The World Price of Credit Risk

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Global asset pricing models have failed to capture the cross-section of country equity returns. Emerging markets display robust positive pricing errors, and country-level characteristics play a role in pricing international equities. This paper offers a risk-based explanation for such asset pricing deviations. A world credit risk factor is significantly priced in the cross-section of country equity returns. In its presence, the positive pricing errors in emerging markets disappear and country-level characteristics no longer play a role. The risk premium for exposure to the credit risk factor is 80 basis points per month and has increased in recent years. (*JEL* G12, G14, G15)

The CAPM of Sharpe (1964) and Lintner (1965) and its intertemporal extension by Merton (1973) apply to a single national market. Extending the model internationally is nontrivial, as discussed by Solnik (1974a). Theoretically, a single world-market factor could explain the cross-section of country asset returns if purchasing power parity (PPP) holds and markets are fully integrated, or, alternatively, if the world-market returns are perfectly correlated with world consumption growth (Stulz 1981). When PPP is violated, however, foreign exchange rate risk is also priced. Moreover, in non-integrated

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financial markets, country-level characteristics play an important role in explaining the cross-section of country returns. Empirically, testing the international CAPM requires the joint hypotheses of model validity, the existence of PPP, and market integration.

Since Solnik (1974b), the evidence on the pricing ability of the international CAPM has been mixed (e.g., Solnik 1977; Stehle 1977; Ferson and Harvey 1993; Dumas and Solnik 1995). While weak support for the conditional version of the model is documented in developed markets (Harvey 1991; Harvey and Zhou 1993), international pricing models have been unable to explain the cross-section of emerging market returns. For example, using a sample of 20 emerging markets, Harvey (1995) rejects the world CAPM, as well as a two-factor model consisting of the world-market and foreign exchange factors. Harvey (1995) also uncovers large, often "massive," positive pricing errors for all emerging countries. Moreover, Harvey shows that emerging market country returns exhibit little correlation with developed markets, and display little exposure to global risk factors. Further, Erb, Harvey, and Viskanta (1995, 1996) show that country-level credit ratings exhibit substantial cross-sectional predictive power, and Harvey (2000) shows that country-level variance and coskewness are important drivers of country returns. The literature primarily attributes this failure of global asset pricing models to deviations from full market integration. Subsequently, the literature tests for the degree of market segmentation by allowing for both local and global factors in asset pricing specifications. A number of studies find evidence of partially segmented markets and suggest a role for both local and global factors (e.g., Karolyi and Stulz 2003; Bekaert, Harvey, and Lundblad 2007; Chaieb and Errunza 2007; Bekaert, Hodrick, and Zhang 2009; Bekaert et al. 2011; Hou, Karolyi, and Kho 2011; Lee 2011).

This paper shows that accounting for a world credit risk factor resolves the above-noted deviations from international asset pricing. Our proposed world credit risk factor is computed as the difference between equity returns of high and low credit risk country portfolios sorted on credit ratings. Our sample consists of 24 developed and 51 emerging countries from January 1989 to December 2009.

The choice of a world credit risk factor is motivated as a response to bad consumption data, as well as the restrictive assumption that the world-market portfolio is perfectly correlated with changes in world consumption. As Cochrane (2001, p. 44) points out, "the consumption-based model is, in principle, a complete answer to all asset pricing questions, but works poorly in practice." Consumption data are low frequency and too smooth. As a result, proxies for consumption risk are plausible alternatives in empirical asset pricing tests (see Savov 2011).

The relevance of credit risk in pricing international assets relies on the economic rationale that high credit risk assets are more likely to do poorly in bad states of nature when consumption is low and the marginal utility of the representative investor is high. This counter cyclical nature of credit risk endogenously generates a counter cyclical credit risk premium. The higher credit risk premium in recessions makes borrowing more costly, causing further declines in investment, productivity, future GDP growth, and future consumption growth. This economic rationale is developed formally in Gomes and Schmid (2010) in a general equilibrium model, whose theoretical predictions are that credit risk is priced and the credit risk premium predicts future GDP growth and consumption growth. Consistent with the Gomes and Schmid (2010) model, we find that our world credit risk factor is priced and predicts world GDP and consumption growth.

We first confirm that sovereign credit ratings are correlated with country equity returns. In our sample, the equities of countries in the high credit risk tercile outperform the equities of countries in the low credit risk tercile by 57 basis points (bps) per month over the 1989–2009 period. This return differential is more pronounced (125 bps per month) in the second half of our sample period. Cross-sectional regressions confirm that sovereign credit ratings exhibit a significant correlation with future country equity returns. The high returns in higher credit risk countries are not explained by previously proposed global risk factors such as the world-market, value, momentum, foreign exchange, and liquidity factors.

In contrast, the world credit risk factor fully captures the high returns of high credit risk countries. It is significantly priced in the cross-section of country equity returns and is robust to the inclusion of alternative factors advocated in the international asset pricing literature. The risk premium for exposure to world credit risk averages 80 bps per month. In the presence of this credit risk factor, the previously documented large positive pricing errors in emerging markets disappear. After adjusting for systematic exposure to world credit risk, country-level attributes, such as credit ratings, variance, and coskewness, do not exhibit any residual explanatory power. Moreover, the efficiency of the world credit risk factor cannot be rejected based on the Gibbons, Ross, and Shanken (1989) finite sample tests, while the efficiency of alternative global factors is typically rejected.

While we document a remarkable pricing ability of the world credit risk factor in both time-series and cross-sectional specifications, Erb, Harvey, and Viskanta (1995, 1996) demonstrate that credit ratings are also directly related to the cross-section of country equity returns. Thus, the question is whether the credit risk factor merely reflects a “repackaging” of the country-level characteristic effect. Put differently, is it the risk or characteristic that impacts country equity returns? In particular, Ferson, Sarkissian, and Simin (1999) argue that portfolios sorted on attributes with an empirically observed relation to the cross-section of returns may appear to be useful risk factors even when the attributes are completely unrelated to risk. To address this concern, we simulate equity returns under the null hypothesis that credit rating, the characteristic, is the only driver of cross-sectional differences.[1] With the simulated data, we construct "spurious" high-minus-low factors and obtain distributions of risk premiums and of cross-sectional R-squared. The results show that the world credit risk factor premium and cross-sectional R-squared based on the actual data are significantly higher than what a spurious high-minus-low factor would imply. Thus, the explanatory power of the world credit risk factor is not spurious and significantly exceeds the explanatory power of the ratings.

The majority of high credit risk countries are also emerging markets. Nevertheless, we show that the world credit risk factor remains strong in the presence of an emerging markets factor, while the emerging markets factor loses explanatory power in the presence of the world credit risk factor. Hence, emerging markets earn higher returns because they display higher exposure to the world credit risk factor, not because they are classified as emerging or have worse credit ratings.

The next section surveys the international asset pricing literature. Section 2 discusses the data, Section 3 presents the results, and Section 4 concludes.

1. International Asset Pricing: Background

A lively debate is centered on whether asset pricing models are able to capture the cross-sectional variation of global equity returns. In developed markets, Ferson and Harvey (1993, 1994) and Dumas and Solnik (1995) show that PPP may indeed be violated, since multifactor models fare much better than the world CAPM and foreign exchange risk is priced. Using latent factors, Harvey, Solnik, and Zhou (2002) find that the first latent factor resembles the world-market portfolio, while the second is related to foreign exchange risk.

While global multifactor models display some explanatory power in developed markets, they fail to explain emerging market country returns. In particular, Harvey (1995) finds no relation between betas and returns in 20 emerging market countries. Every emerging country in his sample exhibits large positive abnormal returns, little exposure to global risk factors, and is mostly influenced by local information, including the variance of country equity returns. Furthermore, Erb, Harvey, and Viskanta (1995, 1996) show that country credit ratings have substantive predictive power for emerging country equity returns, while market betas do not. Bekaert and Harvey (1995) find that emerging market returns are affected by the country's total variance, while Harvey (2000) shows that idiosyncratic variance and coskewness also explain cross-sectional differences in country equity returns. Moreover, Bekaert, Harvey, and Lundblad (2007) show that local market liquidity is

[1] We thank Wayne Ferson for suggesting this test.

an important driver of emerging market returns, and Lee (2011) finds that the relative importance of local and global liquidity factors varies with the degree of financial market integration. In contrast, Rouwenhorst (1999) argues that emerging market premiums do not compensate for illiquidity as he finds no relation between returns and turnover in these markets. He also finds that, while size, value, and momentum effects exist within individual emerging markets, these local factors have little correlation across countries and cannot be explained by global factors.

The documented importance of local factors in pricing international equities suggests some degree of market segmentation. A number of studies find that markets are partially integrated, making both local and global factors important (e.g., Fama and French 1998; Karolyi and Stulz 2003; Bekaert, Harvey, and Lundblad 2007; Bekaert, Hodrick, and Zhang 2009; Bekaert et al. 2011; Hou, Karolyi, and Kho 2011; Lee 2011). For example, Hou, Karolyi, and Kho (2011) show that a multifactor model, including the market, momentum, and cash flow-to-price factors, captures time-series variation in global stock returns better than the world CAPM or size and book-to-market factors. Versions of their multifactor model that include both local and international factors perform better than versions based solely on global factors, especially in emerging markets. Moreover, Chaieb and Errunza (2007) develop an international asset pricing model with segmentation and PPP deviations and find that local factors matter for emerging markets. Bekaert et al. (2011) also find that, while developed markets have been integrated for some time and financial markets liberalization has increased, segmentation in emerging markets remains high. Finally, Fama and French (2012) show that, while the size, value, and momentum factors are significant within most developed markets, market integration across regions is not supported even in developed markets.

A number of recent studies find evidence of increasingly integrated debt markets when examining credit spreads of sovereign debt. For instance, Longstaff et al. (2011) examine sovereign credit default swap (CDS) spreads from 2000 to 2010 to find that the majority of sovereign credit risk is related to global factors and that sovereign credit spreads are more related to U.S. stock and high yield markets than to local economic measures. Examining CDS spreads from 2002 to 2006, Remolona, Scatigna, and Wu (2008) show that, while country-specific fundamentals affect sovereign risk, it is global investors' risk aversion that drives time variation in risk premiums. Borri and Verdelhan (2011) develop a model in which sovereign spreads depend on the exposure of international markets to U.S. business cycle risk. Andrade (2009) finds empirical support for a model in which country risk is priced because it manifests itself during bad states of the global economy. Thus, the sovereign spread literature points to more integration following advances in globalization.

2. Data

Monthly country equity returns are obtained from U.S. dollar denominated total return indexes available in Datastream. Morgan Stanley Capital International (MSCI) total return equity indexes are available for 67 out of the 75 countries in our sample. For the remaining 8 countries, we use country total return equity indexes from Datastream based on alternative data providers. Our sample starts in January 1989, when MSCI emerging market equity returns become available, and ends in December 2009. The "emerging market" classification refers to countries that are experiencing rapid socio-economic growth. Lists of emerging market countries are published by Dow Jones, FTSE Group, S&P, MSCI, and the Economist, among others.[2] Our sample includes 24 developed and 51 emerging countries. Figure 1 displays the country composition through time. The number of developed countries is quite stable, with a minimum of 21 and a maximum of 24. In contrast, there is one emerging market country in January 1989, 29 emerging countries in the middle of the sample, and 50 in December 2009. Emerging countries mostly populate the second half of the sample period.

Sovereign credit ratings are obtained from Standard and Poor's (S&P) RatingsXpress database available in Wharton Research Data Services (WRDS) within "Other Compustat." RatingsXpress provides issuer (entity) ratings for private and public corporations and for sovereign governments. To obtain the sovereign ratings, the search needs to be restricted to "issuers" identified as "sovereign."[3] We use a country's long-term issuer credit rating as our measure of credit risk. RatingsXpress provides ratings on 117 countries dating back to 1941. However, many of these countries do not have active equity markets.

The world credit risk factor is constructed as follows. Each month, countries are sorted into terciles based on their sovereign credit rating at the end of month $t-1$. In month t, the return for each tercile is calculated as the equally weighted average monthly return across all countries in the tercile. We define our world credit risk factor as the return differential between high and low credit risk countries. The world credit risk factor represents the returns on a well-diversified portfolio of traded assets.

Our final sample contains monthly country-level equity return and rating data on 75 countries from January 1989 to December 2009. Panel A of Table 1 displays the 24 developed and 51 emerging countries in our sample and presents their average numeric rating and average monthly equity return.

2 Emerging markets classification is available through http://en.wikipedia.org/wiki/Emerging_markets.

3 Sovereign ratings are identified by their sector, subsector, and SIC attributes. Sovereign issuers are part of the sovereign (SOV) subsector of the global issues (GLOBISS) sector. Sovereign issuers can fall under a number of SIC classifications. Sovereign issuers can be governments, international banks, or organizations such as EBRD or IFC. Sovereign debt issued by governments falls under SIC 9191. We collect ratings only for SOV subsector entities with an SIC of 9191.

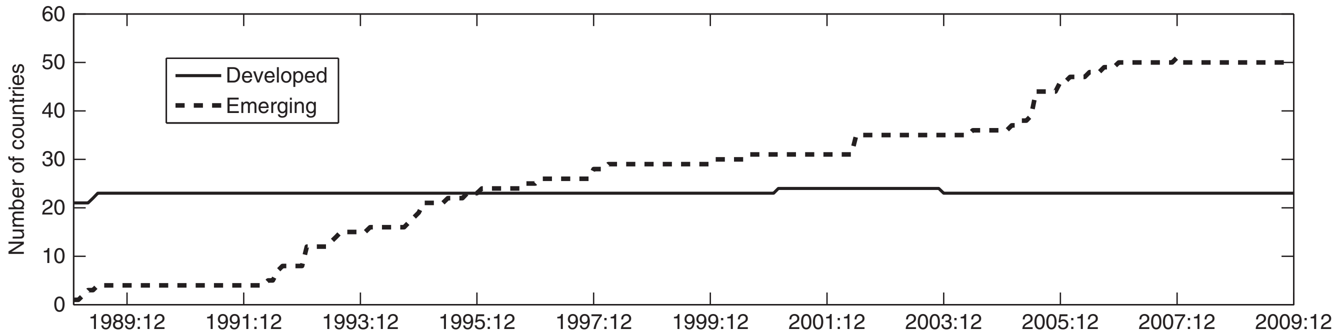

Figure 1
Number of countries in sample
The figure presents the number of developed and emerging countries in our sample that have both rating and return data over January 1989 to December 2009.

Table 1

Descriptive statistics

Panel A: Average credit rating and equity return by country

Country	Average Rating	Equity Return
Developed Countries		
Australia	2.02	1.02
Austria	1.00	0.88
Belgium	1.74	0.75
Canada	1.36	0.98
Denmark	1.43	1.07
Finland	1.94	1.22
France	1.00	0.90
Germany	1.00	0.94
Greece	7.76	1.39
Hong Kong	4.46	1.25
Ireland	2.00	0.44
Italy	2.91	0.71
Japan	2.05	0.04
Luxembourg	1.00	−1.08
Netherlands	1.00	1.01
New Zealand	2.22	0.72
Norway	1.00	1.10
Portugal	3.45	0.76
Singapore	1.40	0.99
Spain	1.98	1.11
Sweden	1.45	1.19
Switzerland	1.00	1.07
USA	1.00	0.84
United Kingdom	1.00	0.78
Average	**1.97**	**0.84**
Emerging Countries		
Argentina	14.47	2.23
Bahrain	6.17	−1.58
Brazil	12.23	2.70
Bulgaria	8.42	−0.70
Chile	6.39	1.70
China	7.97	0.56
Colombia	8.33	1.80
Croatia	8.67	1.29
Cyprus	5.64	2.37
Czech Republic	5.25	1.58
Dubai	6.79	1.64
Ecuador	16.99	0.17
Egypt	9.75	2.00
Estonia	6.32	1.46
Hungary	8.24	1.89
Iceland	7.48	−7.27
India	10.44	1.31
Indonesia	12.75	1.43
Israel	5.36	0.92
Jordan	10.99	0.63
Kazakhstan	9.49	4.01
Kenya	14.20	2.73
Korea	6.23	0.96
Kuwait	4.44	0.02
Latvia	8.43	0.17
Lebanon	16.08	2.15
Lithuania	7.92	1.14
Malaysia	6.57	0.97
Malta	4.89	0.89
Mexico	9.05	1.96
Morocco	10.14	1.21
Nigeria	12.96	1.69
Oman	6.59	−0.11
Pakistan	14.60	1.09
Peru	11.30	1.96
Philippines	10.33	0.85
Poland	8.07	2.20
Qatar	4.37	0.10
Romania	9.96	0.76
Russia	11.92	2.74
Saudi Arabia	4.50	−0.52
Slovak Republic	8.36	1.00
Slovenia	3.74	1.32
South Africa	8.81	1.35
Taiwan	2.86	0.76
Thailand	7.76	1.10
Tunisia	8.73	1.60
Turkey	13.59	2.80
Ukraine	14.05	−2.41
Venezuela	14.33	1.73
Vietnam	11.03	1.38
Average	**9.10**	**1.05**

(*continued*)

Table 1
Continued

Panel B: Frequency distribution of monthly ratings and average country ratings

Rating	By Country-Month Observations			By Average Country Rating		
	Total	Developed	Emerging	Total	Developed	Emerging
AAA	3,489	3,489	0	13	13	0
AA+	1,085	935	150	7	7	0
AA	694	560	134	3	2	1
AA-	768	339	429	4	1	3
A+	664	188	476	4	0	4
A	841	153	688	5	0	5
A-	651	46	605	4	0	4
BBB+	801	0	801	10	1	9
BBB	852	30	822	5	0	5
BBB-	877	81	796	5	0	5
BB+	334	0	334	3	0	3
BB	282	0	282	2	0	2
BB-	556	0	556	2	0	2
B+	243	0	243	5	0	5
B	167	0	167	1	0	1
B-	251	0	251	1	0	1
CCC+	145	0	145	1	0	1
CCC	32	0	32	0	0	0
CCC-	17	0	17	0	0	0
CC	50	0	50	0	0	0
C	0	0	0	0	0	0
D	0	0	0	0	0	0
Total	12,799	5,821	6,978	75	24	51
Average Rating	5.87 A	2.00 AA+	9.10 BBB	6.81 A–	1.97 AA+	9.10 BBB

(*continued*)

The numeric rating is increasing in credit risk: AAA = 1, AA+ = 2, AA = 3, AA– = 4, A+ = 5, A = 6, A– = 7, BBB+ = 8, BBB = 9, BBB– = 10, BB+ = 11, BB = 12, BB– = 13, B+ = 14, B = 15, B– = 16, CCC+ = 17, CCC = 18, CCC– = 19, CC = 20, C = 21, and D = 22. The average rating across developed countries is 1.97 (AA+); for emerging countries it is 9.10 (BBB). The average monthly return of developed countries is 0.84%, while the return for emerging countries is 1.05%.

Sovereign rating observations are widely distributed across the rating spectrum. Panel B of Table 1 shows the frequency distribution of monthly rating observations and average country ratings. The sample contains observations from all but the C and D rating categories. We have a total of 12,799 country-month rating observations—5,821 from developed and 6,987 from emerging markets. All developed country ratings are investment grade, i.e. BBB– or better. All the AAA rating observations belong to developed countries, and 3,489 out of the 5,821 developed country-month observations are AAA. In contrast, emerging market ratings range from AA+ to CC, with the highest frequency around BBB.

Table 1
Continued

Panel C: Transition matrix of sovereign credit ratings

	AAA	AA+	AA	AA–	A+	A	A–	BBB+	BBB	BBB–	BB+	BB	BB–	B+	B	B–	CCC+	CCC	CCC–	CC
AAA	99.40	0.37	0.11	0.11																
AA+	1.20	97.79	0.46	0.09	0.37	0.09														
AA	0.72	1.01	96.54	0.72	0.14	0.29	0.43	0.14												
AA-	0.65		0.79	96.34	1.31	0.39	0.39				0.13									
A+		0.61		1.82	93.64	1.52	0.76	1.21	0.15	0.15	0.15									
A		0.12	0.36	0.36	1.79	94.26	0.96	0.60	1.20	0.24	0.12									
A-			0.15	0.93	0.31	2.32	91.33	1.55	0.15	2.48	0.46	0.15		0.15						
BBB+					0.38	0.63	2.51	92.60	1.13	0.38	1.63	0.75								
BBB			0.12		0.71	0.47	0.47	1.30	93.99	1.65	0.47	0.82								
BBB-					0.12	1.04	1.04	0.35	1.50	93.79	0.92	0.81	0.46							
BB+				0.30	0.30	0.30	0.91	5.14	1.21	2.42	84.29	1.81	3.32							
BB							0.36	1.78	3.20	2.49	4.27	79.72	4.63	3.20	0.36					
BB-									0.18	0.73	1.27	2.54	92.92	2.00	0.18	0.18				
B+										0.41	0.41	4.53	3.29	86.01	3.70	1.65				
B													1.81	6.02	87.35	4.22	0.60			
B-															3.21	90.36	4.42	1.20	0.80	
CCC+															0.70	6.34	91.55	0.70		0.70
CCC																6.25	6.25	84.38	3.12	
CCC-																	5.88	5.88	82.35	5.88
CC															2.00	2.00				96.00

Panel A presents the list of countries in our sample, their average long-term Standard & Poor's sovereign credit rating, and average monthly equity return (in percentages) from January 1989 to December 2009. The numeric rating is increasing in credit risk: AAA = 1, AA+ = 2, . . . , C = 21, and D = 22. Panel B presents the frequency distribution of monthly rating observations and average country ratings. Average country ratings are based on the overall sample period. Panel C presents the full transition matrix of country ratings.

There are 314 downgrades (43 in developed and 271 in emerging markets) and 342 upgrades (50 in developed and 292 in emerging markets) in our sample. The average size of a downgrade is 1.94 notches (1.35 notches in developed and 2.04 in emerging markets). The average upgrade is 1.89 notches (1.36 notches in developed and 1.98 in emerging markets). Investment grade countries have 220 downgrades and 187 upgrades. Non-investment grade countries have 94 downgrades and 155 upgrades. Panel C of Table 1 presents the full transition matrix of sovereign ratings for our sample.

Figure 2 shows that the average rating of emerging market countries deteriorates over the sample period from 5 (A+) to 10.52 (between BBB– and BB+). Since upgrades and downgrades in emerging markets are about equal in number (271 downgrades and 292 upgrades), the deteriorating average credit rating in emerging markets is driven mostly by the addition of new lower-rated countries in the first half of the sample. In contrast, developed countries have a stable average rating of about AA+ throughout. Given the increasing number of emerging market countries and their deteriorating average credit rating, the overall average rating deteriorates from 2.55 (between AA+ and AA) to 6.79 (A–).

Monthly returns for the world-market factor are based on the MSCI World U.S. dollar denominated total return index from Datastream. Monthly returns for the emerging markets factor are obtained from the MSCI Emerging Market U.S. dollar denominated total return index from Datastream. Excess returns are computed relative to the U.S. risk-free rate.

The analysis uses the foreign exchange risk factor following Adler and Dumas (1983) and Ferson and Harvey (1993). The foreign exchange factor is based on the return on a trade-weighted portfolio of U.S. dollar exchange rates. We consider two alternative foreign exchange indexes: one based on a broad basket of currencies and one based on major currencies. Both are available from the Federal Reserve Bank of St. Louis. The broad index is a weighted average of exchange rates of the U.S. dollar against the currencies of a large group of U.S. trading partners. The index weights are derived from U.S. export shares and from U.S. and foreign import shares. The major currencies index is a weighted average of exchange rates of the U.S. dollar against a subset of currencies in the broad index that circulate widely outside the country of issue. The weights are derived from those in the broad index. We take log differences of the monthly index series to obtain foreign exchange factor returns. Since this factor is not traded, we construct a traded foreign exchange factor using factor-mimicking portfolios as in Breeden, Gibbons, and Litzenberger (1989). The traded foreign exchange factor is computed as the explained part from a time-series regression of the non-traded foreign exchange factor on five developed and five emerging countries' equity returns that have data over the entire sample period. The results presented in the paper are based on the traded foreign exchange factor based on major

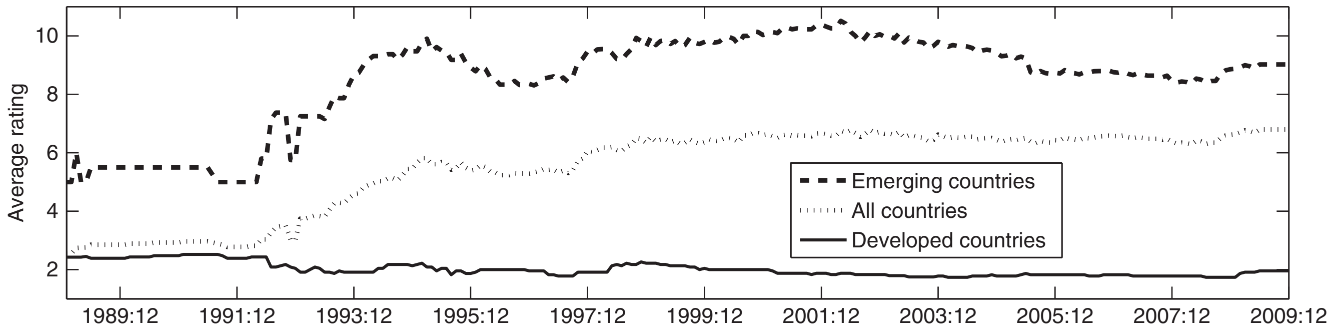

Figure 2
Time series of average credit rating
The figure presents the average numeric Standard & Poor's sovereign credit rating across all countries, as well as across developed and emerging countries. The numeric rating is increasing in credit risk: $1 = \text{AAA}$, $2 = \text{AA+}$, $3 = \text{AA}, \ldots, 20 = \text{CC}$, $21 = \text{C}$, $22 = \text{D}$.

currencies. Results are similar if using the broad foreign exchange factor or the non-traded factor.

3. Results

3.1 Sovereign credit ratings and equity returns

We examine the potential link between sovereign credit rating and average country return over the sample period. The analysis starts with portfolio sorts. In particular, each month, t, countries are sorted into terciles, C1 to C3, based on their sovereign credit rating. For each tercile, we compute the equally weighted cross-sectional mean country equity return for month $t+1$. Panel A of Table 2 reports the average of these monthly means and the difference between the return of worst- versus best-rated portfolios, $C3-C1$. The t-statistics for cumulative returns (from months $t+1$ to $t+6$ or $t+12$) are computed using Newey and West (1987) adjusted heteroscedastic-serial correlation consistent standard errors. The overall evidence from Panel A of Table 2 shows that countries with lower sovereign credit ratings earn higher average returns, consistent with Erb, Harvey, and Viskanta (1995, 1996).

Over the full sample period, 1989–2009, the best-rated countries (C1) realize average equity returns of 84 bps per month and have an average S&P rating of 1.38 (slightly below AAA). Over the same period, the worst-rated countries (C3) have an average S&P rating of 10.92 (a non-investment grade rating of BB+) and realize equity returns of 141 bps per month. The return differential between worst- and best-rated countries is 57 bps per month (t-value of 2.15). The return differential grows to 3.58% (6.77%) for 6 (12) month holding periods. It is economically large and statistically significant at the 1% level.

Over the 1999–2009 period, the worst-rated countries outperform the best-rated countries by 125 bps per month (t-value of 4.10).[4] Over 6 (12) months this return differential becomes 6.64% (13.72%), statistically significant at the 1% level. In the first half of the sample (1989–1998), the returns of the best- and the worst-rated countries are indistinguishable.

Figure 3 further illustrates the strong outperformance of the worst-rated country tercile in the second half of the sample. The top two subplots in Figure 3, Panel (a) show the wealth process of investing in C1 and C3 countries (first plot) and being long in C3 countries and short in C1 countries (second plot). The wealth increases almost monotonically over the second half of the sample. Note from the last graph that the average monthly return differential $(C3-C1)$ is always positive over any 36-month window in the

[4] We use a larger number of countries than previous studies and recognize that there may be a huge amount of heterogeneity in emerging market countries. For robustness, we replicate the results in Panel A of Table 2 excluding "frontier" (i.e., least-developed emerging market) countries. We find that the monthly return differential between best- and worst-rated countries is even higher: 69 bps (t-value of 2.42) in the overall 1989–2009 period and 141 bps (t-value of 3.92) in the 1999–2009 period.

Table 2
Country equity returns by sovereign credit rating group

Panel A: Raw returns

	Sovereign Rating Group (C1 = Lowest, C3 = Highest Risk)			
	C1	C2	C3	C3-C1
Full Sample: 1989–2009				
Average Rating	1.38 (AAA)	5.23 (A+)	10.92 (BB+)	
r_{t+1}	0.84	0.80	1.41	0.57
	(2.71)***	(2.36)**	(3.58)***	(2.15)**
$r_{t+1:t+6}$	5.39	5.78	8.97	3.58
	(4.37)***	(3.97)***	(5.16)***	(3.54)***
$r_{t+1:t+12}$	10.46	11.27	17.23	6.77
	(5.68)***	(5.06)***	(6.23)***	(3.95)***
First Part: 1989–1998				
Average Rating	1.08 (AAA)	3.72 (AA-)	9.10 (BBB)	
r_{t+1}	1.02	0.07	0.85	-0.17
	(2.66)***	(1.38)	(1.50)	(-0.39)
$r_{t+1:t+6}$	5.80	3.72	5.37	-0.43
	(5.70)***	(2.31)**	(2.44)**	(-0.26)
$r_{t+1:t+12}$	12.53	7.61	12.09	-0.44
	(8.07)***	(3.03)***	(3.53)***	(-0.16)
Second Part: 1999–2009				
Average Rating	1.66 (AA+)	6.60 (A-)	12.56 (BB-)	
r_{t+1}	0.68	0.95	1.92	1.25
	(1.40)	(1.96)**	(3.50)***	(4.10)***
$r_{t+1:t+6}$	4.67	6.79	11.31	6.64
	(2.11)**	(2.84)***	(4.30)***	(6.80)***
$r_{t+1:t+12}$	7.95	12.60	21.67	13.72
	(2.37)**	(3.44)***	(5.09)***	(8.23)***
Pre-Financial Crisis Sample: 1989–2007				
Average Rating	1.33 (AAA)	5.08 (A+)	10.78 (BB+)	
r_{t+1}	1.03	1.02	1.63	0.60
	(3.67)***	(3.25)***	(4.20)***	(2.11)**
$r_{t+1:t+6}$	6.34	6.67	9.94	3.60
	(6.88)***	(5.39)***	(6.15)***	(3.23)***
$r_{t+1:t+12}$	13.36	13.99	20.21	6.85
	(8.50)***	(6.68)***	(7.35)***	(3.61)***

(*continued*)

second half of the period, even during the recent financial crisis and after the burst of the dot-com bubble in 2001. The lowest part of Panel A of Table 2 shows that the average C3 – C1 profitability before the recent financial crisis (up to 2007) is 60 bps per month. The recent severe financial crisis reduced this profitability by only 3 bps per month (to 57 bps—top part of Panel A).

The higher relative returns of the worst-rated countries are quite robust in the second half of the sample period. However, note from Figure 2 that there are only a few poorly rated countries in the first half of the period. The sample starts with an average numeric rating of 2.5 (between AA+ and AA) and has a stable average of 6.5 (between A and A–) in the second half. This suggests that the lack of credit rating effect in the first half of the sample is possibly due to the lack of poorly rated countries in that period.

The higher returns of high credit risk countries cannot be explained by existing international asset pricing models. In particular, we run several

Table 2
Continued

Panel B: Portfolio alphas and betas over 1989–2009

	Sovereign Rating Group (C1 = Lowest, C3 = Highest Risk)			
	C1	C2	C3	C3-C1
Panel B1: Adjusting for world market [*MKT*] factor				
Alpha	0.22	0.20	0.81	0.58
	(1.96)**	(0.98)	(2.82)***	(2.21)**
MKT Beta	1.04	0.98	0.98	−0.06
	(40.19)***	(21.37)***	(15.07)***	(−1.01)
Panel B2: Adjusting for *MKT* and foreign exchange [*FOREX*] factors				
Alpha	0.16	0.13	0.75	0.58
	(1.54)	(0.67)	(2.62)***	(2.20)**
MKT Beta	0.86	0.79	0.79	−0.06
	(24.31)***	(11.85)***	(8.30)***	(−0.73)
FOREX Beta	−1.58	−1.71	−1.62	−0.04
	(−6.92)***	(−3.94)***	(−2.62)***	(−0.07)
Panel B3: Adjusting for Fama and French (1998) international *MKT* and *HML* factors				
Alpha	0.23	0.14	0.82	0.58
	(1.78)*	(0.66)	(2.71)***	(2.16)**
MKT Beta	0.88	0.84	0.81	−0.06
	(34.18)***	(20.60)***	(13.79)***	(−1.20)
HML Beta	0.16	0.28	0.16	−0.00
	(3.45)***	(3.78)***	(1.48)	(−0.02)
Panel B4: Adjusting for the Fama and French (1998) international *MKT* and *HML* and *MOM* factors				
Alpha	0.25	0.19	0.89	0.63
	(1.85)*	(0.90)	(2.81)***	(2.24)**
MKT Beta	0.87	0.83	0.81	−0.07
	(32.87)***	(19.85)***	(13.26)***	(−1.22)
HML Beta	0.16	0.26	0.14	−0.02
	(3.15)***	(3.36)***	(1.21)	(−0.18)
MOM Beta	−0.02	−0.07	−0.10	−0.07
	(−0.85)	(−1.53)	(−1.48)	(−1.24)
Panel B5: Adjusting for *MKT* and Lee (2011) global liquidity [*LIQ*] factor over 1999–2007				
Alpha	0.44	0.77	1.77	1.33
	(3.17)***	(3.06)***	(4.76)***	(3.70)***
MKT Beta	1.06	0.81	1.01	−0.05
	(30.92)***	(12.93)***	(10.85)***	(−0.58)
LIQ Beta	−0.25	−0.71	−0.79	−0.54
	(−1.92)*	(−2.92)***	(−2.21)**	(−1.55)
Panel B6: Adjusting for *MKT*, *LIQ*, and Lee (2011) *local liquidity* factors over 1999–2007				
Alpha	0.37	0.52	1.56	1.19
	(2.53)**	(2.02)**	(3.94)***	(3.09)***
MKT Beta	1.06	0.87	1.05	−0.02
	(29.60)***	(13.52)***	(10.68)***	(−0.20)
LIQ Beta	−0.21	−0.22	−0.48	−0.27
	(−1.27)	(−0.76)	(−1.08)	(−0.63)
Local liquidity Beta	0.20	−0.39	0.02	−0.18
	(1.06)	(−1.19)	(0.04)	(−0.36)
Local liquidity 2 Beta	0.23	0.68	0.63	0.40
	(1.50)	(2.54)**	(1.53)	(1.01)
Panel B7: Adjusting for *MKT* and Pastor and Stambaugh (2003) U.S. liquidity [*USLIQ*] factors				
Alpha	0.54	0.49	1.10	0.56
	(4.69)***	(2.40)**	(3.81)***	(2.09)**
MKT Beta	1.03	0.98	0.97	−0.06
	(39.93)***	(21.44)***	(15.03)***	(−1.03)
USLIQ Beta	0.02	0.07	0.06	0.04
	(0.70)	(1.35)	(0.87)	(0.63)

(*continued*)

Table 2
Continued

Panel C: Impact of downgrades or upgrades over 1989–2009

	Sovereign Rating Group (C1 = Lowest, C3 = Highest Risk)			
	C1	C2	C3	C3-C1
Eliminating ±6 months around downgrades				
r_{t+1}	0.84	0.81	1.62	0.78
	(2.65)***	(2.50)**	(3.89)***	(2.57)**
$r_{t+1:t+6}$	5.15	5.12	8.74	3.59
	(4.32)***	(4.45)***	(6.05)***	(3.93)***
Eliminating ±6 months around upgrades				
r_{t+1}	0.83	0.82	1.38	0.55
	(2.65)***	(2.48)**	(3.50)***	(1.87)*
$r_{t+1:t+6}$	5.16	4.87	7.15	1.99
	(4.29)***	(3.91)***	(5.24)***	(2.31)**
Eliminating ±6 months around both downgrades and upgrades				
r_{t+1}	0.81	0.82	1.47	0.66
	(2.55)**	(2.49)**	(3.66)***	(2.18)**
$r_{t+1:t+6}$	4.96	4.41	7.06	2.10
	(4.23)***	(4.11)***	(5.56)***	(2.70)***

Each month t, countries are divided into terciles based on their Standard & Poor's sovereign credit rating. For each tercile, we compute the equally weighted average equity return for month $t+1$ (and cumulative return from months $t+1$ to $t+6$ or $t+12$). Panel A reports the time-series mean of these averages and the return difference between the worst-rated and the best-rated portfolios (in percentages). The t-statistics (in parentheses, *, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively) for cumulative returns are Newey and West (1987) adjusted heteroscedastic-serial consistent t-statistics. In Panel B, we run time-series regressions of each portfolio, C1 to C3, excess return relative to the U.S. risk-free rate and the return differential, C3 – C1, on a constant and various factors and report the portfolio alphas (in percentages per month) and betas. *MKT* is the return of the MSCI World Equity Total Return Index minus the U.S. risk-free rate. *HML* is the Fama and French (1998) international *HML* Factor. *FOREX* is the foreign exchange risk factor, calculated as the log difference on a trade-weighted portfolio of a major basket of exchange rates relative to the U.S. dollar. We use a factor-mimicking portfolio for the *FOREX* factor (see Section 2). *LIQ* is the Lee (2011) global liquidity factor, provided by the author. The international momentum factor, *MOM*, is from Schmidt et al. (2011), provided by the authors. *USLIQ* is the Pastor and Stambaugh (2003) traded value-weighted U.S. liquidity factor. In Panel C, we repeat the analysis in Panel A after removing returns from six months prior to six months after a rating downgrade, upgrade, or both.

time-series asset pricing specifications, where we regress the excess returns of each credit rating sorted portfolio, C1 to C3, and the return differential, C3 – C1, on a constant and various factors and report the portfolio alphas (in percentages per month) and betas in Panel B of Table 2. When only the world-market factor is considered (Panel B1), the world-market betas of C1 and C3 countries are indistinguishable and the world CAPM alpha of C3 – C1 returns is 58 bps per month (t-value of 2.21) versus 57 bps in raw returns (Panel A). The C3 – C1 alpha relative to the world equity market and the traded foreign exchange risk factors is 58 bps per month (t-value of 2.20, Panel B2). Similarly, the C3 – C1 alpha relative to the Fama and French (1998) [FF] international *MKT* and *HML* factors is 58 bps per month (t-value of 2.16, Panel B3).[5] In Panel B4, we add an international momentum

[5] The U.S. dollar denominated international *MKT* and *HML* factors are available at Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The U.S. risk-free rate is subtracted from the international *MKT* factor to obtain excess returns.

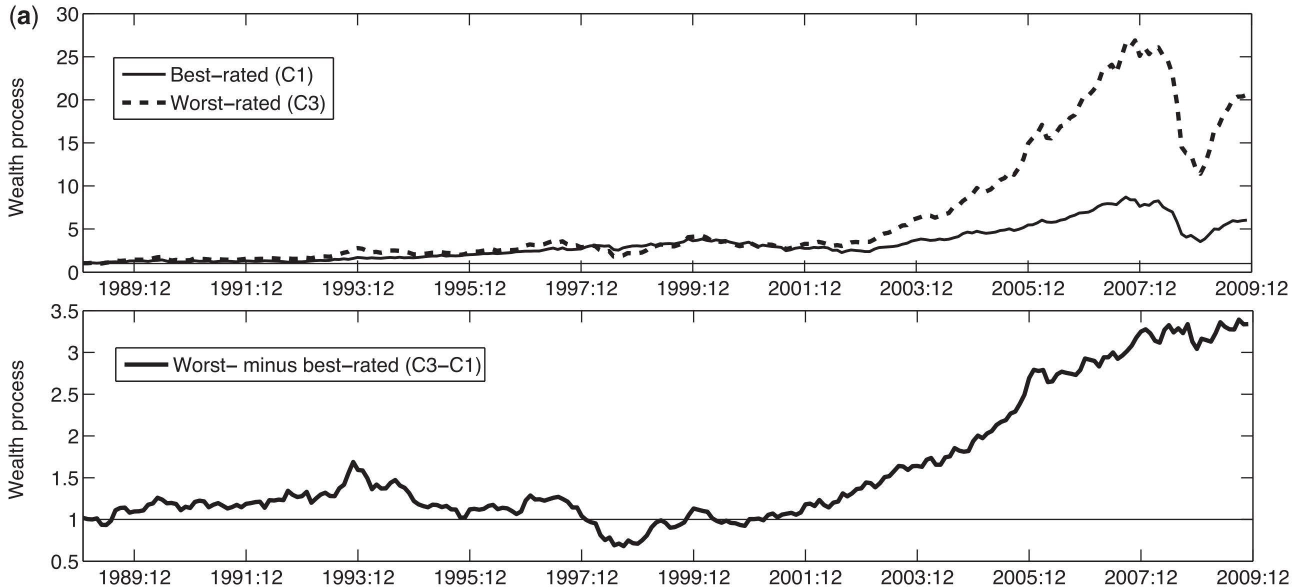

Figure 3
Wealth process from investing in worst-versus best-rated country equity indices
Each month $t-1$, all countries rated by Standard & Poor's and with available equity market index returns are divided into terciles (C1 to C3) based on credit rating. Within each tercile, we compute the equally weighted average return for month t. The figure presents the wealth process starting with [dollar]1 in January 1989 and investing in the worst- (C3) or best-rated (C1) tercile (first plot) or being short the best-rated and long the worst-rated tercile (second plot). The two plots in Panel (b) display the 36-month moving average (MA) monthly returns of C1 and C3 countries and their return differential C3 – C1.

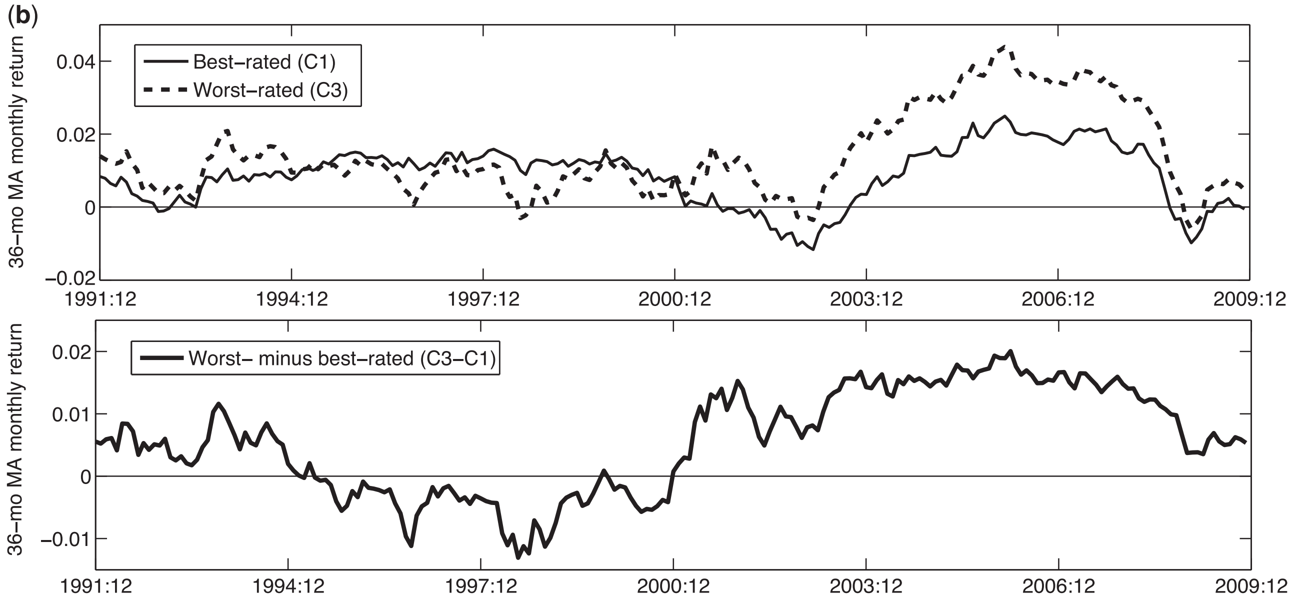

Figure 3
Continued.

factor, *MOM*, to the FF *MKT* and *HML* factors.[6] The alpha of C3 – C1 relative to the international *MKT*, *HML*, and *MOM* factors is 63 bps per month (*t*-value of 2.24). We also attempt to control for the Hou, Karolyi, and Kho (2011) [HKK] market, momentum, and C/P international factors. While the data on their factors are available mostly for the first half of our sample period, when the return differential between high and low credit risk countries is insignificant (Panel A), we find that even for that period, the C3 – C1 HKK alpha is larger than the raw returns.[7]

Following Lee (2011), we also test whether liquidity factors based on global and local liquidity exposure explain the higher returns of high credit risk countries.[8] The liquidity factors of Lee (2011) are mostly available for the second half of our sample period. Over that period, adjusting with the global liquidity factor produces a C3 – C1 alpha of 133 bps per month (*t*-value of 3.70, Panel B5), higher than the raw C3 – C1 return differential of 125 bps (Panel A of Table 2). Adjusting for Lee's (2011) local liquidity factors, along with the global liquidity and world-market factors, results in a C3 – C1 alpha of 119 bps (*t*-value of 3.09, Panel B6). This alpha is only slightly lower than the raw returns differential of 125 bps and the 133 bps alpha with respect to the global liquidity factor. Still, it indicates (as in Lee 2011) that local liquidity factors are more important than global liquidity factors. These results are also consistent with Rouwenhorst (1999), who shows the return premiums in emerging countries do not compensate for illiquidity.

Lee (2011) also shows that the U.S. market is an important driving force for global liquidity risk. Hence, to assess the impact of liquidity risk over the entire sample period, we test whether the high returns of high credit risk countries can be explained by the Pastor and Stambaugh (2003) U.S. liquidity factor, for which data are available over our entire sample period.[9] Over the 1989 to 2009 period, the C3 – C1 alpha is 56 bps per month (*t*-value of 2.09, Panel B7). Overall, the results in Panel B of Table 2 suggest that the higher returns of higher credit risk countries are not captured by existing risk factors.

Next, we examine the impact of sovereign rating changes on country equity returns and investigate whether the credit risk effect in average country equity returns could be attributed to periods around credit rating changes. Rating changes, especially downgrades, have a well-documented major impact on individual stock and bond prices, while sovereign rating changes can have nontrivial consequences for entire financial markets (e.g., Dichev 1998; Kaminsky and Schmukler 2002; Brooks et al. 2004; Hooper, Hume, and

6 Andreas Schrimpf has provided the international momentum factor from Schmidt et al. (2011).

7 We thank Andrew Karolyi for providing us with the Hou, Karolyi, and Kho (2011) factors.

8 We thank Kuan-Hui Lee for providing us with his Lee (2011) liquidity factors. These are traded factors calculated as the return difference between high and low liquidity beta stocks [see Table 11 of Lee (2011)].

9 We use the Pastor-Stambaugh traded value-weighted liquidity factor from WRDS. Alphas based on the Sadka (2006) transitory-fixed factor or permanent-variable liquidity factors (from WRDS) are similar.

Kim 2008). As in Panel A of Table 2, countries are divided into terciles based on their sovereign credit rating. Within each tercile, we focus on countries experiencing either downgrades or upgrades. Figure 4 presents the six-month moving average monthly portfolio returns for the best- (C1) and worst-rated (C3) terciles around periods of downgrades and upgrades.

The top plot of Figure 4 shows that equity prices drop sharply around sovereign rating downgrades in both best-rated and worst-rated countries. A strong impact of rating downgrades has been documented for worst-rated U.S. stocks while best-rated U.S. stocks display only a mild response (see Avramov et al. 2009). However, at the country level, sovereign rating downgrades impact both best- and worst-rated countries. One clear asymmetry between worst- versus best-rated countries is that rating changes are more likely among the worst-rated countries. In particular, there are 39 (141) [134] downgrades and 13 (115) [214] upgrades in the best- (medium-) [worst-] rated country tercile.

In contrast, the bottom plot of Figure 4 shows no clear pattern in country returns around upgrades (the C1 returns are more scattered due to the very few upgrades over the sample period). Hence, the overall impact of rating changes on the credit risk effect is still unclear.

Next we examine whether the higher returns of high credit risk countries originate from periods around rating changes. In particular, we remove country return observations from six months before to six months after a downgrade (upgrade) and recompute the equally weighted average returns by rating terciles. Panel C of Table 2 shows that, after eliminating periods around downgrades or upgrades, the average returns of C1 countries are almost unchanged at 84 and 83 bps per month, respectively, possibly due to the fewer rating changes in these countries. In contrast, after eliminating periods around downgrades, C3 countries' returns increase from 141 bps (Panel A) to 162 bps per month (Panel C). The monthly return differential, C3 – C1, increases from 57 bps (Panel A) to 78 bps (t-value = 2.57, Panel C). Hence, the worst-rated countries outperform the best-rated even more during stable or improving credit conditions. Removing periods around upgrades slightly reduces the outperformance of worst-rated countries, C3 – C1, from 57 bps (Panel A) to 55 bps per month (Panel C). Finally, excluding periods around both downgrades and upgrades slightly increases the C3 – C1 return differential to 66 bps per month (t-value of 2.18). Overall, even though upgrades and downgrades display some effect on country equity returns, they cannot explain the higher returns in high credit risk countries.

The significant positive relation between ratings and equity returns is confirmed in cross-sectional regressions. Specifically, we run monthly cross-sectional regressions of time $t + 1$ country equity excess returns on a constant, sovereign credit ratings at time t, and ratings interacted with an emerging market dummy, indicating whether the country is a developed (0) or an emerging market (1). The dependent variable is either raw (r_{t+1}) or

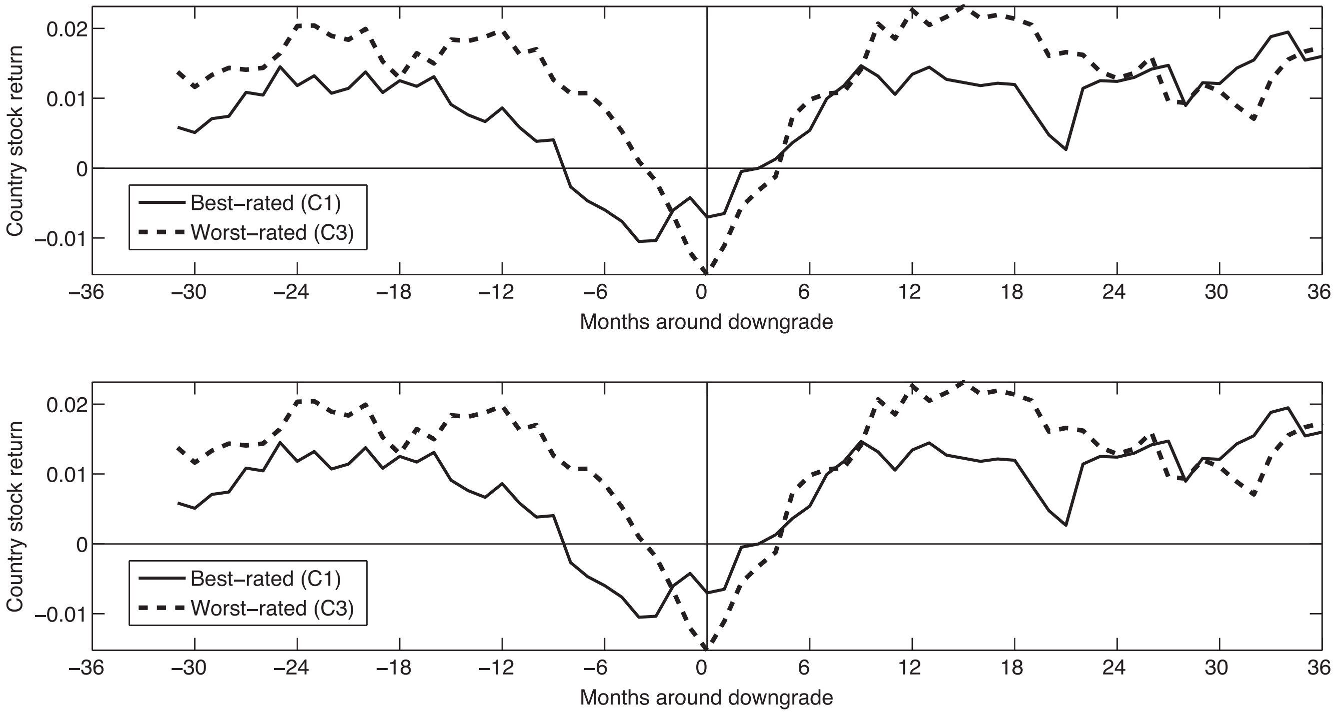

Figure 4
Country equity returns around rating changes (6-month moving average)
Each month $t-1$, all countries rated by Standard & Poor's and with available equity market index returns are divided into terciles (C1 to C3) based on credit rating. Within each tercile, we find countries that have been downgraded (upper plot) or upgraded (lower plot) in month t and compute their equally weighted average returns over each month from $t-36$ to $t+36$. The figure presents the 6-month moving average of these average monthly portfolio returns for the best- (C1) and worst-rated (C3) terciles. Month $t=0$ is the month of downgrade (upgrade). The sample period is from January 1989 to December 2009.

risk-adjusted (r^*_{t+1}) returns. Returns are risk-adjusted as in Brennan, Chordia, and Subrahmanyam (1998). The risk-adjusted return, r^*_{t+1}, is the intercept and residual from time-series regressions of country excess returns on various asset pricing factors. Table 3 presents the results.

The regression coefficient on the rating variable is uniformly 0.07% using both raw and risk-adjusted returns (with any risk factors considered), suggesting that a notch deterioration in credit rating (say from AA to AA–) brings about 7 bps per month in additional risk-adjusted returns.[10] To illustrate, the regression results imply that a BB+ rated country (numeric rating of 11) has on average 70 bps per month higher equity returns than an AAA rated country (numeric rating of 1). All slope coefficients are significant at the 5% level. When rating interacted with the emerging market dummy is included in the regression (specification 3), rating is still significant but at the 10% level, though it is now slightly higher at 8, 9, or 10 bps per month. In contrast, rating interacted with the emerging market dummy is always insignificant in cross-sectional regressions.

In sum, the results, based on both portfolio sorts and cross-sectional regressions, demonstrate a significant relation between sovereign ratings and country equity returns. The higher returns in higher credit risk countries are not explained by existing asset pricing models, consistent with findings in past work. Next, we investigate whether these positive pricing errors in high credit risk countries are compensation for exposure to a world credit risk factor.

3.2 The world credit risk factor

Our goals in assessing the role of the world credit risk factor in international asset pricing are threefold. First, we test whether the world credit risk factor is priced in the cross-section of country equity returns. Second, we examine whether exposure to the world credit risk factor captures the higher returns of high credit risk countries in general, and of emerging equity markets in particular. Third, we analyze whether any pricing errors in emerging and high credit risk countries remain after adjusting for exposure to the world credit risk factor.

3.2.1 Cross-sectional tests. We first examine whether the world credit risk factor is priced in the cross-section of country equity returns. Specifically, we first run time-series regressions of monthly country equity excess returns on a constant and various global factors. Then we run monthly cross-sectional regressions of country excess returns on a constant and the estimated betas from the first pass. The second-pass specification delivers estimates of the factor risk premiums. Table 4 presents these estimated risk premiums for

[10] We have also adjusted for the remaining risk factors from Panel B of Table 2, and the results are similar.

Table 3
Cross-sectional regressions

Specification	Constant	$Rating_t$	$Rating_t \times$ EmDummy
Panel A: Raw returns: r_{t+1}			
1	0.33	0.07	
	(1.01)	(2.06)**	
2	0.48		0.04
	(1.54)		(1.16)
3	0.27	0.10	−0.04
	(0.85)	(1.82)*	(−0.76)
Panel B: Risk-adjusted returns: $r^*_{t+1}\vert[MKT]$			
1	0.04	0.07	
	(0.28)	(2.07)**	
2	0.19		0.04
	(1.55)		(1.20)
3	−0.01	0.10	−0.04
	(−0.06)	(1.75)*	(−0.67)
Panel C: Risk-adjusted returns: $r^*_{t+1}\vert[MKT, FOREX]$			
1	−0.02	0.07	
	(−0.16)	(2.14)**	
2	0.14		0.04
	(1.20)		(1.18)
3	−0.04	0.08	−0.02
	(−0.29)	(1.79)*	(−0.37)
Panel D: Risk-adjusted returns: $r^*_{t+1}\vert[FF\ international\ MKT, HML]$			
1	0.03	0.07	
	(0.22)	(2.05)**	
2	0.18		0.03
	(1.38)		(1.12)
3	−0.00	0.09	−0.03
	(−0.01)	(1.77)*	(−0.57)

Each month t, we run cross-sectional regressions of time $t+1$ country equity excess returns on a constant, time t sovereign credit ratings, and rating interacted with an emerging market dummy, EmDummy. EmDummy indicates whether the country is developed (0) or emerging (1). The dependent variable is either raw (r_{t+1}) or risk-adjusted (r^*_{t+1}) one-month-ahead returns. Returns are risk-adjusted as in Brennan, Chordia, and Subrahmanyam (1998) by running time-series regressions of each individual country excess return on risk factors (as specified in brackets in the heading of each panel and described in Table 2). The risk-adjusted returns, r^*_{t+1}, are the intercept and residual from these time-series regressions. The table presents the time-series average of the cross-sectional regression coefficients (in percentages) with their associated sample t-statistics in parentheses (*, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively). The sample period is from January 1989 to December 2009.

the overall sample (top panel), the first (middle panel), and the second half (bottom panel) of the period.[11] Following Shanken (1992), the reported t-statistics are corrected for sampling error due to the fact that the regressors in the second pass are themselves noisy estimates, not actual data realizations.

Panel A of Table 4 examines combinations of the following factors: *MKT*, *FOREX*, *CREDIT*, and *EMERG*. *MKT* is the world equity market factor, and *FOREX* is the traded foreign exchange risk factor (previously used in Panels B1–B2 of Table 2). *CREDIT* is our world credit risk factor, described in Section 2. *EMERG* is the emerging markets factor (see Section 2), orthogonalized with respect to the *MKT* and *CREDIT* factors. Specifically, it is

[11] When asset pricing tests are performed separately in the first and second halves of the period, the betas are estimated over the same period in the first pass.

Table 4
Asset pricing tests
Panel A: Factors: *MKT*, *FOREX*, *CREDIT*, *EMERG*

	Constant	*MKT*	*FOREX*	*CREDIT*	*EMERG*	Adj.R^2
Full Sample: 1989–2009						
1	0.13	0.72				5.51
	(0.0000	(1.56)				
2	0.22	0.73	−0.02			8.34
	(0.61)	(1.59)	(−0.27)			
3	0.62			0.86		6.03
	(2.16)**			(2.51)**		
4	0.17	0.43		0.73		11.24
	(0.46)	(0.98)		(2.15)**		
5	0.28	0.42	0.03	0.80		14.35
	(0.78)	(0.94)	(0.42)	(2.33)**		
6	0.28	0.40	0.02	0.73	0.14	18.86
	(0.79)	(0.88)	(0.32)	(1.97)**	(0.35)	
7	0.52				0.82	6.43
	(1.93)*				(2.26)**	
8	0.35	0.45	0.00		0.52	13.60
	(1.00)	(1.00)	(0.04)		(1.43)	
First Part: 1989–1998						
1	1.03	−0.24				5.34
	(1.71)*	(−0.33)				
2	1.12	−0.20	0.12			9.29
	(1.86)*	(−0.27)	(1.04)			
3	0.54			1.00		8.97
	(1.54)			(1.71)*		
4	0.48	0.14		0.85		13.06
	(0.91)	(0.20)		(1.46)		
5	0.53	0.24	0.10	1.04		17.29
	(0.99)	(0.35)	(0.92)	(1.73)*		
6	0.71	−0.10	0.11	0.70	0.54	22.78
	(1.37)	(−0.15)	(1.02)	(1.11)	(0.89)	
7	0.43				1.08	10.22
	(1.18)				(1.93)*	
8	1.05	−0.55	0.12		0.96	16.85
	(1.81)*	(−0.74)	(1.08)		(1.72)*	
Second Part: 1999–2009						
1	0.38	0.47				7.61
	(1.29)	(0.98)				
2	0.38	0.49	−0.05			10.60
	(1.53)	(1.02)	(−0.74)			
3	0.66			0.95		4.68
	(1.45)			(2.68)***		
4	0.25	0.30		0.82		12.41
	(0.85)	(0.62)		(2.37)**		
5	0.28	0.29	−0.02	0.84		15.70
	(1.13)	(0.63)	(−0.36)	(2.43)**		
6	0.27	0.27	−0.02	0.87	0.15	19.25
	(1.09)	(0.56)	(−0.28)	(2.56)**	(0.42)	
7	0.70				0.53	4.97
	(1.67)*				(1.38)	
8	0.39	0.41	−0.03		0.34	14.52
	(1.59)	(0.87)	(−0.51)		(0.94)	

(*continued*)

Table 4
Continued

Panel B: Factors: *MKT*, Lee (2011) Global Liquidity [*LIQ*], *CREDIT*, *EMERG* (1999–2007)

	Constant	*MKT*	LIQ	*CREDIT*	*EMERG*	Adj.R^2
1	0.94	0.41				8.87
	(2.78)***	(0.83)				
2	0.82	0.29	−0.38			12.33
	(2.43)**	(0.60)	(−1.89)*			
3	1.00			1.05		6.53
	(2.73)***			(2.62)***		
4	0.89	0.07		1.02		15.47
	(2.65)***	(0.14)		(2.59)***		
5	0.87	0.03	−0.20	0.94		18.41
	(2.63)***	(0.07)	(−1.07)	(2.42)**		
6	0.86	0.15	−0.25	1.00	−0.22	22.17
	(2.66)***	(0.31)	(−1.30)	(2.58)***	(−0.59)	
7	1.28				0.12	5.34
	(3.59)***				(0.31)	
8	0.81	0.42	−0.43		−0.11	16.29
	(2.46)**	(0.85)	(−2.12)**		(−0.28)	

Panel C: Factors: *MKT*, U.S. Liquidity [*USLIQ*], *CREDIT*, *EMERG* (1989–2009)

	Constant	*MKT*	*USLIQ*	*CREDIT*	*EMERG*	Adj.R^2
1	0.15	0.73	−0.59			7.87
	(0.42)	(1.60)	(−0.69)			
2	0.62			0.86		6.03
	(2.16)**			(2.50)**		
4	0.13	0.50	−1.83	0.77		13.17
	(0.36)	(1.12)	(−2.15)**	(2.20)**		
5	0.20	0.32	−1.61	0.62	0.38	17.92
	(0.57)	(0.71)	(−1.77)*	(1.86)*	(0.93)	
6	0.30	0.38	−1.14		0.68	12.64
	(0.85)	(0.85)	(−1.24)		(1.76)*	

Panel D: Factors: *MKT*, *MOM*, *CREDIT*, *EMERG* (1989–2009)

	Constant	*MKT*	*MOM*	*CREDIT*	*EMERG*	Adj.R^2
1	0.18	0.72	0.50			9.10
	(0.51)	(1.56)	(0.61)			
2	0.62			0.86		6.03
	(2.16)**			(2.50)**		
4	0.38	0.28	1.71	0.86		14.51
	(1.07)	(0.63)	(1.96)**	(2.44)**		
5	0.48	0.09	1.82	0.71	0.28	19.95
	(1.38)	(0.20)	(2.02)**	(1.98)**	(0.70)	
6	0.48	0.25	1.18		0.64	14.71
	(1.40)	(0.55)	(1.34)		(1.70)*	

(*continued*)

calculated as the intercept and residual from a time-series regression on the excess return of the *MKT* and *CREDIT* factors. The orthogonalization is made to 1) limit the correlation across factors in the asset pricing tests, and 2) isolate the returns due purely to emerging countries from those driven by world-markets in general and by high credit risk countries in particular.

Table 4
Continued

Panel E: 60-month rolling regression betas (1999–2009)

	Constant	*MKT*	*FOREX*	*CREDIT*	*EMERG*	Adj.R^2
1	0.34	0.49				6.77
	(1.11)	(1.32)				
2	0.24	0.57	−0.06			9.02
	(0.81)	(1.50)	(−1.18)			
3	0.59			0.82		4.00
	(1.29)			(2.98)***		
4	0.21	0.26		0.92		11.37
	(0.70)	(0.69)		(3.30)***		
5	0.12	0.35	−0.03	0.90		13.64
	(0.44)	(0.92)	(−0.66)	(3.22)***		
6	0.15	0.42	−0.04	0.92	−0.17	16.64
	(0.52)	(1.04)	(−0.71)	(3.22)***	(−0.56)	
7	0.72				0.31	4.56
	(1.76)*				(1.02)	
8	0.23	0.63	−0.06		−0.03	11.93
	(0.82)	(1.58)	(−1.27)		(−0.10)	

Panel F: Conditional betas: $Z_{t-1} = [MKT_{t-1}, DY_{t-1}, TED_{t-1}, Term_{t-1}, rf_{t-1}]$ (1999–2009)

	Constant	*MKT*	*FOREX*	*CREDIT*	*EMERG*	Adj.R^2
1	0.69	0.17				13.68
	(2.48)**	(0.36)				
2	0.62	0.14	−0.07			19.50
	(2.60)***	(0.31)	(−1.03)			
3	0.39			1.11		10.76
	(0.94)			(3.25)***		
4	0.44	0.08		1.05		22.71
	(1.79)*	(0.18)		(3.11)**		
5	0.42	0.01	−0.05	1.02		28.62
	(2.00)**	(0.03)	(−0.78)	(3.15)***		
6	0.29	0.05	−0.06	1.09	0.35	35.06
	(1.49)	(0.11)	(−0.94)	(3.38)***	(1.16)	
7	0.88				0.47	9.36
	(2.12)**				(1.48)	
8	0.55	0.16	−0.07		0.34	25.80
	(2.45)**	(0.37)	(−1.12)		(1.12)	

For Panels A to D, we run time-series regressions of monthly country equity excess returns on a constant and the factors to obtain the country factor loadings. Then we run monthly cross-sectional regressions of country excess returns on a constant and the beta estimates from the first pass to estimate the factor risk premiums. The table shows time-series averages of the estimated factor premiums (in percentages) and their sample *t*-statistics (*, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively) adjusted by the Shanken (1992) correction to account for errors in the beta estimates. *CREDIT* is the world credit risk factor, constructed as the difference in equity returns of the worst-rated minus the best-rated tercile, C3 − C1. *EMERG* is the emerging markets factor, orthogonalized relative to *MKT* and *CREDIT*, calculated as the intercept and residual from a time-series regression of the excess return of the MSCI Emerging Market Total Return index on the *MKT* and *CREDIT* factors. The remaining factors are described in Table 2. In Panel E, the 60-month rolling-regression betas, β_{it-1}, used in month *t*'s second-pass cross-sectional regression are estimated in the first pass in time-series regressions of excess returns on the factors from months $t-60$ to month $t-1$. For Panel F, conditional betas are estimated for each country *i* in the following time-series regression: $r_{it} = a_i + b_{0i}F_t + b_{1i}Z_{t-1} \times F_t$, where the conditional betas, $\beta_{it-1} = b_{0i} + b_{1i}Z_{t-1}$, are used in the second-pass cross-sectional regression for month *t*. Z_{t-1} contains the following instruments: MKT_{t-1} (lagged *MKT* return), rf_{t-1} (the U.S. risk-free rate), $Term_{t-1}$ (the term premium: the difference between the yield on 10-year U.S. Treasuries and the U.S. risk-free rate), TED_{t-1} (the TED spread: the difference between the three-month Eurodollar rate and the three-month U.S. T-bill rate), and DY_{t-1} (the dividend yield on the MSCI world market index over the past 12 months).

Notice from Panel B of Table 1 that emerging countries have ratings ranging from AA+ to CC. Thus, the orthogonalization is made to separate the credit risk from the emerging market impact. Our conclusions remain valid if the *EMERG* factor is not orthogonalized.

The international asset pricing models of Solnik (1974a), Sercu (1980), Stulz (1981), and Adler and Dumas (1983) suggest that both a world and a foreign exchange risk factor reasonably capture the cross-section of country returns in the presence of deviations from PPP. While the literature has found some support for these models in developed markets, neither factor seems to explain the higher returns in emerging markets. Indeed, in our overall sample of developed and emerging market countries, Panel A of Table 4 shows that the world-market risk premium (*MKT*) and the foreign exchange risk premium (*FOREX*) are insignificant in all cross-sectional specifications in all subperiods.

In contrast, the world credit risk factor (*CREDIT*) is significantly priced in the cross-section of country equity returns in the overall sample period as well as during the second half of the period, regardless of the remaining factors included. Over the 1989–2009 period, the risk premium for a unit exposure to the *CREDIT* factor is 80 bps per month (*t*-value of 2.33) when the *MKT* and *FOREX* factors are considered. The risk premium in the second half of the period is 84 bps per month (*t*-value of 2.43).[12] The *CREDIT* risk premium is also positive in the first half of the sample, but it is statistically significant at the 10% level: the risk premium is 104 bps (*t*-value of 1.73) when the *MKT* and *FOREX* factors are included. The lack of high credit risk countries in the first half of the sample may account for the lower significance of the world credit risk factor over the earlier period. Alternatively, it could be the case that equity markets are becoming more integrated. The inclusion of *CREDIT* significantly raises the adjusted R-squared in the cross-sectional regressions. Over the 1989–2009 period, the average adjusted R-squared rises from 8.34% (with *MKT* and *FOREX*) to 14.35% (when *CREDIT* is added). Similarly, over 1999–2009 (1989–1998), the inclusion of *CREDIT* raises the adjusted R-squared from 10.60% (9.29%) to 15.70% (17.29%).

The emerging markets factor (*EMERG*) is insignificant in explaining cross-sectional differences in equity returns when the world credit risk factor (*CREDIT*) is included. In other words, emerging market countries earn higher returns because they have higher credit risk exposure, not because of their emerging market classification.

We have also examined (unreported results) the significance of the *CREDIT* factor relative to the Fama and French (1998) international

[12] The risk premiums for *CREDIT* are identical whether we orthogonalize *EMERG* relative to *CREDIT* or not. This is because the inclusion of *CREDIT* in the first-pass regression in essence ortogonalizes *EMERG*. We've also run the analysis with the *CREDIT* factor orthogonalized relative to *MKT*. The risk premiums for *CREDIT* are similar, usually about two bps higher than the ones in Panel A and are always more significant.

MKT and *HML* factors, since Fama and French (1998) find that these factors are priced in the cross-section of developed market returns. In our 1989–2009 sample of 24 developed and 51 emerging countries, the international *MKT* and *HML* factors are not priced. The world credit risk factor (*CREDIT*), however, is significantly priced at the 5% level in both the overall and second half of the sample regardless of the other factors included. When the international *MKT* and *HML* factors are included, the *CREDIT* risk premium is 84 bps per month (*t*-value of 2.40) in the overall period and 87 bps per month (*t*-value of 2.52) in the second half. Over 1989–1998, the *CREDIT* risk premium is 85 bps (*t*-value of 1.51). Over 1989–2009, the average adjusted R-squared almost doubles from 6.73% (when *MKT* and *HML* are considered) to 12.57% (when *CREDIT* is added). The emerging markets factor is again insignificant when *CREDIT* is included.

We have also tested the significance of the world credit risk premium relative to Lee's (2011) global and local liquidity factors. Panel B of Table 4 presents the results for the global liquidity factor (results based on local liquidity factors are similar). The tests cover the second half of the period (1999–2007) as data are unavailable for most of the first half. The *CREDIT* risk premium is 94 bps per month (*t*-value of 2.42) when the *MKT* and global liquidity factors are included. The inclusion of the *CREDIT* factor raises the average adjusted R-squared from 12.33% to 18.41%.

We also test the robustness of the *CREDIT* factor to liquidity risk over the entire period using the Pastor-Stambaugh traded U.S. liquidity factor, following Lee's (2011) finding that the U.S. market is an important driving force for global liquidity. Over the 1989–2009 period, the world credit risk premium amounts to 77 bps per month (*t*-value of 2.20, Panel C) when the world-market and U.S. liquidity factors are included. The average adjusted R-squared again rises from 7.87% to 13.17% with the inclusion of the *CREDIT* factor.

The *CREDIT* risk premium remains strongly significant at 86 bps per month (*t*-value of 2.44) over the 1989–2009 period when the *MKT* and international momentum factors are included (Panel D). The adjusted R-squared rises from 9.10% to 14.51% due to the inclusion of *CREDIT*. However, relative to the other factors studied, the international momentum factor carries a significant positive premium when *CREDIT* is included, but not otherwise.

We also show that the world credit risk premium is robust to using time-varying betas. In Panel E, the 60-month rolling-regression betas, β_{it-1}, used in month *t*'s second-pass cross-sectional regression are estimated in the first pass based on time-series regressions of excess returns on the factors from month $t-60$ to month $t-1$. Since 60 months of past monthly data are needed to estimate the betas for the first cross-sectional regression, we focus on the second half of the sample period. The *CREDIT* risk premium is significant at the 1% level in all specifications. When *MKT* and *FOREX* are included, the *CREDIT* risk premium is 90 bps per month (t-value of 3.22) with rolling-regression betas versus 84 bps per month with constant betas (see Panel A) over the 1999–2009 period. *MKT*, *FOREX*, and *EMERG* are insignificant in all specifications with rolling-regression betas.

For Panel F, conditional betas are estimated for each country i in the following time-series regression: $r_{it} = a_i + b_{0i}F_t + b_{1i}Z_{t-1} \times F_t$, where the conditional betas, $\beta_{it-1} = b_{0i} + b_{1i}Z_{t-1}$, are used in the second-pass cross-sectional regression for month t. Z_{t-1} contains the following instruments: MKT_{t-1} (lagged *MKT* return), rf_{t-1} (the U.S. risk free rate), $Term_{t-1}$ (the term premium: the difference between the yield on 10-year U.S. Treasuries and the U.S. risk free rate), TED_{t-1} (the TED spread: the difference between the three-month Eurodollar rate and the three-month U.S. T-bill yield), and DY_{t-1} (the dividend yield on the MSCI world-market index over the past 12 months). These instruments are used in Ferson and Harvey (1993) in an international setting.

The *CREDIT* risk premium is even higher with conditional betas. Over the 1999–2009 period, when *MKT* and *FOREX* are included, the *CREDIT* risk premium is 102 bps per month (t-value of 3.15) and the adjusted R-squared is 28.62%, almost double that with constant betas (15.70%). For robustness, we have tried alternative instrument subsets of the five mentioned above, as well as including DEF_{t-1} (the default premium calculated as the yield differential between BBB and AAA rated U.S. corporate bonds). The results are similar: the monthly *CREDIT* risk premium ranges between 106 bps and 108 bps (when *MKT* and *FOREX* are included and even higher in some other specifications) and is always significant at the 1% level regardless of the instruments or factors included.

The overall evidence from Table 4 shows that the world credit risk factor is significantly priced in the cross-section of country equity returns. Exposure to this factor carries a monthly risk premium ranging between 77 and 94 bps (even higher with conditional betas). Moreover, it is the most significant factor in explaining the cross-section of country equity returns compared to previously studied world-market, foreign exchange, liquidity, Fama and French (1998) *MKT* and *HML*, momentum, and emerging market factors.

3.2.2 Factor versus characteristic. A potential concern in the analysis implemented here is that the explanatory power of the "high-minus-low" credit risk factor may be spurious. In particular, Ferson, Sarkissian, and Simin (1999) (FSS) argue that high-minus-low attribute-sorted portfolios may appear to be useful risk factors if the chosen attributes are related to the cross-section of stock returns, even when such attributes are completely unrelated to risk. In our context, the impact of the world credit risk factor on the cross-section of country equity returns may simply be a manifestation of the effect of credit ratings on the cross-section of country equity returns, as shown by Erb, Harvey, and Viskanta (1995, 1996).

To address this concern, we perform a simulation analysis in which we generate 1,000 data samples under the null hypothesis that credit rating, the characteristic, is the only cross-sectional driver of country equity returns. We then obtain the distributions of sample risk premiums and R-squared implied by a spurious high-minus-low factor. We assess the likelihood that the risk premiums and R-squared based on actual data come from these distributions.

The simulation study is performed as follows: we first run monthly cross-sectional regressions of country equity excess returns of country i, r_{it}, on lagged credit ratings, $Rating_{it-1}$, as in Table 3:

$$r_{it} = a_t + b_t * Rating_{it-1} + e_{it} \tag{1}$$

to obtain estimates of the average cross-sectional intercept, $\hat{a}$, and slope coefficient, $\hat{b}$. We then generate 1,000 data sets, drawing vectors of monthly returns from a multivariate normal distribution:

$$\begin{bmatrix} \hat{r}_{1t} \\ \vdots \\ \hat{r}_{Nt} \end{bmatrix} \sim MVN\left(\hat{a}+\hat{b}\begin{bmatrix} Rating_{1,t-1} \\ \vdots \\ Rating_{N,t-1} \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_N^2 \end{bmatrix}\right), \tag{2}$$

where $\sigma_i^2, i = 1, \dots, N,$ is the sample variance of country i's regression residuals, e_{it}, in Equation (1) and N is the number of countries. The diagonal covariance matrix imposes the restriction of no common variation in the simulated "unexpected" returns. For each of the 1,000 simulated data sets, we obtain a high-minus-low credit risk factor, $CREDIT_j$. We then repeat the asset pricing tests of Table 4, Panel A, specification 3. We obtain, for each simulated data sample, an average of the monthly estimates of the risk premium, $\hat{\lambda}_j$, and an average adjusted R_j^2 from the cross-sectional regressions.

Table 5 reports the percentiles of the distributions of $\hat{\lambda}_j$ and R_j^2, generated under the null that the characteristic, rather than the factor, drives country equity returns. These distributions provide statistical bounds on the risk premium and cross-sectional R-squared. The last two rows report the risk premium, $\hat{\lambda}$, and adjusted R-squared based on the actual excess returns reported in Table 4, Panel A, specification 3, as well as the implied p-value of $\hat{\lambda}$.

The results show that the world credit risk factor risk premium of 86 bps per month estimated from the actual data is significantly higher (p-value of 0.03) than the premium implied by a spurious high-minus-low factor. Moreover, the average adjusted R-squared of 6.03%, based on the actual data, is significantly higher than the one based on a spurious high-minus-low factor. The results are robust to the inclusion of MKT (Table 4, specification 4) and $FOREX$ (specification 5) factors in the asset pricing tests, as well as in

Table 5
Bounds on a potentially spurious world credit risk factor due to sorting on characteristics

	Risk Premium $\hat{\lambda}$ (%)	Adj.R^2 (%)
Distribution of estimates based on simulated data		
1^{th} percentile	−0.09	2.73
5^{th} percentile	0.05	3.10
10^{th} percentile	0.12	3.28
25^{th} percentile	0.26	3.61
50^{th} percentile	0.42	4.01
75^{th} percentile	0.59	4.44
90^{th} percentile	0.72	4.80
95^{th} percentile	0.79	5.03
99^{th} percentile	0.98	5.45
Estimates based on actual data		
Estimate	0.86	6.03
p-value of estimate	0.03	0.00

We simulate data under the null hypothesis that country equity returns are purely driven by credit rating, the characteristic. First, each month t ($t = 1, \ldots, T$), we run cross-sectional regressions of excess country equity returns on lagged credit ratings and then average the cross-sectional intercepts and slope coefficients:

$$r_{it} = a_t + b_t * Rating_{it-1} + e_{it} \qquad \hat{a} = \frac{1}{T}\sum_{t=1}^{T} a_t \qquad \hat{\beta} = \frac{1}{T}\sum_{t=1}^{T} \beta_t.$$

Then, each month, t, we draw an $N \times 1$ return vector from a multivariate normal distribution:

$$\begin{bmatrix} \hat{r}_{1t} \\ \vdots \\ \hat{r}_{Nt} \end{bmatrix} \sim MVN\left(\hat{a}+\hat{b}\begin{bmatrix} Rating_{1,t-1} \\ \vdots \\ Rating_{N,t-1} \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \ldots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \ldots & \sigma_N^2 \end{bmatrix}\right),$$

where σ_i^2 is the variance of the (time-series vector of) residuals, e_{it}, of country i ($i = 1, \ldots, N$). We draw 1,000 data samples. For each data sample, j ($j = 1, \ldots, 1{,}000$), we construct a high-minus-low credit risk factor, $CREDIT_j$, repeat the asset pricing tests of Table 4 (Panel A, specification 3), and compute $\hat{\lambda}_j$ and R_j^2 as the averages of the monthly cross-sectional regression estimates. The table reports the percentiles of the distributions of $\hat{\lambda}_j$ and R_j^2 across the 1,000 data samples. The last two rows report the risk premium and adjusted R^2 (with their sample p-values) based on the actual excess returns as in Table 4, Panel A, specification 3. The test is performed over the sample period from January 1989 to December 2009.

the second half of the sample.[13] Thus, the impact of *CREDIT* is not spurious and significantly exceeds the explanatory power of credit ratings.

3.2.3 Time-series tests. In the time-series tests, we show that the efficiency of the world credit risk factor cannot be rejected using Gibbons, Ross, and Shanken (1989) finite sample tests. In contrast, the efficiency of traditional combinations of potentially relevant global factors is typically rejected. The GRS sample test statistic is given by

$$J = \frac{T-N-K}{N}\left[1+\hat{E}(f)'\hat{\Omega}^{-1}\hat{E}(f)\right]\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}, \tag{3}$$

[13] Including *MKT* and *FOREX* produces different sample distributions, but the *CREDIT* risk premium and cross-sectional adjusted R-squared estimates based on actual data are again significantly higher than the ones under the null that only the characteristic explains the variation in country equity returns.

Table 6
Gibbons, Ross, and Shanken (1989) finite sample tests

Factor	J-statistic	p-value	95% Critical Value
MKT	1.92	0.00	1.50
FOREX	13.90	0.00	1.50
MKT+ FOREX	14.11	0.00	1.51
FF93 *MKT+ HML*	1.64	0.03	1.51
EMERG	1.57	0.03	1.50
CREDIT	0.96	0.55	1.50

The table presents results from Gibbons, Ross, and Shanken's (1989) (GRS) finite sample tests of the efficiency of a given factor. The GRS sample test statistic is $J = \frac{T-N-K}{N}\left[1+\hat{E}(f)'\hat{\Omega}^{-1}\hat{E}(f)\right]\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}$, where $J \sim F_{N,T-N-K}, \hat{\alpha} = [\hat{\alpha}_1, \hat{\alpha}_2, ..., \hat{\alpha}_N]'$ are the estimated intercepts from individual time-series regressions and $\hat{\epsilon}_t = [\hat{\epsilon}_t^1, \hat{\epsilon}_t^2, ..., \hat{\epsilon}_t^N]'$ for $t = [1, 2, ..., T]$ are the estimated residuals, $\hat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T} \epsilon_t \epsilon_t'$ is the residual covariance matrix, $\hat{\Omega}$ is the estimated covariance matrix of the factors, K is the number of factors, N is the number of test assets, and T is the number of time-series observations. The test assets are country equity returns with non-missing observations from January 1999 to December 2009: a total of 52 countries. The factors are described in Tables 2 and 4.

where $J \sim F_{N,T-N-K}, \hat{\alpha} = [\hat{\alpha}_1, \hat{\alpha}_2, ..., \hat{\alpha}_N]'$ are the estimated intercepts from individual time-series regressions (the statistic tests whether these alphas are jointly equal to zero), $\hat{\epsilon}_t = [\hat{\epsilon}_t^1, \hat{\epsilon}_t^2, ..., \hat{\epsilon}_t^N]'$ for $t = [1, 2, \ldots, T]$ are the estimated residuals, $\hat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T} \epsilon_t \epsilon_t'$ is the residual covariance matrix, $\hat{\Omega}$ is the estimated variance covariance matrix of the factors, K is the number of factors, N is the number of test assets, and T is the number of time-series observations. The GRS test statistic requires a balanced panel of test asset returns with an equal number of non-missing observations. The tests are based on the second half of the sample due to the smaller number of countries with non-missing observations over the entire period. The test assets are country equity returns with non-missing observations over the January 1999 to December 2009 period: a total of 52 countries. Table 6 presents the results.

The efficiency of the world credit risk factor (*CREDIT*) cannot be rejected, as indicated by a p-value of 0.55. In contrast, the efficiency of the world-market factor (*MKT*), the traded foreign exchange factor (*FOREX*), and a two-factor model with *MKT* and *FOREX* are strongly rejected with p-values less than 0.001. Further, the efficiency of the emerging markets factor (*EMERG*) and that of the Fama and French (1998) *MKT* and *HML* factors are also rejected at the 5% level (both test statistics have a p-value of 0.03).

3.2.4 The world credit risk factor and the macroeconomy. In the general equilibrium model of Gomes and Schmid (2010), movements in credit spreads are largely driven by fluctuations in credit risk premiums rather than solely by changes in default rates. Credit risk premiums emerge because default losses more likely occur in bad times, precisely when consumption is low and marginal utility is high. The countercyclical nature of credit spreads also causes

Table 7
World consumption and GDP growth and the credit risk factor

Variable	Time-Series Regression $Y_t = a + b * CREDIT_{t-1} + e_t$ $\hat{b}$	Correlation Coefficient $\rho(Y_t, CREDIT_{t-1})$
Full Sample: 1989–2009		
Y = World Consumption Growth	0.00	0.10
	(0.41)	
Y = World GDP Growth	0.02	0.25
	(1.11)	
First Part: 1989–1998		
Y = World Consumption Growth	−0.00	−0.17
	(−0.46)	
Y = World GDP Growth	−0.00	−0.07
	(−0.18)	
Second Part: 1999–2009		
Y = World Consumption Growth	0.03	0.56
	(1.90)*	
Y = World GDP Growth	0.07	0.62
	(2.23)**	

We annualize returns of the world credit risk factor, *CREDIT*, to match the annual frequency of world Consumption Growth and world GDP Growth data obtained from the World Bank. The world consumption and GDP growth rates are expressed in real terms based on constant 2000 U.S. dollars. We run time-series predictive regressions of Consumption and GDP Growth on a constant and lagged returns of the *CREDIT* factor and report the slope coefficient with its associated *t*-statistic in parentheses (*, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively). The last column reports the correlation coefficients of world Consumption Growth and GDP Growth on lagged returns of the *CREDIT* factor.

credit risk premiums to be countercyclical. Thus, investors require higher compensation for credit risk in recessions, raising the cost of capital, further depressing investments and output growth, and thus amplifying recessions. Therefore, their model endogenously generates a significant credit risk premium and predicts that credit risk premiums forecast future movements in aggregate output by predicting future movements in corporate investment. Our evidence that the credit risk factor is priced and commands a large positive premium is consistent with the first theoretical prediction of the Gomes and Schmid (2010) general equilibrium model. Next we investigate whether the world credit risk premium predicts future world GDP and consumption growth.

We use real growth rates in world GDP and world consumption. The two series are available from the World Bank[14] at the annual frequency under “GDP growth (annual %)” and “Final consumption expenditure, etc. (annual % growth)” for the world, respectively.

Since our world credit risk factor is computed as the realized return differential between high and low credit risk countries (rather than as credit spreads), higher values of our credit risk factor should predict higher future GDP growth and higher future consumption growth. We test these predictions in Table 7. The returns of the world credit risk factor, *CREDIT*, are annualized to match the annual frequency of world consumption growth and

[14] Data are available at http://data.worldbank.org/indicator/all.

Table 8
Abnormal returns and pricing errors

	First Pass: Time-Series Regressions					Second Pass: Cross-Sectional Regressions
	Constant (%)	*MKT*	*FOREX*	*CREDIT*	Adj.R^2 (%)	Average Pricing Errors (%)
24 Developed markets						
1	0.24	1.04			50.27	−0.30
	(1.74)*	(34.62)***				(−2.43)**
2	0.17	0.85	−1.71		52.25	−0.29
	(1.23)	(19.30)***	(−5.31)***			(−2.32)**
3	0.09	0.86	−1.76	0.08	54.00	−0.05
	(0.68)	(19.67)***	(−5.57)***	(2.45)**		(−0.88)
4	0.17	1.06		0.08	51.92	−0.08
	(1.19)	(34.60)***		(2.35)**		(−1.35)
51 Emerging markets						
1	0.57	1.01			21.48	0.36
	(2.73)***	(23.07)***				(2.72)***
2	0.46	0.81	−1.75		22.84	0.34
	(2.16)**	(10.10)***	(−3.04)***			(2.62)***
3	−0.04	0.90	−1.37	0.79	29.49	0.02
	(−0.25)	(14.11)***	(−2.94)***	(15.15)***		(0.37)
4	0.04	1.06		0.79	28.05	0.06
	(0.25)	(33.88)***		(15.13)***		(1.05)

The table presents the abnormal returns (average intercept) from the time-series regressions (first pass) and average pricing errors in the cross-sectional regressions (second pass) for developed and emerging countries. We first run time-series regressions of country equity excess returns on a constant and the factors, and report the average intercept (in percentages per month), factor loadings, and average adjusted R^2. We then run cross-sectional regressions (across all countries) of excess returns on a constant and the estimated betas from the first pass and report the average pricing errors in developed and emerging markets (i.e., the time-series average of the cross-sectional mean error term in developed and emerging markets). *t*-statistics are based on the time-series averages (*, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively). The factors are defined in Table 4. The sample period is from January 1989 to December 2009.

world GDP growth data. We run time-series predictive regressions of consumption growth and GDP growth on a constant and lagged returns of the *CREDIT* factor. Note that the coefficient estimates are positive and significant over the second part of the sample period, during 1999–2009, when markets are more likely to be integrated and the *CREDIT* factor is strongly significant. The correlation between lagged *CREDIT* and world consumption growth and GDP growth during 1999–2009 is as high as 0.56 and 0.62, respectively.

3.2.5 The world credit risk factor and country characteristics. We examine whether the world credit risk factor is able to capture the positive pricing errors in emerging markets reported in the literature, as well as the cross-sectional predictive power of credit ratings and other country characteristics for equity returns.

Table 8 presents coefficient estimates from time-series regressions and average pricing errors from cross-sectional regressions for developed and emerging countries. We first run time-series regressions of country equity excess returns on a constant and asset pricing factors, and report the average intercept, factor loadings, and adjusted R-squared. We then run cross-sectional regressions (across all countries) of excess returns on a constant and the estimated betas from the first pass. We report the average pricing errors in developed and emerging markets, i.e., the time-series average of the cross-sectional mean error term in developed and emerging markets. The average adjusted R-squared of these cross-sectional regressions were reported in the last column of Table 4.

The *MKT* and *FOREX* factors explain on average 52.25% of the time-series variation in developed country equity returns and about 22.84% of that in emerging markets. These results are consistent with findings in the literature that the global *MKT* and *FOREX* factors work better in developed markets. In both developed and emerging markets, the average country *MKT* (*FOREX*) beta is significantly positive (negative), but the average country time-series intercept is significantly positive. The regression intercepts reflect pricing errors, and their significance attests to the pricing failure of the *MKT* and *FOREX* factors.

The world credit risk factor, *CREDIT*, is able to capture the positive pricing errors in emerging markets. Including *CREDIT* in the time-series regressions increases the adjusted R-squared to 54% in developed and to 29.49% in emerging markets. The average *CREDIT* beta is a highly significant 0.79 for emerging markets, and for developed markets it is a significant 0.08. The reported t-statistics are based on standard errors computed to allow for cross-sectional correlation across the residuals. Specifically, the regression equation can be written as $y_m = X_m\beta_m + \eta_m$, where $m = 1, \cdots, M,$ and M is the number of regressions. The $k \times 1$ vector of coefficient estimates from the mth regression is $\hat{\beta}_m$, and the average coefficient estimate that we report is $\hat{\bar{\beta}} = \frac{1}{M}\sum_m \hat{\beta}_m$. The variance of this average estimate is given by

$$\mathrm{Var}(\hat{\bar{\beta}}) = \frac{1}{M^2}\left[\sum_{m=1}^{M}\mathrm{Var}(\widehat{\beta_m}) + \sum_{m=1}^{M}\sum_{n=1,\, n\neq m}^{M}\mathrm{Cov}(\widehat{\beta_m}, \widehat{\beta_n})\right], \tag{4}$$

where $\mathrm{Var}(\widehat{\beta_m}) = \frac{\widehat{(\eta_m'\eta_m)}}{(T-k)}(X_m'X_m)^{-1}$, and $\mathrm{Cov}(\widehat{\beta_m}, \widehat{\beta_n}) = \frac{\widehat{(\eta_m'\eta_n)}}{(T-k)}(X_m'X_m)^{-1}(X_m'X_n)(X_n'X_n)^{-1}$.

The second-pass cross-sectional results in Table 8 confirm previous evidence that when the *MKT* and *FOREX* factors are considered, the average pricing errors in emerging markets are significantly positive—they are on average 34 bps per month. However, when exposure to the *CREDIT* factor is taken into account, the average pricing errors become statistically insignificant two bps per month. We have also checked that the average absolute errors are also much lower with the *CREDIT* factor.

The higher returns in emerging market countries are explained by their higher exposure to the world credit risk factor. This evidence is novel, as the international asset pricing literature has documented consistent positive pricing errors in emerging markets unexplained by existing global factors. Of course, because average pricing errors in each cross-sectional regression average to zero, positive pricing errors in emerging markets imply negative pricing errors in developed markets. In the same vein, pricing errors in developed countries become insignificant in the presence of the *CREDIT* risk factor.

Table 9 shows that the importance of credit ratings for the cross-section of country equity returns disappears after controlling for exposure to the world credit risk factor. Specifically, we obtain risk-adjusted returns as the sum of intercept and residuals in time-series regressions of country equity excess returns on the world-market and world credit risk factors (*MKT* and *CREDIT*). Using risk-adjusted returns, we repeat the analysis previously performed with raw returns in Panel A of Table 2. The worst credit rating tercile (C3) delivers risk-adjusted returns that are only 10 bps higher (statistically insignificant) than those in the best-rated tercile (C1).[15] Recall from Panel A of Table 2 that over that same period (1989–2009), C3 countries generate 57 bps higher raw returns relative to C1 countries. Moreover, recall from Panel B of Table 2 that adjusting for existing international risk factors produces even higher and more significant return differentials.

We further examine the impact of credit ratings on average returns through cross-sectional regressions as in Table 3, but after risk-adjusting returns with the world credit risk factor along with the world-market factor. Note that credit rating was significant in explaining cross-sectional differences in country equity returns among all specifications in Table 3. However, when returns are risk-adjusted with the *CREDIT* factor, all regression coefficients of the credit rating variable in Panel B of Table 9 are insignificant. In other words, controlling for systematic exposure to the world credit risk factor crowds out the power of credit ratings to predict cross-sectional differences in country equity returns. Exposure to the world credit risk factor fully explains the higher returns of high credit risk countries.

The majority of high credit risk countries are also emerging markets. Hence, in Table 10, we test whether the emerging markets factor explains the higher returns of high credit risk countries. Specifically, as in Table 2, we compute the equally weighted average equity return of the best-, medium-, and worst-rated countries, sorted on their prior-month credit rating. We then run time-series regressions of each portfolio, C1, C2, and C3, excess return relative to the risk-free rate and the return differential, C3 − C1, on a constant, the world-market factor (*MKT*), and the emerging markets factor (*EMERG*), orthogonalized relative to the *MKT* and *CREDIT* factors. Table 10 reports portfolio alphas and betas. The evidence suggests the emerging markets factor does not explain the higher returns of high credit risk

[15] Recall that for robustness, we checked the importance of credit ratings in predicting future country returns excluding "frontier" countries. Similarly, in unreported results, we confirmed that the predictive power of credit ratings disappears after controlling for *CREDIT* after excluding "frontier" countries as well.

Table 9
Impact of rating on returns adjusted for exposure to the world credit risk factor

Panel A: Credit-risk-adjusted returns by sovereign credit rating group

	Sovereign Rating Group (C1 = Lowest, C3 = Highest Risk)			
	C1	C2	C3	C3-C1
r^*_{t+1}	0.20	−0.09	0.30	0.10
	(1.79)*	(−0.50)	(2.27)**	(1.42)
$r^*_{t+1:t+6}$	1.31	−0.17	1.60	0.29
	(2.35)**	(−0.22)	(2.19)**	(0.87)
$r^*_{t+1:t+12}$	2.85	0.12	3.07	0.22
	(5.43)***	(0.16)	(3.89)***	(0.53)

Panel B: Cross-sectional regressions of credit-risk factor-adjusted returns

Specification	**Constant**	$Rating_t$	$Rating_t \times EmDummy$
$r^*_{i,t+1}$ = returns adjusted for exposure to *MKT* and *CREDIT*			
1	0.05	0.02	
	(0.43)	(1.42)	
2	0.14		−0.01
	(1.17)		(−0.30)
3	−0.02	0.08	−0.06
	(−0.15)	(1.43)	(−1.14)
$r^*_{i,t+1}$ = returns adjusted for exposure to *MKT*, *FOREX*, and *CREDIT*			
1	−0.00	0.03	
	(−0.03)	(1.44)	
2	0.09		−0.01
	(0.77)		(−0.23)
3	−0.05	0.06	−0.04
	(−0.38)	(1.12)	(−0.82)

For Panel A, we risk-adjust returns by regressing country equity excess returns on the world market (*MKT*) and world credit risk (*CREDIT*) factors following Brennan, Chordia, and Subrahmanyam (1998). The risk-adjusted returns, r^*_{it}, are the intercept and residual from these time-series regressions. We then repeat the analysis in Panel A of Table 2 using risk-adjusted rather than raw returns. For Panel B, returns are again risk-adjusted by the *MKT* and *CREDIT* (or *MKT*, *FOREX*, and *CREDIT*) factors. Then, as in Table 3, we run monthly cross-sectional regressions of time $t+1$ risk-adjusted country equity returns, $r^*_{i,t+1}$, on a constant, time t sovereign credit ratings, $Rating_t$, and rating interacted with an emerging market dummy, *EmDummy*, indicating whether the country is developed (0) or emerging market (1). Panel B presents the time-series average of the cross-sectional regression coefficients (in percentages) with their associated sample t-statistics in parentheses (*, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively). The sample period is from January 1989 to December 2009.

countries. In particular, C3 countries earn 58 bps higher risk-adjusted returns than C1 countries and this difference is significant at the 5% level (t-value = 2.21). These C3 – C1 alphas are slightly higher than the raw C3 – C1 returns of 57 bps per month in Panel A of Table 2. Moreover, the *EMERG* beta of C3 countries is identical to that of C1 countries. Hence, emerging market countries earn higher returns not because they are classified as emerging or have a higher credit rating, but because they have higher exposure to the world credit risk factor.

The world credit risk factor captures the explanatory power of other country characteristics found important in the literature. As in Harvey (2000), we run univariate cross-sectional regressions of average country equity returns on a local risk measure (along with a constant) and report the regression

Table 10
Country equity returns by sovereign credit rating group adjusted for the emerging markets factor

	Sovereign Rating Group (C1 = Lowest, C3 = Highest Risk)			
	C1	C2	C3	C3-C1
Alpha	0.18	0.12	0.76	0.58
	(1.76)*	(0.67)	(2.70)***	(2.21)**
MKT Beta	1.04	0.98	0.98	−0.06
	(45.99)***	(23.75)***	(15.33)***	(−1.01)
EMERG Beta	0.22	0.35	0.22	0.00
	(8.83)***	(7.73)***	(3.13)***	(0.00)

Each month, t, all countries rated by Standard & Poor's are divided into terciles based on their sovereign credit rating. For each tercile, we compute the cross-sectional mean country equity return for month $t+1$. We run time-series regressions of each portfolio, C1 to C3, excess return relative to the risk-free rate and the return differential, C3 − C1, on a constant, the world market factor (*MKT*) and the emerging markets factor (*EMERG*) and report the portfolio alphas (in percentages) and betas. The factors are described in Tables 2 and 4. t-statistics are in parentheses (*, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively). The sample period is from January 1989 to December 2009.

coefficient with respect to the country-level characteristic. Table 11 shows that coskewness and average credit rating are indeed predictors of average equity returns. In addition, when returns are risk-adjusted for exposure to the market factor (second column) as in Brennan, Chordia, and Subrahmanyam (1998), country-level return variance also significantly explains cross-sectional differences in average returns. However, when returns are risk-adjusted with either the world credit risk factor (third column) or both the world credit risk factor and the world-market factor (last column), none of the country characteristics exhibit any explanatory power for the cross-section of risk-adjusted returns.

4. Conclusion

This paper offers a risk-based explanation for previously documented patterns in the cross-section of country equity returns, thus far unexplained by international asset pricing models. Among these prominent patterns are large positive pricing errors among emerging market country returns, as well as the documented important role of a number of country-level characteristics in pricing international equities. Using portfolio sorts and cross-sectional regressions, we present evidence of a significant positive relation between sovereign credit risk and country equity returns. Higher credit risk countries earn higher returns that are not explained by existing asset pricing models.

We find that these higher premiums compensate for exposure to a world credit risk factor. The choice of the world credit risk factor as an alternative to a consumption-based pricing formulation is motivated by a strong link between credit risk and consumption growth risk. Credit risk significantly impacts consumption growth and commands a risk premium.

Table 11
Cross-sectional regressions of average returns on country-level characteristics

Country Characteristic	$\overline{r_{it}}$	$\overline{r^*_{it}\|MKT}$	$\overline{r^*_{it}\|CREDIT}$	$\overline{r^*_{it}\|MKT, CREDIT}$
Rating	0.07	0.08	0.03	0.03
	(2.05)**	(2.61)***	(0.90)	(0.92)
Standard deviation of returns	3.47	7.97	1.33	−2.59
	(0.81)	(2.14)**	(0.31)	(−0.58)
Coskewness 1	2.09	1.60	0.90	1.36
	(2.44)**	(2.14)**	(1.26)	(1.51)
Coskewness 2	0.81	0.53	0.39	0.65
	(1.71)*	(1.21)	(0.88)	(1.34)

We run cross-sectional regressions of average monthly country equity returns on a constant and a country-level characteristic previously found to explain cross-sectional differences in country returns. To compute co-skewness, as in Harvey (2000), we use a world version of the single-factor model: $r_{it} - rft = a_i + b_i(r_{mt} - r_{ft}) + e_{it}$, where r_{it} are country i's equity return in month t, r_{mt} is the return on the MSCI world equity index, r_{ft} is the U.S. risk-free rate, and e_{it} is the residual. Coskew1 is coskewness as per definition 1 of Harvey (2000), computed as $\text{Coskew1} = \frac{\left(\sum_t e_{it} \times e_{mt}^2\right)/T}{\sqrt{\left(\sum_t e_{it}^2\right)/T}\left(\sum_t e_{mt}^2\right)/T}$, where $e_{mt} = r_{mt} - mean(r_{mt})$. Coskew2 is coskewness as per definition 2 of Harvey (2000), computed as $\text{Coskew2} = \frac{\left(\sum_t e_{it} \times e_{mt}^2\right)/T}{\left(\sigma_{e_{mt}}\right)^3}$. The table presents the regression coefficient with respect to the country-level characteristic with its associated t-statistics in parentheses (*, **, and *** indicate the 10%, 5%, and 1% levels of significance, respectively). The first column presents results for raw returns, r_{it}. For the remaining columns, we use risk-adjusted returns, $r^*_{it}|factor$. Returns are adjusted as in Brennan, Chordia, and Subrahmanyam (1998) by running time-series regressions of each individual country return on risk factors (as specified in the heading of each column). The risk adjusted returns, r^*, is the intercept and residual from these time-series regressions. The sample period is from January 1989 to December 2009.

Our analysis shows that the world credit risk factor is significantly priced in the cross-section of country equity returns. The world credit risk factor risk premium averages 80 bps per month over the 1989–2009 period and is robust to alternative risk factors proposed in the international asset pricing literature. Exposure to the credit risk factor explains the higher returns of high credit risk countries. In the presence of the credit risk factor, country-level credit ratings, variance, and coskewness no longer have predictive power for the cross-section of country equity returns. Furthermore, the credit risk factor fully captures the previously documented positive pricing errors in emerging markets. Moreover, the credit risk factor subsumes the explanatory power of the emerging markets factor. Emerging markets earn higher returns not because they are classified as emerging or have worse credit ratings. Rather, they exhibit higher exposure to the world credit risk factor.

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