, the long-run coefficient is taken as the average of estimated coefficients for lags 4 to 7, which is -0.096. This implies that a permanent increase in the composite risk rating is associated with 9.6 basis points decrease in monthly stock market index returns, which makes 1.155 percentage points annually. Therefore, since increased composite risk rating means lower risk, a one percent permanent increase in country (composite) risk is associated with an average 1.16 percentage points increase in annual return. The sign of the coefficient is negative as expected, meaning that higher rating (lower risk) is associated with lower return and vice versa.

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[10] However, the cross-sectional dependence test statistics show that, although there is substantial decrease in the test statistics as compared to the classical ARDL approach (from around 170 to around 12), there still remains statistically significant degree of cross-sectional dependence. Therefore, the results should be interpreted with this consideration.

[11] Although the integer part of $T^{1/3}$ is 6, (the cuberoot of 341 is 6.99), p_x is set equal to 7. This approach is on the safe side, because it enables us to examine coefficient estimates for longer lag-orders, which yield smaller cross-sectional dependence test statistics.

This result is consistent with the main hypothesis of the study that country risk may have bearings on stock market returns and that higher risk should be associated with higher returns.[12]

Finally, it is observed that the coefficient of the dummy variable loses its significance for all lag specifications, which is somewhat expected because of the inclusion of cross-sectional averages in the regressions.

[Table-2 is About Here]

6.5.1.3. Full Sample

The long-run coefficient estimates of the CS-DL approach are given in Table-3. Since the maximum length of the time dimension is 389 for the full sample, p_x is set equal to 7, which is the integer part of the time dimension ($T^{1/3}$).

Table-3 indicates strong evidence of a long-run relation between composite risk ratings and stock market index returns for the full sample. The coefficients of the composite risk rating are statistically highly significant for all truncation lag orders 1 to 7. The coefficients are significant at the 1% level for all lag specifications. The sign of the coefficients are all negative as expected; indicating a negative long-run relation between composite risk rating and stock market index returns (lower returns for higher ratings (lower risk) and higher returns for lower ratings (higher risk)). The magnitude of the coefficients for lag orders 1 to 7 falls into the range (-0.066, -0.097). The robustness of the coefficients to lag orders becomes apparent for higher lag orders (5 to 7). In other words, starting from the fifth lag order, the range that the long-run coefficients fall into becomes narrower and they tend to converge to a value between -0.095 and -0,097. This is an indication that the long-run equilibrium is reached in around 5 months once the system is shocked.

Thus, the long-run coefficient is taken as the average of estimated coefficients for lags 5 to 7, which is -0.096. This implies that a permanent increase in the composite risk rating is associated with 9,6 basis points decrease in monthly stock market index returns, which makes 1.156 percentage points annually. Therefore, since increased composite risk rating means lower risk, a one percent permanent increase in country (composite) risk is associated with an average 1.16 percentage points increase in annual return. The sign of the coefficient is negative as expected, meaning that higher rating (lower risk) is associated with lower return and vice versa.

This result is consistent with the main hypothesis of the study that country risk may have bearings on stock market returns and that higher risk should be associated with higher returns.[13]

The coefficient of the dummy variable loses its significance for all lag specifications, which is somewhat expected because of the inclusion of cross-sectional averages of the regressors, dependent variable and a sufficient number of their lags in

[12] However, the cross-sectional dependence test statistics show that although there is substantial decrease in the test statistics as compared to the classical ARDL approach (from around 90 to around 11) there still remains statistically significant degree of cross-sectional dependence.

[13] However, the cross-sectional dependence test statistics show that, although there is substantial decrease in the test statistics as compared to the classical ARDL approach (from around 240 to around 8), there still remains statistically significant degree of cross-sectional dependence.

the specification, which already accounts for spillover effects and common global factors, possibly including the 2008 global crisis.

[Table-3 is About Here]

6.5.2. Disaggregated Risk Ratings and Stock Market Index Returns

The analysis in the preceding sections shows that there is statistically significant evidence of a long-run relation between composite country risk ratings and stock market index returns. The effect of composite risk ratings on stock market returns is dynamic and its effect occurs over time in as long as 5 months. This result is consistent with the findings of Erb, Harvey and Viscanta (1996), who found that Institutional Investor's semiannual composite risk ratings are related to next period's (6 months ahead) country stock market returns.

However, composite ratings are made up of sub-components and it would be interesting and useful to discern the relative effects of these sub-components (political, economic and financial) to stock market returns. This section is devoted to investigate this possibility. As in the composite rating case, each country group (Developed, Emerging and Full Sample) is analyzed in turn.

6.5.2.1. Developed Countries

Table-4 shows the long-run coefficient estimates for the Developed Country sample. Since the maximum length of the time dimension is 389 for the developed countries sample, p_x is set equal to 7, which is the integer part of $T^{1/3}$. Coefficient estimates for different lag orders p (1 to 7) are also obtained and shown in Table-4.

Coefficient estimates of financial risk rating are statistically significant for only lags 2, 3 and 5. The significance is not robust to different lag orders; coefficient estimates for lags 1, 4, 6 and 7 are insignificant.

Political risk rating coefficients are significant for all lag orders 1 to 7 (all at 10%, except lag 1, which is at 5%). The sign of this coefficient is negative as expected for all lags and its magnitude falls into the range (-0.039; -0.061) across lags 1 to 7. However, this range gets narrower starting from lag 5, at which it seems to converge to a value between -0.050 and -0.060. Therefore, the long-run coefficient of political risk rating is taken as the average of values corresponding to lags 5 to 7, which is -0.058.

Table-4 provides evidence of a long-run relation between economic risk rating and stock market returns for this sample: Long-run coefficient estimates of economic risk rating are all negative as expected and statistically significant for lags 4 to 7 (at 5% and 10%). They fall into the range (-0.054; -0.084); however, this range becomes considerably narrower starting from lag 5. Therefore, the long-run coefficient estimate for the economic risk rating is taken as the average of estimates for lags 5 to 7, which is -0.071.

The coefficient of the dummy variable is insignificant for all lag orders, which is somewhat expected because the model includes cross sectional averages and their lags, which are supposed to account for unobserved common factors and spillover effects. The trend term turns out to be significant for lags 1, 3, 4, 6, but they are all economically insignificant (0.000).

[Table-4 is About Here]

6.5.2.2. Emerging Countries

Table-5 shows firm evidence that political risk rating is associated with stock market returns in the long-run. For all lag specifications, except 1, political risk rating coefficient estimates are statistically significant (at 5% or lags 3, 5, 6 and 7; at 10% for lags 2 and 4). The sign of this coefficient is negative as expected for all lags and its magnitude falls into the range (-0.063; -0.082) across lags 1 to 7. However, this range gets narrower starting from lag 5. Therefore, the long-run coefficient of political risk rating is taken as the average of values corresponding to lags 5 to 7, which is -0.079.

Coefficient estimates of economic and financial risk ratings are insignificant for all lag orders. The coefficient of the dummy variable is insignificant for all lag orders, which is somewhat expected because the model includes cross sectional averages and their lags, which are supposed to account for unobserved common factors and spillover effects. The trend term turns out to be insignificant for all lags; also they are all economically insignificant (0.000).

[Table-5 is About Here]

6.5.2.3. Full Sample

Table-5 presents clear and strong evidence that political and economic risk rating components are significantly related with stock market returns in the long-run. For all lag specifications 1 to 7, political risk rating coefficient estimates are highly significant (all at 1%). The sign of this coefficient is negative as expected for all lags and its magnitude falls into the range (-0.068; -0.092) across lags 1 to 7. However, this range gets narrower starting from lag 5 and the coefficient estimates seem to converge to a value between -0.091 and -0.092. Therefore, the long-run coefficient of political risk rating is taken as the average of values corresponding to lags 5 to 7, which is -0.091. This implies that a one percent increase in political risk rating is associated with 9.1 basis points decrease in monthly stock returns, which makes 1.096 percentage points annually.

Table-5 also provides clear evidence of a long-run relation between economic risk rating and stock market returns for this sample: Long-run coefficient estimates of economic risk rating are all negative as expected and statistically significant for all lag specifications (at 1% for lags 2, 3, 4, 5 and 5% for lags 1, 6, 7). They fall into the range (-0.034; -0.056); however, this range becomes considerably narrower starting from lag 4, and estimates seem to converge to a value approximately between -0.051 and -0.056. Therefore, the long-run coefficient estimate for the economic risk rating is taken as the average of estimates for lags 4 to 7, which is -0.053. This implies that a one percent increase in economic risk rating is associated with 5.3 basis points decrease in monthly stock returns, which makes 0.639 percentage points annually.

Coefficient estimates of financial risk rating are insignificant for all lag specifications. They are positive for lags 1, 2, 3 and 4; but they are close to zero and they become negative after lag 5.

We also test for joint equality of the coefficients of the political, economic and financial risk ratings. Parameter equality tests (not reported) for all lag orders reject the null hypothesis that they are all equal to each other.

The coefficient of the dummy variable is insignificant for all lag orders, which is somewhat expected because the model includes cross sectional averages and their lags, which are supposed to account for at least a considerable part of unobserved common factors and spillover effects.

The trend term estimates are significant for lags 1,2, and 3, but becomes insignificant after lag 4. For all lags, they are economically insignificant (0.000).

Although there is substantial decrease as compared to the classical ARDL results (CD test statistics were around 240 in the classical ARDL), the CD-statistics are still significant (the lowest value in absolute terms is 8.00). Therefore, the results should be interpreted with this consideration.

This latest model is the basis for the empirical model used below. It covers the full sample and immune to many of the specification issues that other alternatives are subject to. The remaining cross-sectional dependence of errors, is hoped to be remedied in the future by further improvement of the econometric model used.

[Table-6 is About Here]

6.5.3. Comparison of the Relation Before and After the 2008 Crisis

The foregoing analysis shows that the 2008 global crisis has a significant impact on stock market returns. The coefficient estimates of the dummy variable that marks the beginning of the 2008 crisis were always statistically highly significant in the classical ARDL approach for all samples and lag specifications. In general, the coefficient of the dummy variable becomes insignificant in CS-ARDL and CS-DL approaches, since they already account for unobserved common factors and spillover effects by augmenting the classical ARDL approach with the cross-sectional averages of regressors, dependent variable and their lags.

Given the evidence provided by the classical ARDL approach about the effect of 2008 crisis on stock market returns, it is an empirical issue to see whether this impact leads to a structural change in the risk rating-stock returns relation. To investigate this possibility, the analysis done for the disaggregated risk rating-stock return relation is repeated for the before- and after-the-crisis periods. For each sub-sample (developed countries, emerging countries and full sample), classical ARDL, CS-ARDL and CS-DL approaches are repeated for both before- and after-crisis periods[14].

Before- and after-crisis analysis shows that the relation between risk ratings and stock market returns disappears (for both composite and disaggregated cases) after the 2008 crisis. Before the crisis, the relation is similar to what has been found for the full period. The disappearance of the relation after the crisis, however, could be due to the lack of data, because the length of the after-crisis period is considerably shorter than that of the before-crisis period. This could have impeded detection of a long-run relation. Thus, repeating the after-crisis analysis when long-enough data accumulates could be the subject of further research.

7. The Proposed Model

[14] Results are not reported but available from the authors upon request.

As discussed in detail in the sections above, the CS-DL-MG approach being selected as the basis for the proposed model, we found that a one percent permanent increase in political risk rating is associated with 9.1 basis points decrease in monthly stock returns across countries, which makes 1.096 percentage points annually. In addition, a one percent permanent increase in economic risk rating is associated with 5.3 basis points decrease in monthly stock returns across countries, which makes 0.639 percentage points annually. Therefore, the long-run[15] relation between stock market returns and disaggregated risk ratings can be expressed as follows:

$$R_{it}=a_t-1.096\ln P_{it} -0.639\ln E_{it} +\mu_i+\varepsilon_{it}$$

Taking expectations of both sides;

$$E(R_{it})=E[a_t-1.096\ln P_{it} -0.639\ln E_{it} +\mu_i+\varepsilon_{it}]$$

Since a_t is a constant $E(a_t)=a_t$

And by construction $E(\mu_i)=E(\varepsilon_{it})=0$, then

$$E(R_{it})=a_t-1.096\ln \overline{P_{it}} -0.639\ln \overline{E_{it}}$$

where $E(R_{it})$ is the expected return, $\overline{P_{it}}$ is the average political risk rating of country i, $\overline{E_{it}}$ is the average economic risk rating of country i. This expression can be used to develop an empirical model that calculates the international cost of equity (and expected returns) relative to a certain benchmark.

To do this, consider two countries with different political and economic risk ratings. Assume that in one of these countries we are able to (in some way) calculate the cost of equity for an average risk investment, and we are interested in calculating the cost of equity in the other country. Assume also that the ratings of these countries did not change for the last 4-5 months[16]. Then, in the long-run;

$$E(R_{it})=a_t-1.096\ln \overline{P_{it}} -0.639\ln \overline{E_{it}}$$

Since we assume that the system is in long-run equilibrium $\overline{P_{it}} = P_{it}$ and $\overline{E_{it}} = E_{it}$, then,

$$E(R_{it})=a_t-1.096\ln P_{it} -0.639\ln E_{it}$$

[15] The "long-run" is around 4-5 months in this model. This comes from the fact that the CS-DL approach on which the empirical model is based indicated that the long-run equilibrium is reached in around 4 months in the case of economic risk rating, and around 5 months in the case of political risk rating.

[16] This assumption is critical, because the coefficient estimates reflect the "long-run" equilibrium relation between risk ratings and stock market returns. Thus, in order for this model to work, one should assume that the system is in the long-run equilibrium.

where, $E(R_{it})$ is the expected annual equity return in country i, P_{it} is the political risk rating of country i at time t and E_{it} is the economic risk rating of country i at time t. For country j,

$$E(R_{jt})=a_t-1.096\ln P_{jt} -0.639\ln E_{jt}$$

where, $E(R_{jt})$ is the expected annual equity return in country j, P_{jt} is the political risk rating of country j at time t and E_{jt} is the economic risk rating of country j at time t. Taking the difference between $E(R_j)$ and $E(R_i)$;

$$E(R_{jt}) - E(R_{it}) = a_t-1.096\ln P_{jt} -0.639\ln E_{jt} -(a_t-1.096\ln P_{it} -0.639\ln E_{it})$$

Then,

$$E(R_{jt}) - E(R_{it})=1.096\ln(\frac{P_{it}}{P_{jt}})+ 0.639\ln (\frac{E_{it}}{E_{jt}})$$

If we call country i as the benchmark country for which $E(R_i)$ is known or can be calculated, then;

$$E(R_{jt}) - E(R_{Bt})=1.096\ln(\frac{P_{Bt}}{P_{jt}})+ 0.639\ln (\frac{E_{Bt}}{E_{jt}})$$

and

$$E(R_{jt})= E(R_{Bt})+1.096\ln(\frac{P_{Bt}}{P_{jt}})+ 0.639\ln (\frac{E_{Bt}}{E_{jt}}) \quad (18)$$

If the benchmark country is taken as the US, where the CAPM is known to work relatively better; then $E(R_{Bt})$ can be estimated using CAPM. Then,

$$E(R_{jt}) = E(R_{USt})+1.096\ln(\frac{P_{USt}}{P_{jt}})+ 0.639\ln (\frac{E_{USt}}{E_{jt}}) \quad (19)$$

and,

$$E(R_{USt})=r_{fUSt} + \beta(R_{MUSt}-r_{fUSt}) \quad (20)$$

where, $E(R_{jt})$ is the expected annual equity return in country j, $E(R_{USt})$is the expected annual equity return in the US, P_{USt} is the political risk rating of the US at time t, E_{jt} is the economic risk rating of country j at time t, r_{fUSt} is the risk free rate in the US at time t, R_{MUSt} is the market return in the US at time t and β is the beta of the project in question.

To give an example, consider the US and Turkey. As discussed before, in order for the model to work, one should find a particular month up to which the political and economic risk ratings in both of the compared countries stayed constant for at east three months (the system should be in the "long-run" equilibrium in both countries). One such month is October 2012. For this month, political and economic risk ratings of the US were 83.5 and 36.5, respectively. Those of Turkey were 56.5 and 33, respectively. Usign the proposed model given above;

$$E(R_{TRt}) = E(R_{USt}) + 1.096 ln(\frac{P_{USt}}{P_{TRt}}) + 0.639 ln(\frac{E_{USt}}{E_{TRt}})$$

$$E(R_{TR}) = E(R_{US}) + 1.096 ln(\frac{83.5}{56.5}) + 0.639 ln(\frac{36.5}{33})$$

$$E(R_{TR}) = E(R_{US}) + 49.3\%$$

Thus, according to this model, the cost of equity is 49.3 percentage points higher in Turkey than in the US annually for an average risk long-term direct capital investment. As suggested before, $E(R_{US})$ can be calculated using CAPM to obtain an absolute, rather than a relative value of the cost of equity in Turkey. This model can be used to calculate the cost of equity in any country of known political and economic risk ratings.

Similar empirical models can also be formulated for the developed and emerging country samples by using the coefficient estimates obtained for the respective country sub-samples. In that case, however, one should be careful, as the empirical model for a specific sub-sample should be used to calculate the international cost of equity relative to a country that is in the same group.

If the model is constructed using composite risk ratings;

For the full sample,

$$E(R_{jt}) = E(R_{Bt}) + 1.156 ln(\frac{C_{Bt}}{C_{jt}}) \quad (25)$$

$$E(R_{Bt}) = r_{fBt} + \beta(R_{MBt} - r_{fBt}) \quad (26)$$

where, $E(R_{jt})$ is the expected annual equity return in country j, $E(R_{Bt})$is the expected annual equity return in the benchmark country, C_{Bt} is the composite risk rating of the benchmark country at time t, C_{jt} is the composite risk rating of country j at time t, r_{fBt} is the risk free rate in the benchmark country at time t, R_{MBt} is the market return in the benchmark country at time t and β is the beta of the project in question.

It should be noted that the composite risk rating of the ICRG includes three sub-components, political, financial and economic. The composite rating-stock returns relation provides a "lump-sum" value of the long-run coefficient, which can be considered as the overall collective effect of the changes in sub-components to stock returns. However, the disaggregated analysis shows that only political and economic risk ratings are significantly related to stock market returns in the long-run and financial risk rating is not significantly related. Moreover, since the variation of political risk ratings across countries is much greater than the variation of the composite risk rating, the disaggregated model suggests much higher cost of equity differences than the composite rating model. To show this, consider the estimations of the cost of equity for Turkey by the full sample models of disaggregated and composite risk rating cases.

The composite rating model is;

$$E(R_{jt}) = E(R_{Bt}) + 1.156 ln(\frac{C_{Bt}}{C_{jt}})$$

The disaggregated rating model is;

$$E(R_{jt}) = E(R_{bt}) + 1.096 ln(\frac{P_{bt}}{P_{jt}}) + 0.639 ln(\frac{E_{bt}}{E_{jt}})$$

If the benchmark country is taken as the US and composite risk ratings are taken as the October 2013 values[17], the composite model estimates would be;

$$E(R_{TRt}) = E(R_{USt}) + 1.156 ln(\frac{75.50}{62.25})$$

$$E(R_{TRt}) = E(R_{USt}) + 22.2\%$$

On the other hand, the diaggregated model would suggest;

$$E(R_{TRt}) = E(R_{USt}) + 1.096 ln(\frac{80}{54}) + 0.639 ln(\frac{38.5}{35})$$

$$E(R_{TRt}) = E(R_{USt}) + 49.2\%$$

As can be seen, the disaggregated model estimate is much higher than the composite model estimate and, in addition, the composite rating model estimate is relatively closer to Erb, Harvey and Viskanta's (1996) credit rating model (in which Institutional Investor's semi-annual composite risk ratings were used) as compared to the disaggregated model estimates. As discussed before, this could be due to the differences in variations of composite risk and political risk ratings across countries. Since the composite rating is a linear weighted combination of political, financial and economic risk ratings, it might be disguising the variation in its sub-components. The disaggregated model captures the effect of this variation.

8. Conclusion

8.1. Country Risk Ratings and Stock Market Returns

[17] We assume that October 2013 values reflect long-run equilibrium.

Given the available theoretical and in particular empirical evidence, this study argues that country risk ratings and country stock market returns should co-move from a long-run perspective and that this relation can provide useful insights in respect of expected equity returns and the cost of equity in international markets. Testing this hypothesis by utilizing relatively rigorous time series techniques and cointegration analyses based on a sample of 45 countries, the study finds statistically significant evidence of a long-run relation between country risk ratings and stock market returns, for both composite and disaggregated risk ratings. The relations are dynamic; the effect of a change in risk ratings lasts for several months after which the long-run equilibrium is reached. In that respect, the term "long-run" in this study refers to 4-5 months, depending on whether composite or disaggregated ratings are used as the independent variables and conditional on the country sample considered.

The study finds that a one percent permanent increase (decrease) in composite risk rating is associated with 8.8, 9.6 and 9.6 basis points decreases (increases) in monthly stock returns in developed, emerging and full sample countries, respectively. The permanent effect occurs in 3, 4 and 5 months for developed, emerging and full countries samples, respectively.

If the sub-components of composite risk ratings are considered, political and economic risk ratings are significantly and negatively (-5.8 and -7.1 basis points, respectively) related to monthly stock market returns in developed countries. In emerging countries, only political risk is significant and negative in influencing stock market returns (-7.9 basis points). For the full sample, political and economic risk ratings are significant, negatively affecting monthly stock market returns by -9.1 and -5.3 basis points, respectively. As the relations are dynamic, the permanent effect occurs in around 5 months for developed, emerging and full counties samples.

Therefore, in the case of the composite rating-stock returns relation, the "long-run" is around 3 months in developed countries, around 4 months in emerging countries and around 5 months for the full sample. In the case of the disaggregated ratings-stock returns relation, the "long-run" is around 5 months in developed countries, developing countries, and for the full sample. Thus, when the long-run equilibrium is shocked in some way, the system reverts back to equilibrium in around in around 5 months for the disaggregated risk ratings case.

There is strong evidence that the 2008 global crisis had significant effects on stock markets for all the samples considered. The crisis caused considerable drops in country stock market index returns in developed, emerging and frontier countries. To investigate whether the 2008 crisis caused a structural change in the risk ratings-stock market return relation, samples are divided into two periods: before and after the crisis.

Before- and after-crisis analysis shows that the relation between risk ratings and stock market returns disappears (for both composite and disaggregated cases) after the 2008 crisis. Before the crisis, the relation is similar to what has been found for the full period. The disappearance of the relation after the crisis, however, could be due to the lack of data, because the length of the after-crisis period is considerably shorter than that of the before-crisis period. This could have impeded detection of a long-run relation. Thus, repeating the after-crisis analysis when long-enough data accumulates could be the subject of further research.

8.2. The Proposed Model of The International Cost of Equity

The statistically significant relation found in this study between country risk ratings and stock market returns can be used to derive an empirical model of the international cost of equity. The long-run coefficients found in the empirical analysis provide the basis for the model. The mean group (MG) estimation of the cross-sectionally augmented distributed lag model (CS-DL) that includes disaggregated risk rating components (political, financial, economic risk ratings) as independent variables and country stock market returns as the dependent variable, yields significant long-run coefficient estimates for political and economic risk rating components. These estimates are used to derive the following empirical model that estimates expected returns for a country of known political and economic risk ratings relative to a benchmark country.

$$E(R_{jt}) = E(R_{Bt}) + 1.096 ln(\frac{P_{Bt}}{P_{jt}}) + 0.639 ln (\frac{E_{Bt}}{E_{jt}})$$

and,

$$E(R_{Bt}) = r_{fBt} + \beta(R_{MBt} - r_{fBt})$$

where, $E(R_{jt})$ is the expected annual equity return in country j, $E(R_{Bt})$is the expected annual equity return in the benchmark country, P_{Bt} is the political risk rating of the the benchmark country at time t, P_{jt} is the political risk rating of country j at time t, E_{USt} is the economic risk rating of the the benchmark country at time t, E_{jt} is the economic risk rating of country j at time t, r_{fBt} is the risk free rate in the the benchmark country at time t, R_{MBt} is the market return in the the benchmark country at time t and β is the beta of the project in question. The benchmark country can be a country where the CAPM is known to work properly. An obvious candidate for this is the US. Thus, the model can calculate the cost of equity in a country of known political and economic risk ratings by adding a "political and economic country risk premium" to the US cost of equity. In the CAPM terminology, the coefficient of the political risk component (1.096, which is also the slope) is the price of "relative political risk" and the coefficient of the economic risk component (0.639, which is also the slope) is the price of "relative economic risk". Then, the terms $ln(P_{Bt}/P_{jt})$ and $ln(E_{Bt}/E_{jt})$ are the quantity of relative political risk and relative economic risk, respectively.

Since country risk ratings provided by the ICRG cover a larger number of countries, the model has broad international applicability. As long as political and economic risk ratings are available[18], the model can provide and estimate of the cost of equity in the country. One should be cautious, however, in using the model to calculate the cost of equity in a frontier country, because the empirical analysis does not provide a statistically significant evidence of a long-run relation between country risk ratings and stock market returns in frontier countries.

[18] As discussed before, in order for the model to work one should assume that political and economic risk rating values used in the model stay constant for at least 4-5 months in both of the countries; i.e., the systems are in the long-run equilibrium state.

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Table 1

Mean Group (MG) Estimates of the Long-Run Effects Based on the Cross-Sectionally Augmented Distributed Lag (CS-DL) Approach (Composite Risk Ratings, Developed Country Sample, 1984m01-2016m05)

	CS-DL (p=1, p_x=7)	CS-DL (p=2, p_x=7)	CS-DL (p=3, p_x=7)	CS-DL (p=4, p_x=7)	CS-DL (p=5, p_x=7)	CS-DL (p=6, p_x=7)	CS-DL (p=7, p_x=7)
θ	**-0.054** (0.037)**	**-0.065*** (0.003)**	**-0.085*** (0.000)**	**-0.085*** (0.000)**	**-0.095*** (0.000)**	**-0.087*** (0.000)**	**-0.086*** (0.001)**
γ	-0.001 (0.778)	-0.001 (0.764)	-0.001 (0.784)	-0.001 0.812	-0.001 (0.783)	-0.001 (0.762)	-0.001 (0.744)
η	**0.000** (0.044)**	**0.000** (0.040)**	**0.000** (0.029)**	**0.000** (0.041)**	**0.000** (0.043)**	**0.000** (0.041)**	**0.000* (0.052)**
CD test statistics	**-12.73*** (0.000)**	**-12.64*** (0.000)**	**-12.60*** (0.000)**	**-12.50*** (0.000)**	**-12.47*** (0.000)**	**-12.42*** (0.000)**	**-12.36*** (0.000)**
Observations	8746	8746	8746	8746	8746	8746	8746

Notes: The cross-sectionally augmented DL specification is given by:

$$\Delta y_{it} = c_{yi} + \theta_i ' x_{it} + \sum_{l=0}^{p-1} \delta_{il} \Delta x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \omega_{y,il} \Delta \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \omega'_{x,il} \bar{x}_{t-l} + \gamma_i Dummy_{it} + \eta_i T + u_{it}$$

where y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, $\boldsymbol{x}_{it} = lnC_{it}$, $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, lnC_{it} is the natural logarithm of Composite Risk Rating provided by International Country Risk Guide(ICRG), *Dummy* is a dummy variable marking the beginning of the 2008 global financial crisis on December 2007, T is a linear trend term and $p=1,2,3,\ldots 7$, $p_y=0$, $p_x=7$. Symbols ***, ** and * denote significance at 1%, 5% and 10% respectively. Numbers in parenthesis are p-values.

Table 2

Mean Group (MG) Estimates of the Long-Run Effects Based on the Cross-Sectionally Augmented Distributed Lag (CS-DL) Approach (Composite Risk Ratings, Emerging Country Sample, 1984m01-2016m05)

	CS-DL (p=1, p_x=7)	CS-DL (p=2, p_x=7)	CS-DL (p=3, p_x=7)	CS-DL (p=4, p_x=7)	CS-DL (p=5, p_x=7)	CS-DL (p=6, p_x=7)	CS-DL (p=7, p_x=7)
θ	**-0.063*** (0.051)**	**-0.081**** (0.015)**	**-0.077**** (0.020)**	**-0.086**** (0.018)**	**-0.093**** (0.025)**	**-0.104***** (0.008)**	**-0.102***** (0.006)**
γ	0.003 (0.360)	0.003 (0.414)	0.003 (0.426)	0.004 (0.366)	0.003 (0.411)	0.004 (0.353)	0.003 (0.458)
η	-0.000 (0.347)	-0.000 (0.325)	-0.000 (0.331)	-0.000 (0.303)	-0.000** (0.302)	-0.000 (0.281)	-0.000 (0.393)
CD test statistics	**-12.08***** **(0.000)**	**-12.06***** **(0.000)**	**-12.03***** **(0.000)**	**-11.96***** **(0.000)**	**-11.93***** **(0.000)**	**-11.78***** **(0.000)**	**-11.76***** **(0.000)**
Observations	6318	6318	6318	6318	6318	6318	6318

Notes: The cross-sectionally augmented DL specification is given by:

$$\Delta y_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1} \delta_{il} \Delta x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \omega_{y,il} \Delta \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \omega'_{x,il} \bar{x}_{t-l} + \gamma_i Dummy_{it} + \eta_i T + u_{it}$$

where y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, $\boldsymbol{x}_{it} = lnC_{it}$, $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, lnC_{it} is the natural logarithm of Composite Risk Rating provided by International Country Risk Guide(ICRG), *Dummy* is a dummy variable marking the beginning of the 2008 global financial crisis on December 2007, T is a linear trend term and $p=1,2,3,\ldots7$, $p_y=0$, $p_x=7$. Symbols ***, ** and * denote significance at 1%, 5% and 10% respectively. Numbers in parenthesis are p-values.

Table 3

Mean Group (MG) Estimates of the Long-Run Effects Based on the Cross-Sectionally Augmented Distributed Lag (CS-DL) Approach (Composite Risk Ratings, Full Sample, 1984m01-2016m05)

	CS-DL (p=1, p_x=7)	CS-DL (p=2, p_x=7)	CS-DL (p=3, p_x=7)	CS-DL (p=4, p_x=7)	CS-DL (p=5, p_x=7)	CS-DL (p=6, p_x=7)	CS-DL (p=7, p_x=7)
θ	**-0.066*** (0.000)**	**-0.077*** (0.000)**	**-0.085*** (0.000)**	**-0.087*** (0.000)**	**-0.097*** (0.000)**	**-0.095*** (0.000)**	**-0.097*** (0.001)**
γ	0.001 (0.759)	0.001 (0.753)	0.001 (0.811)	0.001 (0.712)	0.001 (0.738)	0.001 (0.654)	0.001 (0.782)
η	0.000 (0.129)	**0.000* (0.099)**	0.000 (0.100)	**0.000* (0.099)**	0.000 (0.118)	0.000 (0.106)	**0.000* (0.082)**
CD test statistics	**-8.91*** (0.000)**	**-8.81*** (0.000)**	**-8.71*** (0.000)**	**-8.60*** (0.000)**	**-8.61*** (0.000)**	**-8.60*** (0.000)**	**-8.49*** (0.000)**
Observations	15064	15064	15064	15064	15064	15064	15064

Notes: The cross-sectionally augmented DL specification is given by:

$$\Delta y_{it} = c_{yi} + \theta_i ' x_{it} + \sum_{l=0}^{p-1} \delta_{il} \Delta x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \omega_{y,il} \Delta \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \omega'_{x,il} \bar{x}_{t-l} + \gamma_i Dummy_{it} + \eta_i T + u_{it}$$

where y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, $\boldsymbol{x}_{it} = lnC_{it}$, $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, lnC_{it} is the natural logarithm of Composite Risk Rating provided by International Country Risk Guide(ICRG), *Dummy* is a dummy variable marking the beginning of the 2008 global financial crisis on December 2007, T is a linear trend term and $p=1,2,3,\ldots 7$, $p_y=0$, $p_x=7$. Symbols ***, ** and * denote significance at 1%, 5% and 10% respectively. Numbers in parenthesis are p-values.

Table 4

Mean Group (MG) Estimates of the Long-Run Effects Based on the Cross-Sectionally Augmented Distributed Lag (CS-DL) Approach (Disaggregated Risk Ratings, Developed Country Sample, 1984m01-2016m05)

	CS-DL (p=1, p_x=7)	CS-DL (p=2, p_x=7)	CS-DL (p=3, p_x=7)	CS-DL (p=4, p_x=7)	CS-DL (p=5, p_x=7)	CS-DL (p=6, p_x=7)	CS-DL (p=7, p_x=7)
θ_{lnP}	**-0.048**** **(0.033)**	**-0.039*** **(0.057)**	**-0.042*** **(0.069)**	**-0.050*** **(0.086)**	**-0.061*** **(0.089)**	**-0.055*** **(0.094)**	**-0.057*** **(0.077)**
θ_{lnF}	-0.018 (0.367)	**-0.031*** **(0.083)**	**-0.038**** **(0.040)**	-0.038 (0.116)	**-0.045*** **(0.080)**	-0.037 (0.214)	-0.024 (0.581)
θ_{lnE}	-0.017 (0.292)	-0.016 (0.425)	-0.027 (0.177)	**-0.054**** **(0.029)**	**-0.061*** **(0.054)**	**-0.068*** **(0.060)**	**-0.084*** **(0.095)**
γ	-0.001 (0.812)	-0.001 (0.788)	-0.000 (0.874)	0.000 (0.936)	0.000 (0.975)	0.000 (0.998)	0.000 (0.915)
η	**0.000*** **(0.062)**	0.000 (0.164)	**0.000*** **(0.082)**	**0.000*** **(0.063)**	0.000 (0.107)	**0.000*** **(0.098)**	0.000 (0.133)
CD test statistics	**-12.45***** **(0.000)**	**-12.39***** **(0.000)**	**-12.34***** **(0.000)**	**-12.21***** **(0.000)**	**-12.14***** **(0.000)**	**-11.99***** **(0.000)**	**-11.76***** **(0.000)**
Observations	8746	8746	8746	8746	8746	8746	8746

Notes: The cross-sectionally augmented Panel DL specification is given by:

$$\Delta y_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1} \delta_{il} \Delta x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \omega_{y,il} \Delta \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \omega'_{x,il} \bar{x}_{t-l} + \gamma_i Dummy_{it} + \eta_i T + u_{it}$$

where y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, $x_{it} = (lnP_{it}, lnF_{it}, lnE_{it})'$, $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, lnP_{it} is the natural logarithm of Political Risk Rating, lnF_{it} is the natural logarithm of Financial Risk Rating, lnE_{it} is the natural logarithm of Economic Risk Rating provided by International Country Risk Guide(ICRG), *Dummy* is a dummy variable marking the beginning of the 2008 global financial crisis on December 2007, T is a linear trend term and $p=1,2,3,\ldots 7$, $p_y=0$, $p_x=7$. Symbols ***, ** and * denote significance at 1%, 5% and 10% respectively. Numbers in parenthesis are p-values.

Table 5

Mean Group (MG) Estimates of the Long-Run Effects Based on the Cross-Sectionally Augmented Distributed Lag (CS-DL) Approach (Disaggregated Risk Ratings, Emerging Country Sample, 1984m01-2016m05)

	CS-DL (p=1, p_x=7)	CS-DL (p=2, p_x=7)	CS-DL (p=3, p_x=7)	CS-DL (p=4, p_x=7)	CS-DL (p=5, p_x=7)	CS-DL (p=6, p_x=7)	CS-DL (p=7, p_x=7)
θ_{lnP}	-0.054 (0.134)	**-0.066*** **(0.056)**	**-0.071**** **(0.036)**	**-0.063*** **(0.080)**	**-0.080**** **(0.027)**	**-0.082**** **(0.028)**	**-0.076**** **(0.035)**
θ_{lnF}	0.013 (0.592)	0.006 (0.835)	0.018 (0.463)	-0.002 (0.929)	0.002 (0.951)	-0.016 (0.647)	-0.026 (0.436)
θ_{lnE}	-0.033 (0.156)	-0.039 (0.125)	-0.035 (0.129)	-0.033 (0.172)	-0.034 (0.181)	-0.035 (0.277)	-0.031 (0.391)
γ	-0.001 (0.825)	-0.002 (0.690)	-0.002 (0.712)	-0.002 (0.735)	-0.001 (0.797)	-0.002 (0.768)	-0.001 (0.792)
η	-0.000 (0.619)	-0.000 (0.760)	-0.000 (0.721)	-0.000 (0.673)	-0.000 (0.567)	-0.000 (0.615)	-0.000 (0.412)
CD test statistics	**-11.80***** **(0.000)**	**-11.71***** **(0.000)**	**-11.59***** **(0.000)**	**-11.35***** **(0.000)**	**-11.15***** **(0.000)**	**-10.89***** **(0.000)**	**-10.92***** **(0.000)**
Observations	6318	6318	6318	6318	6318	6318	6318

Notes: The cross-sectionally augmented Panel DL specification is given by:

$$\Delta y_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1} \delta_{il} \Delta x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \omega_{y,il} \Delta \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \omega'_{x,il}\, \bar{x}_{t-l} + \gamma_i Dummy_{it} + \eta_i T + u_{it}$$

where y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, $\boldsymbol{x}_{it} = (lnP_{it}, lnF_{it}, lnE_{it})'$, $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, lnP_{it} is the natural logarithm of Political Risk Rating, lnF_{it} is the natural logarithm of Financial Risk Rating, lnE_{it} is the natural logarithm of Economic Risk Rating provided by International Country Risk Guide(ICRG), *Dummy* is a dummy variable marking the beginning of the 2008 global financial crisis on December 2007, T is a linear trend term and $p=1,2,3,\ldots 7$, $p_y=0$, $p_x=7$. Symbols ***, ** and * denote significance at 1%, 5% and 10% respectively. Numbers in parenthesis are p-values.

Table 6

Mean Group (MG) Estimates of the Long-Run Effects Based on the Cross-Sectionally Augmented Distributed Lag (CS-DL) Approach (Disaggregated Risk Ratings, Full Sample, 1984m01-2016m05)

	CS-DL ($p=1$, $p_x=7$)	CS-DL ($p=2$, $p_x=7$)	CS-DL ($p=3$, $p_x=7$)	CS-DL ($p=4$, $p_x=7$)	CS-DL ($p=5$, $p_x=7$)	CS-DL ($p=6$, $p_x=7$)	CS-DL ($p=7$, $p_x=7$)
θ_{lnP}	**-0.068*** (0.000)**	**-0.073*** (0.000)**	**-0.081*** (0.000)**	**-0.081*** (0.000)**	**-0.091*** (0.000)**	**-0.092*** (0.000)**	**-0.091*** (0.000)**
θ_{lnF}	0.024 (0.335)	0.016 (0.522)	0.019 (0.420)	0.009 (0.732)	-0.000 (0.988)	-0.003 (0.927)	-0.013 (0.674)
θ_{lnE}	**-0.034** (0.036)**	**-0.042*** (0.007)**	**-0.046*** (0.002)**	**-0.051*** (0.004)**	**-0.051*** (0.010)**	**-0.056** (0.029)**	**-0.055** (0.047)**
γ	-0.001 (0.780)	-0.001 (0.741)	-0.001 (0.711)	-0.001 (0.849)	-0.001 (0.787)	-0.001 (0.813)	-0.001 (0.742)
η	**0.000* (0.096)**	**0.000* (0.087)**	**0.000* (0.090)**	0.000 (0.108)	0.000 (0.156)	0.000 (0.148)	0.000 (0.155)
CD test statistics	**-8.95*** (0.000)**	**-8.86*** (0.000)**	**-8.77*** (0.000)**	**-8.52*** (0.000)**	**-8.34*** (0.000)**	**-8.00*** (0.000)**	**-8.04*** (0.000)**
Observations	15064	15064	15064	15064	15064	15064	15064

Notes: The cross-sectionally augmented Panel DL specification is given by:

$$\Delta y_{it} = c_{yi} + \theta_i' x_{it} + \sum_{l=0}^{p-1} \delta_{il} \Delta x_{i,t-l} + \sum_{l=0}^{p_{\bar{y}}} \omega_{y,il} \Delta \bar{y}_{i,t-l} + \sum_{l=0}^{p_{\bar{x}}} \omega'_{x,il} \bar{x}_{t-l} + \gamma_i Dummy_{it} + \eta_i T + u_{it}$$

where y_{it} is the natural logarithm of Morgan Stanley Capital International's (MSCI) country stock market US Dollar price index, $\boldsymbol{x}_{it} = (lnP_{it}, lnF_{it}, lnE_{it})'$, $\bar{x}_t = N^{-1}\sum_{i=1}^{N} x_{it}$, $\bar{y}_t = N^{-1}\sum_{i=1}^{N} y_{it}$, lnP_{it} is the natural logarithm of Political Risk Rating, lnF_{it} is the natural logarithm of Financial Risk Rating, lnE_{it} is the natural logarithm of Economic Risk Rating provided by International Country Risk Guide(ICRG), *Dummy* is a dummy variable marking the beginning of the 2008 global financial crisis on December 2007, T is a linear trend term and $p=1,2,3,\ldots 7$, $p_y=0$, $p_x=7$. Symbols ***, ** and * denote significance at 1%, 5% and 10% respectively. Numbers in parenthesis are p-values.

APPENDIX-A: Panel Unit Root Tests

Table A 1: Panel Unit Root Tests-Developed Countries

	Im, Pesaran, Shin*			***Fisher Type Dickey-Fuller****				***Fisher Type Phillips-Pherron****			
	t-bar	***t-tilde-bar***	***Z-t-tilde-bar***	***Inverse chi-squared***	***Inverse normal***	***Inverse logit t***	***Modified inv. chi-squared***	***Inverse chi-squared***	***Inverse normal***	***Inverse logit t***	***Modified inv. chi-squared***
dlnMSCIC	-17.062	-12.499	-64.502 (0.000)	1730.095 (0.000)	-39.807 (0.000)	-97.750 (0.000)	171.678 (0.000)	1730.095 (0.000)	-39.809 (0.000)	-97.750 (0.000)	171.678 (0.000)
lnC	-2.161	-2.145	-3.686 (0.000)	84.059 (0.001)	-3.741 (0.000)	-3.666 (0.000)	3.680 (0.000)	84.059 (0.001)	-3.741 (0.000)	-3.666 (0.000)	3.680 (0.000)
lnP	-2.143	-2.127	-3.581 (0.000)	84.536 (0.001)	-3.608 (0.000)	-3.621 (0.000)	3.729 (0.000)	84.536 (0.001)	-3.608 (0.000)	-3.621 (0.000)	3.729 (0.000)
lnF	-1.946	-1.933	-2.441 (0.007)	69.748 (0.022)	-2.377 (0.009)	-2.496 (0.007)	2.220 (0.013)	69.748 (0.022)	-2.377 (0.009)	-2.496 (0.007)	2.220 (0.013)
lnE	-2.768	-2.733	-7.142 (0.000)	151.280 (0.000)	-7.367 (0.000)	-8.037 (0.000)	10.541 (0.000)	151.280 (0.000)	-7.367 (0.000)	-8.0371 (0.000)	10.541 (0.000)

*Ho: All panels contain unit roots; Ha: Some panels are stationary

**Ho: All panels contain unit roots; Ha: At least one panel is stationary

Notes: dlnMSCIC is the first difference of the natural logarithm (namely, return) of country MSCI index, lnC is the natural logarithm of composite risk rating, lnP is the natural logarithm of political risk rating, lnF is the natural logarithm of financial risk rating, lnE is the natural logarithm of economic risk rating, Numbers in paranthesis are p-values

Table A2: Panel Unit Root Tests-Emerging Countries

	*Im, Pesaran, Shin**			*Fisher Type Dickey-Fuller***				*Fisher Type Phillips-Pherron***			
	t-bar	***t-tilde-bar***	***Z-t-tilde-bar***	***Inverse chi-squared***	***Inverse normal***	***Inverse logit t***	***Modified inv. chi-squared***	***Inverse chi-squared***	***Inverse normal***	***Inverse logit t***	***Modified inv. chi-squared***
dlnMSCIC	-14.997	-11.089	-52.740 (0.000)	1513.833 (0.000)	-37.238 (0.000)	-91.489 (0.000)	160.590 (0.000)	1513.833 (0.000)	-37.238 (0.000)	-91.489 (0.000)	160.590 (0.000)
lnC	-2.504	-2.466	-5.247 (0.000)	115.376 (0.000)	-5.476 (0.000)	-5.977 (0.000)	8.006 (0.000)	115.376 (0.000)	-5.476 (0.000)	-5.977 (0.000)	8.006 (0.000)
lnP	-2.360	-2.330	-4.496 (0.000)	100.628 (0.000)	-4.758 (0.000)	-4.887 (0.000)	6.397 (0.000)	100.628 (0.000)	-4.758 (0.000)	-4.887 (0.000)	6.397 (0.000)
lnF	-2.855	-2.807	-7.125 (0.000)	140.477 (0.000)	-7.391 (0.000)	-8.104 (0.000)	10.745 (0.000)	140.477 (0.000)	-7.391 (0.000)	-8.104 (0.000)	10.745 (0.000)
lnE	-2.919	-2.870	-7.471 (0.000)	147.887 (0.000)	-7.752 (0.000)	-8.519 (0.000)	11.553 (0.000)	147.887 (0.000)	-7.752 (0.000)	-8.519 (0.000)	11.553 (0.000)

*Ho: All panels contain unit roots; Ha: Some panels are stationary

**Ho: All panels contain unit roots; Ha: At least one panel is stationary

Notes: dlnMSCIC is the first difference of the natural logarithm (namely, return) of country MSCI index, lnC is the natural logarithm of composite risk rating, lnP is the natural logarithm of political risk rating, lnF is the natural logarithm of financial risk rating, lnE is the natural logarithm of economic risk rating, Numbers in paranthesis are p-values

Table A3: Panel Unit Root Tests-Full Sample

	Im, Pesaran, Shin*			***Fisher Type Dickey-Fuller*****				***Fisher Type Phillips-Pherron*****			
	t-bar	***t-tilde-bar***	***Z-t-tilde-bar***	***Inverse chi-squared***	***Inverse normal***	***Inverse logit t***	***Modified inv. chi-squared***	***Inverse chi-squared***	***Inverse normal***	***Inverse logit t***	***Modified inv. chi-squared***
dlnMSCIC	-15.941	-11.711	-87.418 (0.000)	3676.453 (0.000)	-58.031 (0.000)	-142.190 (0.000)	250.262 (0.000)	3676.453 (0.000)	-58.031 (0.000)	-142.190 (0.000)	250.262 (0.000)
lnC	-2.361	-2.332	-7.003 (0.000)	235.712 (0.000)	-7.221 (0.000)	-7.633 (0.000)	9.362 (0.000)	235.712 (0.000)	-7.221 (0.000)	-7.633 (0.000)	9.362 (0.000)
lnP	-2.249	-2.224	-6.078 (0.000)	214.459 (0.000)	-6.271 (0.000)	-6.517 (0.000)	7.874 (0.000)	214.459 (0.000)	-6.271 (0.000)	-6.517 (0.000)	7.874 (0.000)
lnF	-2.361	-2.333	-7.007 (0.000)	233.667 (0.000)	-7.152 (0.000)	-7.664 (0.000)	9.219 (0.000)	233.667 (0.000)	-7.152 (0.000)	-7.664 (0.000)	9.219 (0.000)
lnE	-2.890	-2.843	-11.383 (0.000)	355.699 (0.000)	-11.789 (0.000)	-13.108 (0.000)	17.763 (0.000)	355.699 (0.000)	-11.789 (0.000)	-13.108 (0.000)	17.763 (0.000)

*Ho: All panels contain unit roots; Ha: Some panels are stationary

**Ho: All panels contain unit roots; Ha: At least one panel is stationary

Notes: dlnMSCIC is the first difference of the natural logarithm (namely, return) of country MSCI index, lnC is the natural logarithm of composite risk rating, lnP is the natural logarithm of political risk rating, lnF is the natural logarithm of financial risk rating, lnE is the natural logarithm of economic risk rating, Numbers in paranthesis are p-values

APPENDIX-B: Panel Cointegration Tests

Table B1: Panel Cointegration Tests-Full Period

	Composite Risk Rating-Return Relation								Disaggregated Risk Ratings-Return Relation							
	Developed		Emerging		Frontier		Full Sample		Developed		Emerging		Frontier		Full Sample	
	Panel	Group	Panel	Group	Panel	Group	Panel	Group	Panel	Group	Panel	Group	Panel	Group	Panel	Group
v	46.26	-	36.13	-	12.18	-	59.83	-	31.8	-	25.22		7.85	-	41.51	-
rho	-246.8	-212.8	-178.1	-152.8	-132.5	-76.02	-320.9	-271.4	-165.2	-163.4	-118.7	-116.6	-88.26	-56.17	-214.8	-207.7
t	-90.25	-96.47	-72.54	-77.49	-55.3	-51.64	-122	-130	-85.1	-93.79	-68.29	-75.29	-51.99	-49.94	-115.2	-126.4
adf	-78.61	-80.09	-58.5	-56.78	-43.59	-40.05	-103.1	-102.7	-74.09	-77.75	-53.7	-53.99	-43.21	-39.77	-97.25	-99.9

Note: All test statistics are distributed N(0,1), under a null of no cointegration and diverge to negative infinity (save for panel v).

Table B2: Panel Cointegration Tests-Comparison of the Relation Before and After the 2008 Crisis

	Disaggregated Risk Ratings-Return Relation															
	Before the Crisis								After the Crisis							
	Developed		Emerging		Frontier		Full Sample		Developed		Emerging		Frontier*		Full Sample**	
	Panel	Group	Panel	Group	Panel	Group	Panel	Group	Panel	Group	Panel	Group	Panel	Group	Panel	Group
v	22.67	-	17.23		1.664		29.29		4.746	-	5.29		N/A	N/A	N/A	N/A
rho	-130.2	-128.2	-85.51	-81.21	-74.18	-30.01	-166.4	-155.9	-25.72	-24.16	-25.57	-24.07	N/A	N/A	N/A	N/A
t	-78.78	-86.86	-58.44	-63.82	-41.72	-32.53	-103.9	-112.7	-28.7	-30.81	-28.96	-31.28	N/A	N/A	N/A	N/A
adf	-63.16	-63.16	-40.4	-39.36	-37.47	-26.62	-81.32	-79.1	-27.26	-28.47	-22	-21.84	N/A	N/A	N/A	N/A

Note: All test statistics are distributed N(0,1), under a null of no cointegration and diverge to negative infinity (save for panel v).
*Test statistics could not be calculated due to inadequate observations.
**Test statistics could not be calculated due to inadequate observations as a result of the inclusion of frontier countries sample in the full sample

APPENDIX-C: The List of Countries

Table C1: The List of Countries in Each Sample

DEVELOPED			EMERGING		
Group Size	**24**		**Group Size**	**21**	
Max. # of Observations	**358**		**Max. # of Observations**	**310**	
MAX [INT(T^(1/3))]	**7**		**MAX [INT(T^(1/3))]**	**6**	
Country	**Data From**		**Country**	**Data From**	
Australia	01-Jan-84		Brazil	01-Jan-88	
Austria	01-Jan-84		Chile	01-Jan-88	
Belgium	01-Jan-84		Greece	01-Jan-88	
Canada	01-Jan-84		Indonesia	01-Jan-88	
Denmark	01-Jan-84		Malaysia	01-Jan-88	
Finland	01-Jan-84		Mexico	01-Jan-88	
France	01-Jan-84		Philippines	01-Jan-88	
Germany	01-Jan-84		Korea	01-Jan-88	
Hongkong	01-Jan-84		Taiwan	01-Jan-88	
Ireland	01-Jan-88		Thailand	01-Jan-88	
Israel	01-Jan-93		Turkey	01-Jan-88	
Italy	01-Jan-84		China	01-Jan-93	
Japan	01-Jan-84		Colombia	01-Jan-93	
Luxemburg	01-Jan-88		India	01-Jan-93	
Netherlands	01-Jan-84		Peru	01-Jan-93	
Newzealand	01-Jan-84		Poland	01-Jan-93	
Norway	01-Jan-84		South Africa	01-Jan-93	
Portugal	01-Jan-88		CzechRep	01-Jan-95	
Singapore	01-Jan-84		Egypt	01-Jan-95	
Spain	01-Jan-84		Hungary	01-Jan-95	
Sweden	01-Jan-84		Russia	01-Jan-95	
Switzerland	01-Jan-84				
UK	01-Jan-84				
USA	01-Jan-84				