Comovement or Safe Haven? The Effect of Corruption on the Market Risk of Sovereign Bonds of Emerging Economies during Financial Crises

Michal Paserman*

Graduate Institute of International and Development Studies, Geneva

and Webster University Geneva

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Abstract

In this study I explore the role of corruption in the cross-market time-varying linkage between sovereign bonds of emerging markets and the US stock market. It shows that corruption plays a prominent role in the behaviour of CAPM beta under different market conditions. The sensitivity of sovereign bonds issued by countries perceived as more corrupt to systematic shocks, increases during financial crises. The prices of bonds issued by less corrupt countries are determined more idiosyncratically under extreme market conditions, and realize more hedging benefits against S&P 500 risk. To explain these findings I integrate results from behavioural finance. I propose a comovement model built on Barberis et al. (2005) where investors load more worldwide news on sovereign bonds issued by more corrupt countries when their sentiment deteriorates.

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* Tel.: +41.(0)78.771.43.37, Email Address: paserman@webster.ch

1. Introduction

The main hypothesis of this study is that prices of sovereign bonds issued by more corrupt EMs (emerging markets) move more closely with global markets during crises, and are thus more prone to sell-offs when sentiment deteriorates.

Panel data and GARCH estimations provide evidence supporting this hypothesis. I show that under extreme market conditions, returns on more corrupt countries exhibit greater comovement with returns on the S&P 500 index.

Corruption is defined as "the misuse of entrusted authority for private benefit" (Transparency International). It is pervasive in all countries, however on different scales. Debate has been developing on the effects of corruption on investment, development and economic growth of emerging markets (Mauro, 1995 and Shleifer and Vishny, 1993), and it is widely regarded as an important player in financial crises (e.g. Ciocchini, Durbin and Ng, 2003).

Sovereign bonds are the main form of finance for sovereign borrowers, and have become an important asset class in portfolios.[1] Many EMs depend on foreign capital for their development and to cover financial needs, and rely on continuous inflows of funds through international bond markets.

Thus, intriguing questions are: Is a country's level of corruption an important determinant in sovereign risk? Furthermore, what role does corruption play for emerging markets cost of capital during periods of financial crises? One recent example of such a possible link is the Greece debt crisis triggered by the Subprime Crisis and the collapse of Lehman Brothers in 2008. The corruption in Greece was regarded by many commentators as a key driver of the spillover[2].

A sovereign's creditworthiness is linked to corruption through both the sovereign's ability and willingness to repay its debt. Corruption drives unofficial economic activity. Thus, all else being equal, higher corruption decreases tax collection, the sovereign's income, and its ability to repay its debt (Johnson et al., 1997). Corruption is also associated with resource misallocation, which could be harmful to economic growth and affect solvency (Depken et al., 2006). Furthermore, corruption is an immoral and unethical phenomenon of dishonest or illegal behaviour, especially of people in the authority (Seldadyo and Haan, 2006). In the

[1] For survey of the literature on sovereign debt see Panizza, Sturzenegger, and Zettelmeyer, 2009.
[2] See for example Atkins and Hope, 2010.

absence of direct bankruptcy code to protect sovereign bond holders in the event of default, redeeming a country's debt is largely a political decision and depends on the willingness of the people in power to repay it. More corrupt countries supply less legal protection during normal times, and are more likely to violate investors' rights during crises. Adama (2013) discusses the effect of corruption on debt repayment and default under different market conditions. It shows that the level of corruption affects borrowing and default decisions together with business cycle fluctuations, and that corruption amplifies the effect of negative shocks. Corrupt officials may confiscate loans or other sources of government income, limiting the government's ability to meet debt obligations. Officials may be willing to borrow substantial funds even with high interest rates in order to create room for stealing (Shleifer and Vishny, 1993 and Ciocchini, Durbin and Ng, 2003).

In this study I estimate panel data with fixed effects and GARCH models to study the behaviour of the comovement of returns on sovereign bonds, with these on S&P 500 over different investor sentiments. The literature on contagion highlights the comovement of sovereign bond returns with world equity markets, during times of financial turmoil, as well as in "normal" times. Longstaff et al. (2011) suggest that sovereign CDS spreads of developed and emerging markets are highly correlated, with little or no country-specific credit risk premium. They argue that global liquidity, market sentiments, and contagion account for much of the variation of sovereign spreads (see also Mauro, Sussman and Yafeh, 2002, and Gonzales-Rozada and Levy Yeyati, 2008).

In this work I provide evidence that the behaviour of EM systematic risk under different market conditions is altered by the level of corruption. Bonds issued by countries perceived as more corrupt are found to be significantly more vulnerable to global systemic events, and consequently suffer a greater increase in their relative[3] betas during financial crises. When observing betas ex post, bonds issued by less corrupt EMs, have realized more hedging opportunities during periods of crises over the last three decades.

The explanation I propose to these findings builds on Barberis et al. (2005). It generates bond prices comovement with world markets, based on news on fundamentals and investor sentiments. Beta is altered by the issuing country's level of corruption, postulating that when sentiment deteriorates information uncertainty about more corrupt countries increases more

[3] The estimation controls for time fixed effects. Thus, the estimated beta is a relative one, rather than the one originally defined in Sharpe (1964). It focuses on comovement patterns, which is of most direct interest of this study.

than it does for cleaner countries. Then, more world-wide news is capitalized into these bonds' prices, increasing their comovement with global markets.
The cross-market linkage study in the center of this paper sheds light on the relationships between EMs' level of corruption, the borrowing costs they face, and global economic cycles. The findings have important implications for global financial stability and portfolio risk management. Furthermore, this study suggests that by reducing corruption, emerging markets could benefit from global integration while decreasing potential side effects of sudden capital outflows during crises.

The remainder of the paper is organized as follows: I start in section II with the empirical evidence on the way corruption moderates the comovement of bond returns with global markets under different market conditions. Then, section III provides a theoretical framework to explain the empirical findings. In this study, I report the data first, and then provide a theoretical explanation, as the latter was motivated by the observed evidence. Section IV concludes.

2. Empirical Tests

This section documents the effect of corruption on the way bond comovement with global markets behaves under different market conditions. I show that when investor sentiment deteriorates, returns of issuers perceived as more corrupt move more closely with returns on the US market, compared with countries perceived as cleaner.
The sample covers weekly returns on international sovereign bonds of up to 50 EMs, for which J.P. Morgan's EMBI indices are available over the period January 1994-August 2011. These indices track US dollar denominated debt instruments with a requirement of minimum liquidity. This property should help reduce the bias toward zero of calculated betas over relatively high frequency, which could arise when bonds are traded infrequently relative to S&P 500 (the "Epps Effect", Epps, 1979). The market index used is the S&P 500, as in practice it is used more than any other index, such as MSCI World for world equity. Thus, it is most in line with the economic meaning of the CAPM "market portfolio".
The main corruption indicator I use for the empirical tests is Corruption Perception Index. This index is produced by Transparency International and measures the perceived levels of public sector corruption. The index is a composite index, which aggregates different sources of corruption-related data produced by a variety of independent institutions (3-13 sources for

each country, for a list of sources see Appendix 1). Consequently, it reconciles different viewpoints on corruption and is more suitable for this work than each source taken separately. The index covers more countries than any of the individual sources alone, and can efficiently differentiate the level of corruption between countries, unlike some sources where a large number of countries is assessed at the same level of corruption. Other advantages of the index for this work are that it is available for the sample period, and more importantly, it reflects financial market participants' perceptions. Thus, it is in line with the hypothesis which focuses on investor behaviour. Most alternative corruption indicators do not reflect investors' perceptions, but are rather facts or analyst opinions, that are less directly related to demand for bonds (for other advantages of the Corruption Perceived Index over other available institutional indicators see Saisana and Saltelli, 2012). [4]

Table 1 shows average corruption levels, as well as other commonly used institutional indicators averages, by split of countries according to the correlation of their returns with returns on S&P 500. EM that realize negative correlation of returns with these on S&P, are characterized by less corruption and more developed institutions on average, as measured by the different indicators. When observing the changes correlations exhibit during crises compared with normal times, it could be seen that countries which realize hedging benefits, are associated with less corruption (and stronger institutions in general).

Table 1

Institution Scores by Correlations during Crises

	Corruption (TI)	Law and Order	Bureaucracy	Corruption (ICRG)	SDDS
Negative correl. during crises	4.1	4.0	2.6	3.7	0.6
Positive correl. during crises	3.2	3.1	1.9	2.6	0.5
Negative change in correl. During crises	3.6	3.4	2.1	3.0	0.7
Positive change in correl. During crises	3.2	3.2	2.1	2.7	0.4

Notes: Higher values of the indicators imply less corruption and more developed institutions. Countries within sub-group are equally weighted. Corruption (TI) ranges from 1.6-7.2. For definition of the variables see Appendix 1.

Table 2 summarizes average betas and correlations of EM bond returns with these on S&P 500 by different percentiles of corruption levels (see Appendices 2 and 3 for full lists of countries by corruption, correlations, and betas over different market conditions). The table shows that bonds issued by countries perceived as less corrupt seem to benefit from less dependency on global markets. Furthermore, during crises, while more corrupt countries'

[4] All results are robust to replacing Correlation (Corruption Perceived Index) by ICRG's Corruption index.

comovement with the market increases, less corrupt issuers exhibit decline to even negative correlations and betas. I.e. the prices of bonds issued by cleaner countries are determined more idiosyncratically under extreme market conditions, and realize hedging benefits against S&P 500 risk. The relationship between corruption and the way returns move with the market is shown graphically in figures 1 and 2. The cleaner a country is perceived, the less closely it moves with global markets, and the less the correlation rises during crises.

Table 2

Betas and Correlations with S&P, by Corruption Level

	beta			crisis beta			correlation			crisis correlation			
	average	90% confidence interval		average	90% confidence interval		average	90% confidence interval		average	90% confidence interval		n
full sample	0.07	0.04	0.10	0.08	0.02	0.15	0.17	0.14	0.21	0.14	0.09	0.20	46
10% least corrupt	-0.01	-0.04	0.03	-0.04	-0.12	0.05	0.08	-0.08	0.24	-0.02	-0.14	0.11	5
25% least corrupt	0.02	0.00	0.03	0.00	-0.04	0.04	0.11	0.04	0.18	0.03	-0.07	0.12	12
50% least corrupt	0.04	0.02	0.06	0.05	0.01	0.08	0.15	0.10	0.20	0.09	0.01	0.16	23
50% most corrupt	0.10	0.05	0.16	0.12	0.00	0.25	0.20	0.15	0.25	0.20	0.12	0.28	23
25% most corrupt	0.14	0.06	0.23	0.19	-0.03	0.41	0.26	0.18	0.34	0.28	0.18	0.39	13
10% most corrupt	0.21	0.03	0.39	0.30	-0.25	0.85	0.22	0.15	0.29	0.23	0.14	0.32	5

Note: Countries within sub-group are equally weighted. Data are calculated weekly.

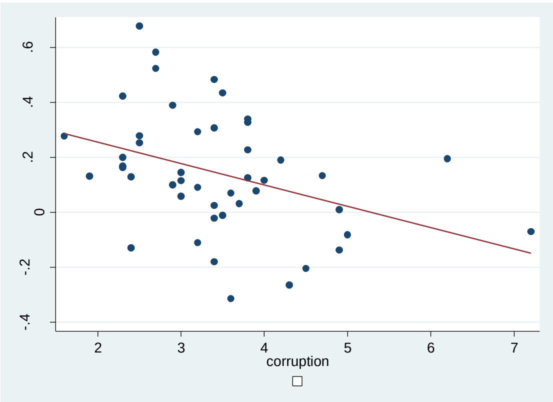

Fig. 1. Correlation of Bond Returns with Return on S&P during Crises by Corruption

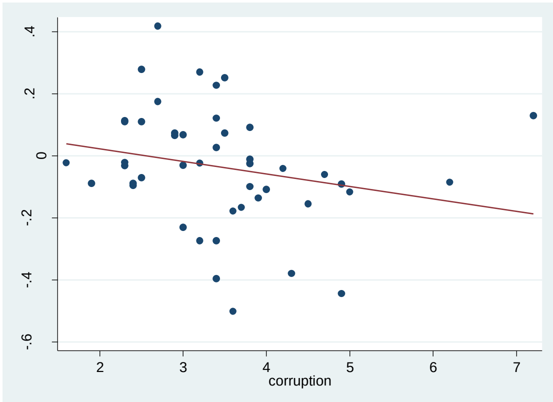

Fig. 2. Change in Correlation during Crises by Corruption

Note: Higher values of Corruption (Corruption Perceived Index) imply less corruption.

2.1. The Empirical Model

I now regress returns on EM bonds on a set of explanatory variables in a panel regression with time and country fixed effect. I encompass a series of models to study how corruption alters the way EM returns move with the market over different economic periods.

The equation estimated is:

$$r_{i,t} = \alpha_i + \tau_t + \delta' X_{i,t} + S\&P_t * \left[\eta Corr_i + \theta' X_{i,t}\right] + VIX_t * \left[\mu Corr_i + \pi' X_{i,t}\right] \quad (1)$$
$$+ S\&P_t * VIX_t * \left[\varphi + \psi Corr_i + \omega' X_{i,t}\right] + \varepsilon_{i,t}$$

In which α_i and τ_t are country and time fixed effects respectively and $X_{i,t}$ is a control matrix of determinants of sovereign bond prices (GDP growth, default history, foreign currency reserves, external debt and credit rating). The triple-interacted variable S&P*VIX*Corr aims to capture the effect of corruption on the joint comovement of EM returns with these on S&P over different investor sentiments, and is the main interest of this study. (For a discussion on VIX as a measure of investor sentiment, see Whaley, 2000). With respect to the coefficients in equation (1), the main hypothesis of this work is that:

$$\psi < 0 \quad (2)$$

A negative ψ implies that when investor sentiment deteriorates (see Whaley, 2000, for the relation between VIX and fear), bond returns are more tightly related to global markets returns whenever the issuer is perceived as more corrupt. I.e., more corrupt EMs are more vulnerable to decrease in investor sentiments, compared with cleaner issuers.

The focus of the empirical analysis in this study is on the correlation component of CAPM beta, as it most directly measures the dependency of the issuer's cost of capital on the market (see Ang and Chen, 2002, for the relationship between stock correlations and betas). Controlling for time fixed effect results in an estimated relation which represents a relative beta, rather than beta as originally defined in Sharpe (1964), which is of most direct importance to the hypothesis of this study on comovement.

The data include weekly returns on EM bonds (the dependent variable), and Corruption. Corruption is calculated as the index average over the whole sample periods, as it evolves only rather slowly. Time and country fixed effects are controlled, as well as a wide range of sovereign risk and return determinants. These include GDP growth rate, the issuer's default history since 1970, foreign currency reserves as % of import and external debt as % of GDP (see Appendix 1 for variable definitions). Other potential determinants of bond returns according to economic theory that were found consistently insignificant in earlier stages are not reported in this work. These variables include development indicators of GDP pc, infrastructure, education and infant mortality, as well as the economy size, and inflation.

Additionally, the RHS of the equation includes sovereign credit rating. One potential concern is multicollinearity generated by the inclusion of both credit rating and its components. As I show hereafter, credit rating affects bond prices beyond the creditworthiness evaluation it provides, which correlate with the other determinants. Its inclusion in the model improves, in fact, the specification.

All variables, excluding dummies, are standardized to have mean zero and standard deviation one. That helps creating comparable scales that enable detecting the relative contributions of the variables. Non-time-varying variables enter only as interacted with S&P and VIX, when the level effect is captured by the country fixed effect.

In Table 3 I summarize the main results based on the model given in equation (1). Columns 1 and 2 employ the full EM data set. The model in column 1 studies the second-order interactions and provides the general impact of corruption on the way returns correlate with S&P and VIX, as a basis for further analysis. The specification is then augmented to include the triple-interactions in Model 2, which enables countries' corruption level modify the interacted terms in column 1. If estimation improves by this modification, such a 3rd order interaction does exist. I.e. the behaviour of EM betas during different sentiments is modified by corruption. In variants 3-7 of the model I analyse the effect of corruption on the comovement of returns over various market sentiments within subsamples. Overall, the estimated coefficient ψ is found consistently negative and significant, in line with the paper main hypothesis. That implies that the comovement of bond prices with world markets during crises depends on the country's level of corruption. The higher the perceived corruption, the more sensitive the country is to global shocks.

The results for column 1 provide evidence, as expected, first, that comovement of EM returns with these of S&P significantly increase when investor sentiments fall. This is indicated by the positive and significant at the 1% level second-order interacted coefficient of S&P*VIX, and further supports theories of Contagion and Comovement. More specifically, it assesses that for every one z-score increase in VIX, which reflects increase in investor fear, the (standardized) slope of returns on S&P increases by 0.21. The results also suggest that cleanness from corruption decreases the general comovement between EM returns with these on S&P. This is indicated by the negative and significant at the 1% coefficient of S&P*Corr, and is in line with expectations too. The prominent effects of default history and external debt are noteworthy. With a significant coefficient of 0.55 countries which have defaulted since

1970 comove closer with world markets. This is also the case for high external debt levels, as evident by the significant coefficient of 0.03.
When letting corruption moderate the effect of VIX on return comovement in column 2, the estimation improves. The inclusion of the triple interaction increases r-squared, indicating that column 2 fits the data better than the restricted model, and that the behaviour of bond comovement over different sentiments *does* depend on corruption. The triple coefficient of -0.23 is negative and significant with a p-value of 0.000, in line with the hypothesis. It implies that cleaner countries are less vulnerable to comovement when sentiments deteriorate. More specifically, an increase of corruption by one z-score, reflecting a cleaner country, reduces the joint increase of returns with S&P and VIX, by 0.23. I.e., betas increase less during crises for less corrupt countries.

While increasing efficiency, the full sample used for the first two estimations might conceal differences between countries and over different periods. Models 3 -7 take a closer look at such sub-samples and assess possible heterogeneity of the comovement within the full dataset. Variables are scaled to have mean zero and standard deviation 1for the full sample, rather at the sub-sample level. Thus, the magnitude of the coefficients is directly comparable.
Model 3 refines EM definition, by focusing on countries rated as “speculative” by S&Ps. I.e. it only includes countries that were assigned a credit rating below BBB- on average over the sample period. Issuers not rated by the agency are categorized for this purpose as “speculative” and include Algeria, Cote d’Ivoir and Iraq (for a list of countries by credit rating categories see Appendix 4). The distinction between speculative and investment grade countries is widely used by institutional investors, and might result in two different patterns of demand for bonds. When excluding investment-grade EMs from the sample I lose about 6,000 observations (a third). Nevertheless, both the importance and significance level of the triple-interacted effect increase. The relative contribution of the interacted variable doubles from (negative) 0.23 to 0.45. EM issuers with lower credit risk ratings are more vulnerable to investor sentiments when perceived as more corrupt.
In variants 4-6 of the model I analyse the effect of corruption on betas during crises periods. A financial crisis is defined for this purpose as a period when VIX level exceeded two standard deviations above the index average for the sample period, i.e. higher than 38.14 (for a list of crises see Appendix 5). Column 4 includes all crises, and in columns 5 and 6 I further split the sample into US originated crises and EM originated crises respectively. The crisis sample is largely dominated by US originated crises, constituting 1,136 observations out of

the total 1,304. I find that the main result stands and that the effect increases, particularly during EM originated crises. The (negative) effect of corruption increases from 0.23 in the full sample in column 2 to 0.27 during crises periods, and to as high as 3.10, 13 times higher, during EM originated crises. The statistical significance is somewhat attenuated as expected, due to decrease of sample size, as well as to increased volatility, and higher correlations between the variables during crises.[5] Consequently p-value obtained for EM originated crises is 16.7%. The coefficients obtained for the triple interaction during crises suggest that investors attribute more importance to corruption, when making decisions to buy/sell bonds during crises. The results for EM originated crises remain also when excluding from the data set EM that originated the crises themselves (Russia and Argentina) during the crises periods. The coefficient then slightly increases to (negative) 3.28 from 3.10, still with a p-value of 16.7% (not shown in the table). It should be also noted that despite the small sample, the r-squared obtained for EM crises estimation slightly improves, reflecting a better fit of the model to the data during EM crises.

The last split of the sample is geographical. Corruption appears to play a particularly important role for Asian bonds, with a coefficient of -0.53, compared with -0.23 in the full sample and p-value of 0%. Data limitations do not enable similar analysis for other geographical sub samples. The simple correlation coefficients between returns on bonds of other regions with the triple interacted variable though, are negative too: -0.07 in the Middle East, -0.04 in Europe, -0.02 in LA (Latin America) , and -0.02 in Africa.

The coefficients of lower-order interactions in this model are not of direct interest. They are conditional ones and merely capture effects at average values of the other variables.

[5] Standardized sd increases from 1 for the whole period to 1.9 during crises and to 2.8 during EM originated ones. The correlation coefficient between S&P and VIX increases (in absolute value) from -0.09 to -0.16 during crises and -0.50 during EM originated crises.

Table 3

Panel Regression

	(1) Full sample 2nd order	(2) Full sample 3rd order	(3) Speculative	(4) All Crises	(5) US originated crises	(6) EM originated crises	(7) Asia
S&P*VIX	0.205***	0.149**	-0.128	-0.088	-0.035	-3.935*	-0.234
	(6.460)	(2.120)	(-0.930)	(-0.460)	(-0.190)	(-1.960)	(-1.600)
S&P*Corr	-0.308***	-0.055	0.078	0.179	0.051	5.901	-0.044
	(-3.820)	(-0.970)	(0.650)	(0.620)	(0.180)	(1.600)	(-0.330)
S&P*Rating	-0.088	-0.212***	-0.207**	-0.191	-0.011	-2.486	-0.199
	(-0.920)	(-2.800)	(-2.020)	(-0.680)	(-0.040)	(-0.730)	(-0.770)
VIX*Corr	-0.016	-0.028*	-0.036**	-0.043	-0.040	-0.059	-0.033
	(-0.820)	(-1.670)	(-2.400)	(-1.480)	(-1.310)	(-0.430)	(-0.700)
VIX*Rating	0.042*	0.053***	0.062***	0.081***	0.079***	-0.049	0.016
	(1.820)	(2.720)	(2.730)	(3.040)	(2.850)	(-0.380)	(0.250)
S&P*VIX*Corr		**-0.225*** **	**-0.449*** **	**-0.273*** **	**-0.241** **	**-3.096**	**-0.525*** **
		(-4.740)	**(-5.000)**	**(-2.700)**	**(-2.500)**	**(-1.490)**	**(-4.690)**
S&P*VIX*Rating		0.181***	0.199***	0.158**	0.117	1.025	0.140
		(6.020)	(5.440)	(2.150)	(1.440)	(0.550)	(1.260)
Reserves	-0.004	-0.004	-0.001	-0.209	-0.247*	-0.479	-0.008
	(-0.640)	(-0.680)	(-0.110)	(-1.530)	(-1.690)	(-0.730)	(-0.930)
S&P*Debt	0.034***	0.224***	0.247***	0.034	0.130	-0.523	-0.468
	(3.250)	(3.950)	(3.750)	(0.440)	(1.420)	(-0.430)	(-1.440)
S&P*GDP	-0.002	-0.080	-0.034	-0.217	-0.171	-4.116**	-0.454***
	(-0.240)	(-1.290)	(-0.470)	(-0.910)	(-0.630)	(-2.790)	(-3.750)
S&P*default	0.553***	0.302***	0.467***	0.068	0.458	9.279	0.334
	(4.760)	(2.900)	(3.730)	(0.110)	(0.720)	(1.440)	(1.230)
S&P*VIX*Debt		0.087***	0.096***	0.035	0.009	0.234	-0.212
		(3.490)	(3.330)	(1.390)	(0.330)	(0.380)	(-1.500)
S&P*VIX*GDP		-0.038	-0.018	-0.026	-0.036	1.868*	-0.203***
		(-1.370)	(-0.570)	(-0.240)	(-0.340)	(2.060)	(-3.830)
S&P*VIX*default		0.156**	0.048	0.240	0.151	-4.768	0.025
		(1.930)	(0.660)	(1.170)	(0.740)	(-1.480)	(0.170)
Constant	0.012***	0.008**	0.017**	-0.181***	-0.200***	-1.219	0.018
	(3.170)	(1.830)	(2.300)	(-3.240)	(-3.660)	(-1.810)	(0.700)
N	18,708	18,708	12,688	1,304	1,136	168	4,426
R^2	0.019	0.027	0.020	0.060	0.069	0.108	0.089

Notes: The dependent variable is returns on EM bonds. Time and country fixed effects are controlled. The table presents only indicators to which results are significant. Variable definitions are in Appendix 1. T-Statistics are given in parentheses (based on robust standard errors, allowing for clustering by country). *p<0.10, **p<0.05, ***p<0.01.

The results obtained for credit rating reveal its additional important impact on bond prices, beyond pricing-relevant information. Rating's coefficients of the triple interaction are positive in all estimates and significant in columns (2)-(4), both statistically and in magnitude. This result means that as investor sentiments deteriorate, betas are altered by credit ratings in a way that less credit risk is associated with more beta risk. To further understand this pattern I show in figures 3-5 below three dimensions of the correlation between EM returns and S&P, by credit ratings. I start with the general correlations of returns with S&P during crises in figure 3. It shows that better creditworthiness is associated in general with lower betas, as expected, and realizes more negative correlations. The pattern seems to be more polynomial than linear, with the highest correlations for countries rated between B+ to BBB-. The least creditworthy issuers, with rating below B are less correlated, and investment ratings, above BBB, are associated with the lowest, even negative, correlations. Then, in Figure 4 I show the change in correlation from "normal" to crises periods. A clear distinction is apparent between "speculative" (rating of BB+ and less) and "investment" grades. Responsiveness of investors during crises is significantly stronger for investment-graded EMs, with mainly negative changes, reflecting decrease of correlations with the market. Last, to plot figure 5, I estimate a restricted version of column (2) in Table 3, which excludes ratings. I then correlate the residuals with S&P.[6] That enables isolating the effect of rating, beyond the effects of its components. A clear structural break is evident in the series around BB. Returns on more creditworthy bonds, higher than BB, comove significantly more tightly with the market, beyond what could be explained by the components comprising the credit rating model.

The explanation I suggest for these findings is that more better rated, and particularly investment-grade bonds are held by ETFs and other regulated institutional investors which track EM sovereign bonds and employ style investing approach (Barberis and Shleifer, 2003). These financial institutions have come to dominate financial markets. Better rated bonds classified into "investment grade" benefit from greater allocations by them. Speculative ones tend to be less actively traded. Consequently investment-rated bonds are more liquid and their prices react faster to global news. The style investing generates a comovement return factor which is unrelated to the fundamental cash-flows of the bonds. When an EM is classified into the "investment" style it comoves more with that style and with world markets particularly under extreme conditions. Thereby the correlation of more creditworthy countries such as China, Turkey and Mexico with S&P increases more during crises than that of countries which are not classified into the investment style and are less tracked.

Furthermore, low-rated countries in many cases are associated with idiosyncratic major political or economic issues. Few examples from recent years include Venezuela, Pakistan and Argentina, compared with countries which do not have major idiosyncratic issues such as

[6] A similar exercise with VIX does not result in a clear pattern.

Mexico, Brazil, or South Korea. These country-specific aspects are captured by the ratings, and make investors attitude toward these bonds more specific, on a case by case study and in a less categorical manner, particularly during crises.

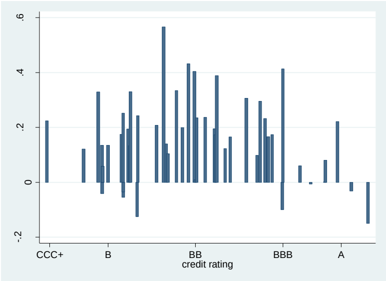

Fig. 3. Correlation during Crises by Credit Rating

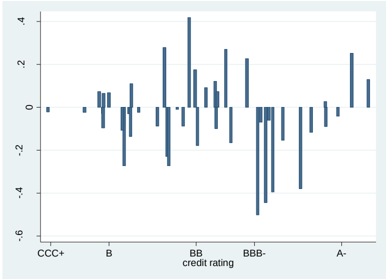

Fig. 4. Change in Correlation during Crises by Credit Rating

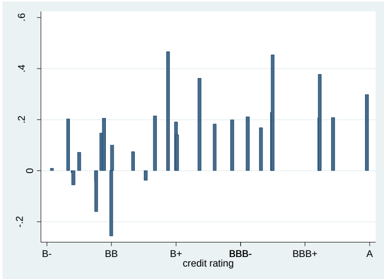

Fig. 5. Correlation of Residuals from Restricted Model with S&P by Credit Rating

Another prominent determinant of market risk during crises is external debt. With a significant coefficient of 0.09, it increases the cost of capital heavily-indebted countries face during crises.

2.2. Robustness

In Table 4 I show the results of a robustness test. One potential concern regarding the results obtained in Table 3 is that the corruption index captures other political risk characteristics of the issuers, rather than the perceived corruption itself. Consequently, the change of betas over different sentiments might not be altered by corruption, but rather by other variables that correlate with the index (for correlations between the variables see Appendix 6). When making investment decisions during crises, investors might increase the weight they attribute to political risk, and increase correlation of returns with these on S&P 500 for countries with less democratic regimes, for example. In order to test for such alternative explanation I introduce "Polity", a political regime indicator (see Appendix 1 for details) into the model in a "horse race" approach. An expected outcome would be increase in standard errors and decrease in the magnitude of Corruption. In column 2 in Table 4 Polity enters into the specification and interacts with S&P, VIX, and as a triple interaction with both, in a similar way to Corruption. I find that the results obtained for corruption remain robust to the inclusion of Polity. The coefficient obtained for the triple interacted variable slightly decreases to -0.21 (from -0.23) and remains significant at the 1%.

Table 4

Robustness

	(1) Base model	(2) With polity
S&P*VIX	0.149**	0.129*
	(2.120)	(1.900)
S&P*Corr	-0.055	-0.120**
	(-0.970)	(-2.170)
S&P*Polity		0.436***
		(6.130)
S&P*Rating	-0.212***	-0.215***
	(-2.800)	(-2.900)
VIX*Corr	-0.028*	-0.023
	(-1.670)	(-1.340)
VIX*Polity		-0.029*
		(-1.890)
VIX*Rating	0.053***	0.052***
	(2.720)	(2.580)
S&P*VIX*Corr	**-0.225*** **	**-0.206*** **
	(-4.740)	**(-4.240)**
S&P*VIX*Polity		-0.036
		(-1.300)
S&P*VIX*Rating	0.181***	0.173***
	(6.020)	(5.510)
S&P*Debt	0.224***	0.220***
	(3.950)	(3.840)
S&P*default	0.302***	0.160
	(2.900)	(1.470)
S&P*VIX*Debt	0.087***	0.085***
	(3.490)	(3.420)
S&P*VIX*GDP	-0.038	-0.020
	(-1.370)	(-0.690)
S&P*VIX*default	0.156**	0.154*
	(1.930)	(1.850)
Constant	0.008**	0.007*
	(1.830)	(1.730)
N	18,708	18,490
R^2	0.027	0.029

The dependent variable is returns on EM bonds. Time and country fixed effects are controlled. The table presents only indicators to which results were significant. Variable definitions are in Appendix 1. T-Statistics are given in parentheses (based on robust standard errors, allowing for clustering by country). *p<0.10, **p<0.05, ***p<0.01.

Additional robustness tests introduce into the model other variables of rule of law, development and political regime, which might correlate with corruption. These variables include Law and Order (ICRG), Bureaucracy Quality (ICRG), Rule of Law (ICRG), Quality of Institutions (ICRG), Democratic Accountability (ICRG), Legal Origin (LLSV, 1997), Accounting Opacity (LLSV, 1998), Voice and Accountability (WB), Government Effectiveness (WB), Regulatory Quality (WB), Rule of Law (WB), Political Stability and Absence of Violence/Terrorism (the WB), SDDS (IMF), O- Factor Composite (Gelos and Wei, 2005), Macrodata Opacity (Gelos and Wei, 2005), Macropolicy Opacity I (Gelos and Wei, 2005), Macropolicy Opacity II (Gelos and Wei, 2005), Corporate Opacity II (Gelos and Wei, 2005), full range of authority characteristics (Polity IV project[7]), Property rights index (Holmes, Johnson and Krkpatrick, 1997), Business regulation index (Holmes, Johnson and Krkpatrick, 1997), Democracy score (LLSV), Freedom indices for political rights and civil liberties (Freedom House), GDP pc, infrastructure quality (BERI's Operation Risk Index), Adult illiteracy rate (WB), infant mortality rates (WB).

None of these indicators is found statistically significant as a determinant of beta under different market conditions, when introduced into the model in a “horse race” approach with corruption. Full results to be provided upon request.

2.3. ARCH Estimation

In this section I employ an alternative approach to testing the hypothesis by estimating an ARCH model. The model now allows for interaction with Corruption in both the mean and the variance of returns.

The following two ARCH(1) equations are jointly estimated:

$$\begin{aligned} r_{i,t} = \alpha + \gamma Corr_i + \delta' X_{i,t} + S\&P_t * \left[\zeta + \eta Corr_i + \theta' X_{i,t}\right] + VIX_{i,t} \\ * \left[\vartheta + \mu Corr_i + \pi' X_{i,t}\right] + S\&P_t * VIX_t * \left[\varphi + \psi Corr_i + \omega' X_{i,t}\right] \\ + \varepsilon_{i,t} \end{aligned} \quad (3)$$

$$\begin{aligned} h_{i,t} = a + bCorr_i + S\&P_t * [c + dCorr_i] + VIX_t * [f + gCorr_i] \\ + S\&P_t * VIX_t * [j + kCorr_i] + lh_{i,t-1} \end{aligned} \quad (4)$$

A significant coefficient k in the variance equation (4) would imply that the comovement of return variance with S&P and its dependency on sentiments is altered too by corruption. The expected sign is positive, which means that less corruption reduces the negative effect of S&P

[7] These include flag, fragment, democ, autoc, polity2, durable, xrreg, xrcomp, xropen, xconst, parreg, parcomp, xrec, exconst and polcomp. For indicator description and details see Jaggers and Marshall, 2007.

on the positive raletion between volatility and VIX. I.e., cleanness reduces the dependency of volatility on the joint (negative) comovement of S&P with sentiments.

The results are summarized in Table 5. The effect of Corruption in the mean equation remains robust over both specifications, and in line with both findings in the previous empirical section and the hypothesis. With consistently significant negative coefficients of 0.05 and 0.08 in columns (2) and (3) respectively, it is apparent that corruption plays a prominent role in the behaviour of beta over different sentiments.

In the variance equation the triple-interacted effect of corruption has the expected sign, but is not statistically significant. The positive coefficient of 0.04 in column (2) indicates that the positive relation between return volatility and VIX increases more when S&P decreases for more corrupt issuers. For a one unit joint increase of VIX with S&P and Corruption, the variance of returns increases by 0.04 on average. P-value, though, is 22%, leaving much room for the null hypothesis that such an effect does not exist.

The ARCH estimation highlights the increasing importance of GDP growth and external debt for bond market risk during crises. The significant and robust coefficients of 0.12 and 0.09 respectively in column (2) in the mean equation imply that when sentiments deteriorate comovement with world markets increases more for heavier-indebted issuers and lower economic growth, as expected.

The most important determinant of return variance response to world markets during crises is credit rating. The negative significant coefficient of -0.12 implies that the (positive) relation between volatility and VIX increases more for more creditworthy issuers when S&P decreases. Here too, I suggest that this is a result of style investing. “Investment”-rated bonds are traded more actively and realize higher volatility during crises. Thus, credit rating has additional effect on bond prices, beyond pricing-relevant information, through both return and variance. Bonds with lower credit risk are exposed to greater market risk and their volatility is more sensitive to investors’ sentiments too.

Two other variables that alter the second moment of the comovement are foreign reserves and external debt. The effects of both are significant and robust, with the expected sign. The effect of sentiment on volatility increases when the issuer has less foreign reserves or more external debt.

Table 5

ARCH Estimations

	(1) 2nd order	(2) 3rd order	(3) Speculative	(4) Crises	(5) Asia	(6) With Polity
Mean equation						
S&P	0.180***	0.529***	0.620***	0.056	0.739***	0.619***
	(5.970)	(13.030)	(8.430)	(0.250)	(4.310)	(14.590)
VIX	0.019***	0.021***	0.016	-0.101**	0.015	0.025***
	(2.720)	(3.170)	(1.200)	(-2.420)	(0.920)	(3.370)
Corr	-0.014***	-0.015***	-0.026**	0.015	-0.015	-0.015***
	(-2.830)	(-3.110)	(-2.270)	(0.140)	(-1.010)	(-3.320)
Polity						0.007
						(0.890)
rating	-0.008	-0.007	-0.029**	-0.132	0.002	-0.008
	(-1.240)	(-1.070)	(-2.480)	(-0.960)	(0.100)	(-1.380)
S&P*VIX	0.250***	0.223***	0.049	0.149*	0.219**	0.248***
	(14.230)	(9.930)	(0.850)	(1.880)	(2.470)	(9.820)
S&P*Corr	-0.275***	-0.345***	-0.123	-0.388	-0.251***	-0.372***
	(-9.840)	(-10.570)	(-1.570)	(-1.190)	(-2.580)	(-11.150)
S&P*Polity						0.344***
						(5.540)
S&P*Rating	-0.052	0.046	-0.284***	0.130	-0.059	0.024
	(-1.550)	(1.070)	(-3.140)	(0.360)	(-0.560)	(0.580)
VIX*Corr	0.007	0.004	-0.024	-0.027	0.001	0.005
	(1.090)	(0.620)	(-1.390)	(-0.510)	(0.070)	(0.810)
VIX*Polity						-0.007
						(-0.670)
VIX*Rating	-0.009	-0.011	-0.006	0.059	-0.042**	-0.011
	(-1.040)	(-1.240)	(-0.390)	(0.870)	(-2.450)	(-1.370)
S&P*VIX*Corr		**-0.082*** **	**-0.576*** **	**-0.022**	**-0.135**	**-0.054** **
		(-3.140)	**(-6.850)**	**(-0.180)**	**(-1.420)**	**(-2.180)**
S&P*VIX*Polity						0.006
						(0.180)
S&P*VIX*Rating		-0.046*	0.135*	-0.025	-0.089	-0.068***
		(-1.780)	(1.800)	(-0.180)	(-1.250)	(-2.870)
Debt	0.009	0.014**	0.017**	-0.180	0.009	0.016***
	(1.470)	(2.400)	(2.340)	(-1.500)	(0.500)	(2.730)
GDP	-0.017***	-5.800***	-0.026***	-0.219*	-0.028***	-0.022***
	(-4.360)	(-5.800)	(-3.870)	(-1.650)	(-3.180)	(-5.430)
Default	0.016*	0.009	0.004	-0.166	0.018	0.005
	(1.820)	(1.050)	(0.330)	(-0.890)	(0.720)	(0.490)
S&P*Reserves	-0.044***	0.014	-0.023	0.193*	0.001	0.053***
	(-4.160)	(0.790)	(-0.590)	(1.920)	(0.040)	(2.860)
S&P*Debt	0.041***	0.218***	0.406***	-0.064	0.107	0.227***
	(3.930)	(6.020)	(8.180)	(-0.550)	(0.870)	(6.310)
S&P*GDP	-0.025***	-0.284***	-0.136***	-0.771***	-0.322***	-0.240***
	(-3.840)	(-11.170)	(-2.910)	(-3.580)	(-5.820)	(-9.220)
S&P*default	0.664***	0.451***	0.395***	0.106	0.239	0.296***
	(11.350)	(7.330)	(4.160)	(0.200)	(1.540)	(4.540)

VIX*Reserves	0.005	0.006	0.017**	-0.047	0.008	0.004
	(1.250)	(1.570)	(1.980)	(-1.460)	(1.310)	(1.030)
VIX*Debt	-0.017**	-0.014*	-0.013	0.045	-0.044**	-0.012
	(-2.260)	(-1.800)	(-1.400)	(0.770)	(-2.370)	(-1.530)
VIX*GDP	-0.008	-0.013**	-0.013	0.086	-0.013	-0.014***
	(-1.420)	(-2.490)	(-1.410)	(1.310)	(-1.060)	(-2.580)
S&P*VIX*Reserves		0.012	-0.007	-0.068*	0.006	0.026***
		(1.300)	(-0.410)	(-1.650)	(0.380)	(2.680)
S&P*VIX*Debt		0.090***	0.174***	0.006	0.043	0.096***
		(5.550)	(7.910)	(0.120)	(0.800)	(5.970)
S&P*VIX*GDP		-0.123***	-0.060***	0.086	-0.139***	-0.105***
		(-10.840)	(-2.940)	(0.920)	(-5.710)	(-9.040)
S&P*VIX*default		-0.046	-0.076	0.189	-0.139	-0.097*
		(-0.840)	(-1.050)	(0.910)	(-1.300)	(-1.670)
Constant	0.017**	0.025***	0.016	0.240**	0.015	0.030***
	(2.350)	(3.530)	(1.620)	(2.360)	(0.610)	(4.140)
Variance equation						
S&P	-0.104**	-0.088	-0.798***	-1.217**	-1.726***	0.043
	(-2.190)	(-1.280)	(-6.580)	(-2.330)	(-3.120)	(0.580)
VIX	0.557***	0.563***	0.662***	0.505***	1.302***	0.588***
	(56.990)	(59.380)	(45.550)	(8.420)	(19.860)	(55.920)
Corr	-0.326***	-0.330***	-0.538***	0.538**	-0.803***	-0.403***
	(-33.620)	(-34.650)	(-35.950)	(2.550)	(-7.650)	(-38.430)
Polity		-0.226***				0.238***
		(-24.710)				(13.200)
Rating	-0.214***		-0.492***	-1.364***	-0.249***	-0.150***
	(-23.740)		(-35.300)	(-6.540)	(-2.860)	(-14.620)
S&P*VIX	0.063***	0.034	0.210***	0.279*	0.238	0.031
	(3.270)	(1.180)	(3.530)	(1.790)	(1.060)	(0.910)
S&P*Corr	0.298***	0.210**	0.011	1.273*	-0.734	0.150*
	(4.170)	(2.490)	(0.080)	(1.860)	(-1.260)	(1.690)
S&P*Polity						0.364**
						(2.480)
S&P*Rating	-0.342***	-0.311***	-0.799***	-0.980	-0.082	-0.264***
	(-5.310)	(-4.040)	(-6.360)	(-1.530)	(-0.170)	(-3.320)
VIX*Corr	0.048***	0.062***	0.144***	-0.308***	0.354***	-0.009
	(5.180)	(6.580)	(8.520)	(-4.010)	(5.090)	(-0.790)
VIX*Polity						0.272***
						(14.020)
VIX*Rating	-0.106***	-0.117***	-0.117***	0.292***	0.309***	-0.057***
	(-14.960)	(-16.260)	(-7.520)	(4.130)	(5.600)	(-6.630)
S&P*VIX*Corr		**0.043**	**-0.104**	**-0.334**	**0.214**	**0.047**
		(1.230)	**(-1.230)**	**(-1.610)**	**(1.020)**	**(1.170)**
S&P*VIX*Polity						-0.036
						(-0.440)
S&P*VIX*Rating		-0.117***	0.117*	0.177	0.322*	-0.123***
		(-3.570)	(1.690)	(0.930)	(1.840)	(-3.300)
Reserves	-0.302***	-0.299***	-0.271***	-0.658***	-1.655***	-0.282***
	(-52.940)	(-51.250)	(-30.020)	(-4.860)	(-23.650)	(-45.580)
Debt	0.839***	0.828***	0.854***	0.778***	0.752***	0.840***

	(130.540)	(122.130)	(96.250)	(5.820)	(10.270)	(121.410)
GDP	-0.318***	-0.309***	-0.220***	-0.585***	-1.082***	-0.277***
	(-50.960)	(-49.430)	(-24.520)	(-3.820)	(-27.700)	(-38.840)
Default	0.140***	0.155***	0.216***	-0.831***	-0.794***	0.139***
	(11.070)	(12.140)	(12.910)	(-3.290)	(-9.740)	(9.250)
S&P*Reserves	-0.181***	-0.032	-0.027	-0.452**	-0.188	-0.016
	(-7.240)	(-0.950)	(-0.640)	(-2.210)	(-1.040)	(-0.450)
S&P*Debt	-0.029	-0.180***	-0.042	-0.055	-0.140	-0.197***
	(-1.370)	(-5.000)	(-0.830)	(-0.360)	(-0.520)	(-5.490)
S&P*GDP	-0.037**	-0.080**	-0.204***	-1.927***	-0.010	0.001
	(-2.120)	(-2.270)	(-4.360)	(-4.720)	(-0.080)	(0.020)
S&P*default	-0.374***	-0.463***	-0.546***	1.058	0.371	-0.625***
	(-4.630)	(-4.590)	(-4.200)	(1.470)	(1.080)	(-5.370)
VIX*Reserves	0.118***	0.118***	0.151***	0.074	0.259***	0.142***
	(18.510)	(17.810)	(16.340)	(1.510)	(6.550)	(20.620)
VIX*Debt	-0.319***	-0.320***	-0.315***	-0.088	0.316***	-0.313***
	(-45.020)	(-43.750)	(-33.840)	(-1.510)	(6.850)	(-42.490)
VIX*GDP	0.044***	0.039***	0.059***	0.194***	0.474***	0.082***
	(6.730)	(5.860)	(6.400)	(3.050)	(13.750)	(10.850)
VIX*default	0.118***	0.110***	0.047***	0.334***	0.169***	0.027*
	(10.600)	(9.820)	(3.000)	(3.420)	(2.810)	(1.810)
S&P*VIX*Reserves		0.104***	0.087***	0.070	-0.123	0.101***
		(6.200)	(4.290)	(0.970)	(-1.570)	(5.840)
S&P*VIX*Debt		-0.075***	-0.001	-0.090	-0.063	-0.079***
		(-4.250)	(-0.020)	(-1.480)	(-0.540)	(-4.520)
S&P*VIX*GDP		-0.036**	-0.087***	0.510***	0.005	0.001
		(-2.240)	(-4.230)	(3.600)	(0.100)	(0.040)
constant	-1.701***	-1.722	-2.072***	-1.308***	-2.596***	-1.744***
	(-157.680)	(-161.040)	(-134.580)	(-7.320)	(-21.460)	(-143.950)
ARCH1	0.119***	0.116***	0.063***	0.177***	0.131***	0.112***
	(58.120)	(57.520)	(30.630)	(11.360)	(30.810)	(57.390)
N	18,708	18,708				18,490
χ^2	829	1,055				1,101

Notes: The dependent variable is returns on EM bonds. The table presents only indicators to which results were significant. Z-Statistics are given in parentheses. *p<0.10, **p<0.05, ***p<0.01

3. Theoretical Framework

In this section I integrate theories and evidence from behavioural finance to explain the empirical findings. I suggest a comovement model, where bonds' systematic risk is moderated by corruption.

Building on Barberis et al. (2005), I consider an economy with riskless asset in perfectly elastic supply and with zero rate of return. There are then 2n risky assets in fixed supply in two categories, X and Y. Assets 1 through n are stocks issued by companies in developed countries, and constitute category X. This class represents the market as in CAPM (Sharpe, 1964), and is a bellwether of business cycles such as the S&P index. Assets n+1 through 2n are sovereign bonds issued by EM in category Y. Risky assets i and j are claims to single liquidating dividend $D_{i,T}$ in category X, and a single liquidating bond value $C_{j,T}$ in group Y to be paid at time T. These eventual cash-flows equal:

$$D_{i,T} = D_{i,0} + \varepsilon_{i,1} + \cdots + \varepsilon_{i,T} \tag{5}$$

$$C_{j,T} = C_{j,0} + \varepsilon_{j,1} + \cdots + \varepsilon_{j,T} \tag{6}$$

In which $D_{i,0}$ and $C_{j,0}$ are announced at time 0, $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ are announced at time t, and

$$\varepsilon_t = \left(\varepsilon_{1,t}, \dots \varepsilon_{2n,t}\right)' \sim N(0, \Sigma_R), \text{ i.i.d. over time.} \tag{7}$$

The price of any risky asset k, share i or bond j, at time t is $P_{k,t}$, and for simplicity, the returns on these assets between t-1 and t are the changes in their prices:

$$\Delta P_{k,t} \equiv P_{k,t} - P_{k,t-1} \tag{8}$$

I assume that categories X and Y are used by some investors to simplify their investment decision-making by allocating funds at the category level, rather than at the asset level. These categories are also adopted by noise traders, who channel funds depending on their sentiments. The returns are then

$$\Delta P_{i,t} = \varepsilon_{i,t} + \Delta u_{Xt} \quad\quad i \in X \tag{9}$$

$$\Delta P_{j,t} = \varepsilon_{j,t} + \Delta u_{Xt} \quad\quad j \in Y \tag{10}$$

in which

$$u_{Xt} \sim N(0, \sigma_u^2), \text{ i.i.d. over time} \tag{11}$$

u_{Xt} is a variable which tracks sentiments and risk-aversion of noise traders who invest in X and Y. Therefore, the returns on bonds in Y are affected by both news about fundamentals, $\varepsilon_{j,t}$, and by change in sentiment about the market, u_{Xt}. When noise traders become more bearish during financial crises, sentiment is negative and returns on EM bonds decrease.
As in Barberis et al., I further assume that the cash-flow shock to a sovereign bond has three components: a market-wide shock, a category-specific cash-flow shock and an idiosyncratic country shock. So that for an individual bond $j \in Y$

$$\varepsilon_{j,t} = \psi_{M,j,i} f_{M,t} + \psi_{S,j} f_{Y,t} + \sqrt{\left(1 - \psi_{M,j,i}^2 - \psi_{S,j}^2\right)} f_{j,t} \tag{12}$$

in which $f_{M,t}$ is the market-wide shock, $f_{Y,t}$ is an EM-group shock and $f_{j,t}$ is a country-specific shock. Each shock has unit variance and is orthogonal to the other shocks. $\psi_{M,j,i}$ and $\psi_{S,j}$ control the relative importance of the three components and reflects the load of world-wide news and category news on cash-flow shock to an EM bond respectively. These weights could be thought as falling between zero and 1. Then, given the way the model is set up, $0 \leq \psi_M + \psi_S \leq 1$.
Using the formula for regression coefficients and several assumptions in a similar way to Barberis et al., the OLS estimate of $\beta_{j,i}$ of an individual bond in the regression

$$\Delta P_{j,t} = \alpha_j + \beta_{j,i} \Delta P_{X,t} + \upsilon_{j,t} \tag{13}$$

in which

$$\Delta P_{X,t} = \frac{1}{n} \sum_{l \in X} \Delta P_{l,t} \tag{14}$$

is given by

$$\beta_{j,i} = \frac{\psi_{M,j,i}^2 + 2\sigma_u^2}{\psi_{M,j,i}^2 + \psi_{S,j}^2 + 2\sigma_u^2} \tag{15}$$

In order to generate the variation of beta over different periods, I relax $\psi_{M,j}$, the load of world-wide news, from being constant for an individual country. It could get one of two values for different market conditions. For $\psi_{M,j,i}$, i could be either "Normal", during "normal" market conditions, or "Crisis" when investor sentiment deteriorates during crisis, i.e. i=(N,C). The relative importance of the components of news about fundamentals changes during crises. The relaxation of $\psi_{M,j}$ from being constant generates a link between $\psi_{M,j,i}$ and u_t, which incorporates sentiment into the news component of returns. I suggest that during periods of crises, when f_M, the market-wide shock, is negative and sentiment decreases (negative Δu_{Xt}), the load of world-wide news on cash-flow shock to an EM bond, $\psi_{M,j}$, increases, so that $\psi_{M,j,C} > \psi_{M,j,N}$. Then, $\beta_{j,i}$ increases with $\psi_{M,j}$, when sentiment deteriorates. As could be seen:

$$\frac{d\beta_{j,i}}{d\psi_{M,j}} = \frac{2\psi_{M,j,i}\psi_{S,j}^2}{\left(\psi_{M,j,i}^2 + \psi_{S,j}^2 + 2\sigma_u^2\right)^2} > 0 \tag{16}$$

I further propose that the increase from $\psi_{M,j,N}$ to $\psi_{M,j,C}$ is moderated by corruption in a way that the load of world-wide news on cash-flow shock during crises, raises with the sovereign's level of corruption. Consequently, a relatively greater increase in the country's market risk is evident. Idiosyncratic shock's load decreases accordingly, while the weight of EM group-shock is assumed to remain constant.

One possible explanation of the role corruption plays in the differential increase in $\psi_{M,j}$, could be based on the link between corruption and the perceived completeness of information disseminated by the issuers.

Expected Utility theory assumes that all possible outcomes and their probabilities are known. Yet, in real life bond investors occasionally miss information required for the calculation of probabilities and face uncertainty about expected utility when rebalancing portfolios. The IMF emphasizes the importance of data's integrity and the transparency in the compilation and dissemination of statistics.[8] In order to be complete, information released by a country needs to be accessible, frequently and consistently updated, and with wide coverage. It also has to be valid, accurate, precise and reliable. Therefore, EMs with more developed institutions, such as central banks and national statistical agencies, are more likely to disseminate more complete information.

Financial crises are periods of high volatility and sharp decrease of asset prices, when investors are required to respond fast in readjusting portfolios. Updated data are only disseminated within a time lag, and relevant information might not be available for investors soon enough. This results in ambiguity. Ellsberg (1961) defines Ambiguity as the "quality depending on the amount, type, reliability, and 'unanimity' of information". Ambiguity here refers to information uncertainty with respect to the implications of new information for a bond's value.

The existence of corruption is conditional on weak institutions too. Seldadyo and Haan (2006) shows that regulatory capacity of the country is the most robust determinant of corruption (see Appendix 7 for correlations between corruption and other institutional indicators). Both corruption and incomplete information are results of lack of transparency. Thus, it makes sense that corruption correlates with the completeness of information.[9] Goel and Ram (2013) find sizable and significant positive association between economic uncertainty and corruption. Therefore, corruption is associated with weaker institutions, less complete information and greater ambiguity.

When markets are in turmoil the completeness of information is difficult to evaluate given its multiplicity and complex nature. Investors then face more "unknown unknowns" than "known unknowns"[10] about the creditworthiness of EMs than they do during "normal" times. In Ellsberg's (1961) experiment, subjects are explicitly informed when the odds are known and when they are not. I.e. the experimenters provide the subjects with full information about how complete the information is about the probabilities of drawing balls of different colours from the urn. Yet, in real life, such experimenters do not exist. Even when an issuer does disseminate the information needed to evaluate the implications of news for the bond's value, investors might still doubt its reliability, validity, preciseness and accuracy. The controversies over the figures of Greek debt in 2002 and Chinese economic growth in 2015 are two such

[8] Special Data Dissemination Standard.

[9] SDDS, the only indicator which exists for the completeness of information to my best knowledge, does not succeed to capture that. It does not capture any link between information and any other institutional indicator either. I suggest that the reason for that is the complexity in evaluation the completeness of information (its reliability, validity, accuracy, preciseness etc.).

[10] Based on a phrase from Donald Rumsfeld, United States Secretary of Defense (2002).

examples (see Rauch et al., 2011 and Chang, 2014, respectively). Thus, investors might be uncertain about how complete the information is for each issuer. Corruption, compared with the completeness of information, is perceived as “known”, or at least a “known unknown”, given its illegality and need for secrecy (Shleifer and Vishny, 1993). It is a simple indicator, stable over time, easy to explain and justify in terms of a priority ordering defined on the bonds, and provides notable difference between EMs. Its close correlation with institutional development makes it a proxy for the unobservable and immeasurable completeness of information. During crises, an issuer’s corruption level which had been hard-coded by investors over the years is used as a signal to the unknown completeness of information[11] (and possibly as a proxy for additional unobservable institutional, cultural and development indicators). Information disseminated by more corrupt countries is perceived as less complete, driving greater load of world-wide news on the cash-flow shock of these bonds. They experience higher increase in $\psi_{M,j}$ when sentiment deteriorates, more sell-offs and greater increase in comovement, as exhibited in the empirical findings.

The conceptual link between corruption and information uncertainty suggests ambiguity aversion as an additional factor enhancing corruption-dependent comovement. Ellsberg (1961) shows that people persistently prefer betting on events whose likelihoods they know more about. Camerer and Weber (1992) review evidence from experimental studies which shows that people are reluctant to bet on events on which they miss information[12]. These suggest "ambiguity aversion". Given the “unknown” and immeasurable nature of the completeness of information disseminated by EMs, corruption might act as a mediatory proxy to bridge the gap. Investors are then averse to more corrupt countries when bad world-wide news arrives and require higher risk premium. Their reluctance to keep these bonds capitalizes into their prices more world-wide news and amplifies comovement.

The idea of corruption acting as an anchor when ambiguity increases, is supported by the findings in Paserman (2015). Paserman employs experimental methods to study the way financial professionals adjust investment strategies when rebalancing portfolios of EM sovereign bond during crises. It finds that while under crisis treatment, investors consistently decrease information search in an attribute-based way. They then focus on corruption when acquiring information to make decisions to sell bonds. At the same time they neglect other

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[11] As reported in the previous section, a robustness test that introduces SDDS into the model in a “horse race” approach with corruption, results in an insignificant coefficient of SDDS, while the coefficient of corruption is significant.

[12] For the effect of ambiguity on stock returns see Zhang, 2006.

aspects of the issuer which they consider relevant at baseline (during "normal" times), such as the country's forecasted economic growth. The increase in the weight of corruption during crises could reflect rational behaviour. I.e. the importance of corruption as a default-risk determinant objectively increases during market turmoil (this mechanism is discussed in the next section). Yet, the fact that financial professionals consistently neglect the only two return-related indicators (economic growth and coupon) and focus on corruption implies a bias. The various country indicators are generally correlated. Acquiring a random sub-sample of information would merely introduce noise. However, for corrupt issuers, corruption is a negative aspect, while the coupon they pay and economic growth are typically positive ones. Increasing the importance of negative information consistently when rebalancing portfolio, results in a bias from what fundamentals would "justify", disfavouring more corrupt countries.

3.1. Additional Explanations

I now propose that additional mechanisms could generate the observations reported in section 2. This section discusses two such channels which provide different angles of the effect of corruption. These two channels, together with the main comovement model developed above, could complement each other and are not necessarily mutually exclusive. They could be combined to create a synergistic and fuller description of investors' systematic aggregate behaviour under extreme market conditions. I provide here intuitions and a conceptual discussion that could be a basis for further research. Technical details, the way the three mechanisms interact, and controversies between the different approaches are beyond the scope of this study. (For literature suggesting that rationality in decision-making and behavioural phenomena are complementary rather than antithetical, and for discussion on their synthesis see Lo, 2004, Camerer and Weber, 1992, Camerer et al., 2005, and Gigerenzer, and Goldstein, 1996).

3.1.1. State-Dependent Probability Distributions

One additional explanation of the evidence reported in section 2 is in line with Expected Utility (von Neumann and Morgenstern, 1947). It suggests that the probability distribution is time-varying conditionally on market conditions. Investors are assumed to have full information about the probabilities of different possible outcomes, based on which they maximize their expected utility. The probability distribution, however, has two states, one for "normal" times and another for crises. Financial crises take market participants by surprise.

They have major impacts on economies, and when they erupt, investors face a different state of nature and revise their risk assessments and expectations. When evaluating creditworthiness during crises, corruption becomes an objectively more important aspect and is assigned greater weight in the model than during normal times. Other determinants become objectively less important under this state of nature. Consequently, the default probability during "crisis" increases with corruption, resulting in lower demand and greater comovement with world markets. Adama (2013) shows that a country's level of corruption affects its borrowing and default decisions and amplifies the effect of negative shocks. When sentiment deteriorates, corrupt policy makers may be willing to borrow substantial funds even with high interest rates in order to create room for stealing (Ciocchini, Durbin and Ng, 2003). Moreover, corrupt officials may confiscate loans or other support packages given to a country during crises, limiting the government's ability to meet debt obligations. As a result, corruption may lead to a higher probability of loss during crises, decreasing demand for these bonds. A greater comovement of bond prices will be then observed with world markets.

Figure 6 demonstrates the difference between the ambiguity aversion mechanism proposed in section 3.1. and the conditional Expected Utility approach. It illustrates the probability distributions of utility from investing in bonds issued by two countries, a corrupt and a clean one. I assume that possible bond returns and their utilities $u(f(r_i))$ are known, and focus on probabilities $p(r_i)$. For simplicity, the base "normal" state probability distribution is assumed to be equal for both the clean and corrupt countries. The solid line shows the probability distribution during normal times and the dashed during crises. In 6a and 6b investors do not know which return will be realized, but they do know the precise probabilities of different outcomes. During crises, the default probability of the corrupt country as assessed by investors increases more than that of the clean one for the reasons mentioned in this section. The probability of low utility associated with low returns raises accordingly.
In figures 6c and 6d investors know possible outcomes, but do not know which return will be realized. Now, however, they are uncertain about the probabilities too. The ambiguity in these graphs is expressed by a set of probability distributions. The number of possible distributions depends on the amount and nature of the missing information (Camerer and Weber, 1992). The clean country has stronger institutions and could release information of higher quality during crises. Consequently investors are less ambiguous about it.

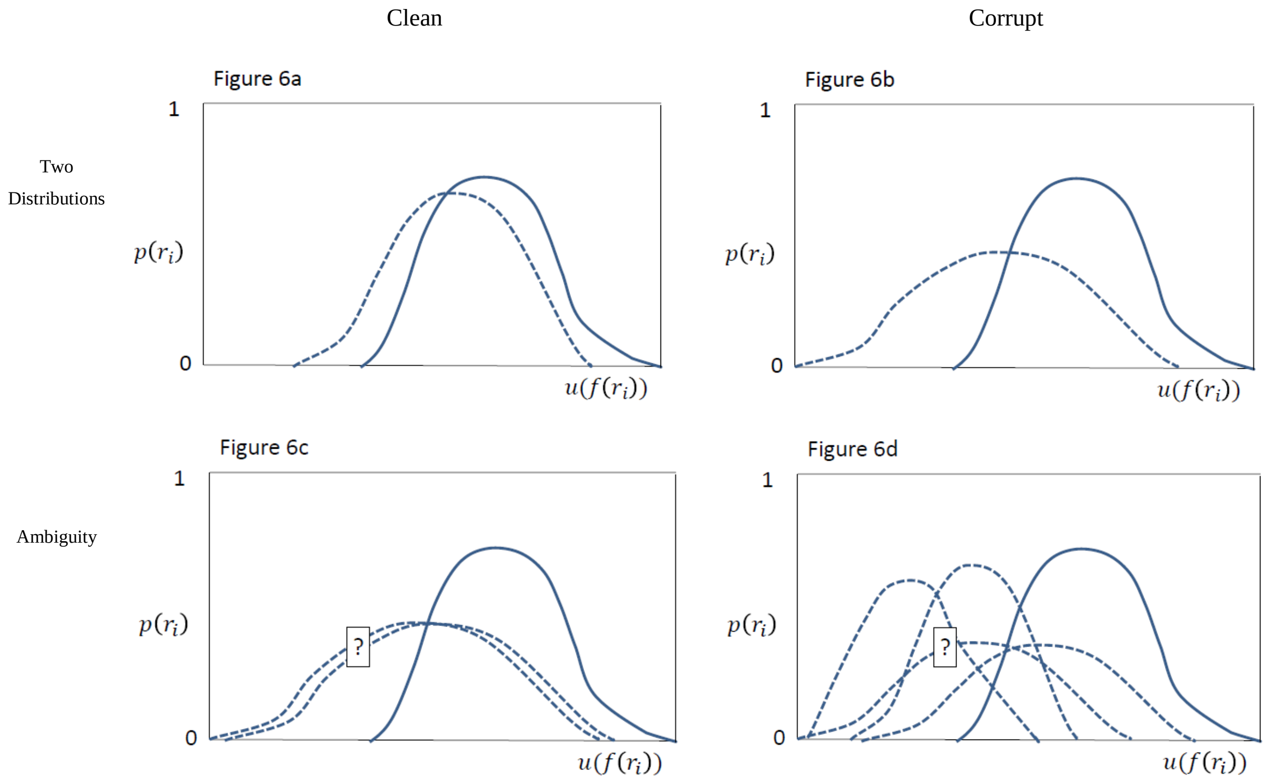

Fig. 6: Probability Distributions (solid=”normal” times, dash=crises)

3.1.2. Adaptive Decision-Making under Pressure

An additional strand of literature that could explain the observed effect of corruption on beta during crises is that of adaptive decision-making. It assumes that investors’ processing of information may not be stable under different conditions, and that they adapt decision-making[13] strategies under pressure. Even though largely relying on computation, investment activity still remains mainly a human decision-making. It is therefore helpful to account for the human aspect involved, in order to better understand and predict bond prices (for research about markets’ ability to eliminate individual investors’ irrationality and biases see Gode and Sunder, 1993 and Camerer and Fehr, 2006). I conjecture that when faced with a complex environment of a crisis, given human limited cognitive capacity, investors shift strategy from expected utility maximization. They then process only part of the relevant data, where corruption acts as a bond aspect, on which investors focus under pressure.

[13] Decision-making is defined as “the ability to react to information in the environment, and to take one of a few different action alternatives in order ultimately to better the decision maker” (Arieli and Zakai, 2001).

Decision-making literature proposes that when making choices, individuals employ multiple different strategies under different conditions (Payne et al., 1993). [14] One of the factors on which the adaptation of strategy is contingent is the complexity of the task. Environmental stressors, such as time pressure and task load, affect the complexity of the task and could drive a shift in decision strategy. Stress may result in cognitive effects such as narrowed attention, decreased search behaviour, tunnel vision and degraded problem solving (Salas et al. 1996). Given the cognitive limitations of the mind, the adaptation enables humans to cope with the requirement to make choices in complex environments (Simon, 1955). Individuals then shift decision strategies in a way which is often systematic. Strategies individuals employ to process information range from careful and reasoned calculation of all attributes of all alternatives to various simplified heuristic methods. An individual sometimes uses a compensatory strategy, where all relevant information is processed and the good and bad aspects of all alternatives are traded-off (Payne et al., 1993). Expected utility maximization (von Neumann and Morgenstern, 1947), is consistent with this normative strategy, where all relevant information is processed. In other cases the same person might employ noncompensatory strategies. Then he might avoid trade-offs by processing only part of the relevant information. Some strategies explicitly ignore potentially relevant information (Payne et al., 1993). When faced with time pressure, individuals adapt by reducing information search, processing, and the range of alternatives and dimensions that are considered. They ignore parts of the information ("filtration" and "omission", Miller, 1960). Newell and Simon (1972) suggest that when performing particularly complex tasks, individuals utilize different heuristics that keep the information processing demands of the situation within the bounds of their limited capacity, in a kind of cognitive shortcut. One such judgemental heuristic is the Anchoring-and-Adjustment, which refers to a tendency for judgements to be biased towards an initial value arrived from partial information or no computation (Maule and Hodkingson, 2002). The conjunctive decision rule is another heuristic in which the decision maker establishes minimum required performance standards for each of several attributes of an alternative and rejects alternatives that do not meet the minimum criteria. A shortfall in one attribute is not offset by excessive endowment in another attribute.[15] To sum, individuals adapt to complex environments when making decisions by

[14] Payne et al. (1993) define decision strategy as a "sequence of mental and effector (actions on the environment) operations used to transform an initial state of knowledge into a final goal state of knowledge where the decision maker views the particular decision problem solved".

[15] Few more examples include the Elimination-by-Aspect theory (Tversky, 1972) and the Lexicographic rules (Svenson, 1979, respectively). Simon (1955) argues that people in choice situations "satisfice" a decision

increasing the selectivity of processing. They increase the use of information filtration, focusing on part of the aspects.

Another prominent pattern, with implications to investor behaviour during crises, is the effect of dispersion. Payne et al. (1988) show that higher dispersion in outcome probabilities leads to reduced, more selective and more attribute-based information processing. Financial crises are periods of high asset price volatility and greater dispersion in probabilities.

The complexity which characterises the environment of investor professional activity further increases during financial crises. Decisions have to be made under greater time shortage, incomplete information and higher uncertainty and ambiguity. In these situations investors could experience psychological pressure, which happens when an individual feels that the resources available do not meet the ones needed.[16] [17]

Given limited-capacity of information processing and the demand of a particularly complex environment, I conjecture that investors adapt decision-making during crises in a systematic way. They shift strategy towards simplifying heuristics when only part of the relevant data is processed. A sovereign bond is a set of aspects, which represent values along quantitative and qualitative risk and return dimensions (e.g. foreign reserves, and debt ratios). In contemplating the purchase/sale of a bond during crises, investors focus on few specific aspects. I suggest that corruption acts as such an aspect. When the processing of information becomes more selective, investors focus on corruption and increase its weigh in decision-making, due to its advantages in facilitating complex decision, and to its “strength” (Griffin and Tversky, 1992). Thus, bonds issued by more corrupt countries will be more vulnerable to sell-offs when sentiment deteriorates.

Corruption has several attributes that could enhance its weight during crises. First, the level of corruption is a relatively stable indicator over time which evolves only rather slowly, compared with other sovereign risk determinants (e.g. foreign reserves ratio). As such, it is easier for investors to follow it. Next, corruption is a qualitative variable and its evaluation involves no numerical computations. It is easy to explain and justify in terms of a priority ordering defined on the aspects. It is simple and provides notable difference between

heuristic that involves choosing the first alternative that meets their minimum requirements. For an overview of simplifying heuristics see Payne et al., 1993.

[16] For the relationship between time pressure, emotion arousal and psychological stress in human judgment and decision-making see Edland and Svenson (1993), Keinan, Friedland, and Ben Porath (1987), Lundberg (1993) and Maule and Hockey (1993).

[17] The precise magnitude of the effect of insufficient resources on the feeling of psychological stress depends on investor’s individual assessment of the available resources and those needed (Svenson and Benson, 1993). The individual’s ability, personality characteristics, earlier experiences, and genetic dispositions may further contribute to the idiosyncrasy of the stress responses (Lundberg, 1993).

sovereigns. The differences between countries' levels of corruption are hard-coded by investors over the years, prepared to be used as anchors under extreme market conditions. Satisfying corruption minimum requirement is a much simpler cognitive operation, which makes fewer demands on scarce mental resources during periods of crises. Corruption becomes an anchor on which bond investor focus.
As a result, when stock markets are under pressure, issuers hard-coded as "corrupt" suffer greater load of global shocks capitalized into their bonds. When investors readjust portfolios, they either covertly or consciously eliminate these bonds from purchases or sell them, and switch out of corrupt to clean countries.

This approach is supported too by the evidence in Paserman (2015). It finds that under pressure, investors shift from strategies consistent with expected utility maximization to ones in which they reduce information processing. When facing a financial crisis, investors focus on a selective subset of bond aspects, neglecting other relevant information. Corruption is found to be an aspect on which investors focus during crises. The amount of information searched on coupon and economic growth, typically positive aspects of more corrupt issuers, decreases. That implies that more corrupt emerging markets are more prone to bond sell-offs and comovement under extreme market conditions.

Evidence from Neuroeconomics seems to further support this approach. Coates and Herbert (2008) run an experiment with male traders in the City of London under real working conditions. They find that trader cortisol levels rise with both the variance of trading results and the volatility of the market. Cortisol is a steroid hormone released in response to a stressful stimulus (for the full physiological mechanism and research survey see Coateset al., 2010). Cortisol has powerful cognitive and emotional effects. Consequences of raised cortisol levels include a shift in risk preferences. Van Honk et al. (2003) find that Cortisol levels are positively correlated with risk aversion (see also Kandasamya, 2014). When elevated Cortisol level persists, it promotes a selective attention to mostly negative precedents and produces a tendency to find threat and risk where they do not exist (Coates and Herbert, 2008, and Erikson et al., 2003). Financial crises are periods of high uncertainty and volatility. Thus Cortisol is then likely to be released into investors' blood. If these periods are prolonged, investors might experience Cortisol's effect on information processing and decision-making. Their attention may be more selective. Corruption is a bond indicator more directly related to default risk, rather than to return. Coupon and the country's economic growth, for example, are determinants more related to return (or long-term solvency). Corruption might therefore act as such a “most negative” aspect, on which investors focus while under prolonged pressure. It should be noted that brain research in this area is still very preliminary. More remains to be studied in order to better understand the link between investor body and mind and how it alters decision-making under extreme market conditions.

4. Conclusions

This study finds that the perceived corruption level of an emerging market has a prominent effect on its vulnerability to investor sentiment. During financial crises bond market risk rises with the issuing country’s corruption level. This pattern is found robust to various specifications and to the inclusion of alternative explanations that could correlate with corruption. The effect of corruption on the comovement with world markets during crises is found particularly strong within several sub-samples. The impact is greater in countries assigned “speculative” grades by credit rating agencies. Corruption also plays a much greater role for Asian countries, than it does for non-Asian. Furthermore, the effect is more prominent during crises originated in emerging markets, rather than those initiated in the US.

The issuing country’s default history and its external debt are two other important determinants of sovereign bonds’ comovement with global markets, particularly under extreme market conditions.

The explanation I propose to the empirical finding on the role of corruption is based on comovement generated by news on fundamentals and investor sentiments (built on Barberis et al., 2005). I conjecture that information uncertainty is higher for more corrupt issuers and further increases during crises. Investors then capitalize more world-wide news into the prices of bonds issued by such countries, making them more prone to sell-offs.

Two additional approaches are then discussed. The first is in line with Expected Utility theory. It assumes complete information, and two different probability distributions for two states of the market. The “crisis distribution” attributes more weight to corruption, as it objectively becomes a more important determinant of default risk when sentiment deteriorates. The second additional approach assumes that investors adapt their information processing and decision-making strategies under the pressure of a financial crisis. As a result of limited cognitive capacity, they attribute more weight to the corruption level of the issuer, neglecting other relevant aspects. More research remains to be done to truly understand the way the three mechanisms combine to generate the behaviour of comovement.

The analysis in this study has important implications for global financial stability and portfolio management. Furthermore, it suggests that by reducing corruption, emerging markets could benefit from global integration while decreasing potential side effects of sudden capital outflows.

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Appendices

Appendix 1

Variable Descriptions

Abbreviation	Description
Returns	Weekly average returns on J.P. Morgan's EMBI indices.
S&P	Weekly average returns on the S&P 500 stock index
VIX	Weekly average value of the Chicago Board Options Exchange Market Volatility Index.
Corruption	Transparency International's Corruption Perceived index measures perceptions of corruption in the public sector. CPI Sources of Information (2012) include: 1. African Development Bank Governance Ratings (AFDB) 2. Bertelsmann Foundation Sustainable Governance Indicators (BF-SGI) 3. Bertelsmann Foundation Transformation Index (BF-BTI) 4. Economist Intelligence Unit Country Risk Ratings (EIU) 5. Freedom House Nations in Transit (FH) 6. Global Insight Country Risk Ratings (GI) 7. IMD World Competitiveness Yearbook (IMD) 8. Political and Economic Risk Consultancy Asian Intelligence (PERC) 9. Political Risk Services International Country Risk Guide (ICRG) 10. Transparency International Bribe Payers Survey (TI) 11. World Bank - Country Performance and Institutional Assessment (WB) 12. World Economic Forum Executive Opinion Survey (WEF) 13. World Justice Project Rule of Law Index (WJP) The data used in the study are averages of the sample periods, while higher values of the index are associated with less corruption.
SDDS	The Special Data Dissemination Standard is published by the IMF, and reflects data transparency. It covers data coverage, periodicity, and timeliness, as provided by the respective countries. A dummy variable which gets the value of 1 when the country is subscribed to Metadata, i.e. higher values are associated with more developed institutions.
Rule of Law Bureaucracy Corruption	Ratings published by The International Country Risk Guide (ICRG). The assessment is made on the basis of subjective analysis of analysts of available information. Averages of the observed period. Higher values of the index are associated with more developed institutions.
Reserves	Foreign reserves to import ratios. IMF's International Financial Statistics monthly figures interpolated to weeks.
GDP growth	World Bank annual data interpolated to weeks.
Debt	World Bank averages of external debt stocks, % of exports of goods, services and income.
Default	A dummy variable which gets the value of 1 if the country has defaulted since 1945 (same as since 1970). Default definition is based on Reinhart and Rogoff (2008).
Polity	A political regime index from INSCR, which codes the authority characteristics of states in the world for purposes of comparative, quantitative analysis. Higher values are associated with greater democratic and less autocratic institutionalized authority traits. Averages per country over the samples are used.
GDP pc	World Bank averages over the observed period.
Rating	Standard and Poo'rs Sovereign Foreign Currency Credit Ratings. Averages over the observed periods. Higher values reflect better creditworthiness.

Appendix 2

Correlation of Returns with S&P during crises and normal periods and corruption by Countries

country	corruption	correlation			
		full sample	normal	crisis	change during crises
Croatia	3.6	0.098	0.189	-0.314	-0.502
Poland	4.3	0.060	0.116	-0.264	-0.380
Tunisia	4.5	-0.101	-0.050	-0.205	-0.155
Thailand	3.4	0.174	0.216	-0.180	-0.396
Greece	4.9	0.232	0.307	-0.137	-0.444
Pakistan	2.4	-0.042	-0.034	-0.129	-0.096
Sri Lanka	3.2	-0.036	0.164	-0.110	-0.274
Hungary	5.0	-0.007	0.036	-0.081	-0.117
Chile	7.2	-0.151	-0.200	-0.070	0.130
Serbia	3.4	0.104	0.252	-0.022	-0.274
Trinidad & Tobago	3.5	-0.032	-0.263	-0.011	0.252
Malaysia	4.9	0.080	0.101	0.010	-0.091
China	3.4	0.001	-0.002	0.025	0.027
Bulgaria	3.7	0.165	0.199	0.032	-0.167
Gabon	3.0	0.140	0.289	0.059	-0.230
Morocco	3.6	0.235	0.248	0.070	-0.178
Ghana	3.9	0.133	0.215	0.079	-0.136
Jamaica	3.2	0.121	0.115	0.091	-0.024
Lebanon	2.9	0.058	0.035	0.100	0.065
Dominican Republic	3.0	0.135	0.145	0.115	-0.030
Georgia	4.0	0.175	0.224	0.116	-0.108
El Salvador	3.8	0.173	0.225	0.126	-0.099
Russia	2.4	0.199	0.219	0.130	-0.089
Nigeria	1.9	0.208	0.221	0.132	-0.089
South Africa	4.7	0.166	0.193	0.133	-0.061
Belize	3.0	0.135	0.079	0.146	0.068
Cote d ‘Ivoire	2.3	0.075	0.049	0.163	0.114
Ukraine	2.3	0.194	0.200	0.169	-0.031
South Korea	4.2	0.221	0.232	0.191	-0.041
Uruguay	6.2	0.252	0.281	0.196	-0.085
Ecuador	2.3	0.224	0.221	0.200	-0.022
Turkey	3.8	0.243	0.252	0.227	-0.025
Algeria	2.5	0.172	0.143	0.253	0.110
Iraq	1.6	0.292	0.300	0.277	-0.023
Kazakhstan	2.5	0.295	0.348	0.278	-0.070
Egypt	3.2	0.123	0.023	0.293	0.270
Panama	3.4	0.195	0.187	0.308	0.121
Brazil	3.8	0.334	0.338	0.328	-0.011
Peru	3.8	0.237	0.247	0.339	0.092
Argentina	2.9	0.329	0.316	0.389	0.074
Venezuela	2.3	0.330	0.314	0.424	0.110
Colombia	3.5	0.389	0.362	0.435	0.073
Mexico	3.4	0.306	0.256	0.483	0.227
Philippines	2.7	0.404	0.348	0.524	0.175

Vietnam	2.7	0.432	0.165	0.583	0.418
Indonesia	2.5	0.566	0.400	0.678	0.279
Belarus	2.5	-0.056	-0.056	n.a.	n.a.
Jordan	4.5	0.009	0.009	n.a.	n.a.
Lithuania	4.9	0.413	0.413	n.a.	n.a.
Senegal	2.9	-0.125	-0.125	n.a.	n.a.

Data are sorted by correlation during crises. Calculated over the period 1/1994-8/2011.

Appendix 3

S&P Betas during crises and normal periods and corruption by Countries

		S&P CAPM Beta			
country	corruption	full sample beta	normal beta	crises beta	change during crises
Iraq	1.58	0.02	0.02	0.07	0.06
Nigeria	1.86	0.09	0.09	0.11	0.03
Cote d'Ivoire	2.30	0.62	0.61	1.62	1.02
Venezuela	2.31	0.24	0.24	0.15	-0.09
Ukraine	2.33	0.05	0.05	0.14	0.09
Ecuador	2.34	0.25	0.27	-0.29	-0.56
Pakistan	2.35	0.01	0.00	0.06	0.06
Russia	2.39	0.19	0.20	0.15	-0.05
Belarus	2.45	0.16	0.16		
Algeria	2.50	0.27	0.28	-0.08	-0.36
Indonesia	2.51	0.04	0.03	0.12	0.09
Kazakhstan	2.52	0.02	-0.01	0.18	0.18
Philippines	2.68	0.05	0.05	0.06	0.01
Vietnam	2.68	0.01	-0.01	0.18	0.19
Lebanon	2.88	0.01	0.00	0.02	0.01
Argentina	2.88	0.37	0.37	0.23	-0.14
Senegal	2.90	-0.07	-0.07		
Belize	2.95	0.03	0.03	0.01	-0.03
Gabon	2.95	0.02	0.02	0.04	0.02
Dominican	3.02	-0.02	-0.03	0.07	0.10
Egypt	3.15	0.04	0.03	0.05	0.01
Jamaica	3.20	-0.02	-0.02	0.00	0.02
Sri	3.20	0.07	0.08	0.05	-0.02
Serbia	3.35	-0.01	-0.01	-0.07	-0.06
Thailand	3.35	-0.01	-0.01	-0.06	-0.05
Panama	3.39	-0.06	-0.06	0.07	0.13
Mexico	3.41	0.14	0.14	0.12	-0.02
China	3.44	0.00	0.00	-0.07	-0.07
Colombia	3.52	0.10	0.11	0.10	-0.01
Trinidad	3.53	-0.05	-0.08	0.01	0.09
Croatia	3.55	0.07	0.07	0.16	0.09
Morocco	3.64	0.05	0.05	0.28	0.23
Bulgaria	3.71	0.14	0.14	0.11	-0.03
Turkey	3.78	0.09	0.09	0.07	-0.01
El Salvador	3.78	0.02	0.03	0.00	-0.03
Brazil	3.79	0.23	0.23	0.23	0.00
Peru	3.80	0.05	0.05	0.12	0.08
Ghana	3.90	0.01	0.01	0.01	0.00
Georgia	3.98	0.02	0.02	-0.01	-0.04
South Korea	4.21	0.03	0.03	0.06	0.02
Poland	4.27	0.05	0.05	0.00	-0.05
Jordan	4.50	0.20	0.20		
Tunisia	4.51	0.02	0.02	0.00	-0.02
South Africa	4.73	0.03	0.03	-0.01	-0.04
Lithuania	4.90	0.08	0.08		

Greece	4.90	0.02	0.02	-0.14	-0.16
Malaysia	4.91	-0.02	-0.02	-0.04	-0.01
Hungary	5.02	-0.03	-0.02	-0.04	-0.02
Uruguay	6.15	0.04	0.04	0.10	0.06
Chile	7.21	-0.04	-0.04	-0.07	-0.03

Averages of weekly Betas. Data are sorted by CPI.

Appendix 4

Countries by Credit Rating

Speculative	Investment
Algeria	Bulgaria
Argentina	Chile
Belarus	China
Belize	Croatia
Brazil	Greece
Colombia	Hungary
Cote d'Ivoire	Kazakhstan
Dominican Republic	Lithuania
Ecuador	Malaysia
Egypt	Poland
El Salvador	South Africa
Gabon	South Korea
Georgia	Thailand
Ghana	Trinidad and Tobago
Indonesia	Tunisia
Iraq	
Jamaica	
Jordan	
Lebanon	
Mexico	
Morocco	
Nigeria	
Pakistan	
Panama	
Peru	
Philippines	
Russia	
Senegal	
Serbia	
Sri Lanka	
Turkey	
Ukraine	
Uruguay	
Venezuela	
Vietnam	

Investment grade is S&P’s BBB and above on average over the observed period. Not-graded countries are categorized as “Speculative” and include Algeria, Cote d’Ivoir and Iraq.

Appendix 5

Crisis Periods

EM Originated Crises	
4/9/1998-12/10/1998	The Russian Crisis
18/9/2001-25/9/2001	Argentina Default
US Originated Crises	
26/7/2002-14/10/2002	Dot Com Crisis
2/10/2008-9/4/2009	The Subprime Crisis
9/4/2009-28/7/2011	The Debt crisis in the EU

Crises periods are weeks when average VIX value exceeded 38 (two sd above the index average over the observed period).

Appendix 6

Correlations between Variables

	corruption	reserves	GDP growth	debt	default	rating	Polity
corruption	1						
reserves	-0.06	1					
GDP growth	-0.04	0.14	1				
debt	-0.19	0.17	-0.19	1			
default	-0.04	-0.01	-0.06	0.30	1		
rating	0.72	0.07	0.11	-0.44	-0.27	1	
Polity	0.19	-0.45	-0.26	0.03	0.28	-0.00	1

Appendix 7

Correlations between Institutions Variables

	corruption (TI)	*law and order*	*Bureaucracy Quality*	*Democratic Accountability*	*rule_law*	*Corruption (F)*
corruption (TI)	1					
law and order	0.35	1				
Bureaucracy Quality	0.59	0.31	1			
Democratic Accountability	0.44	-0.04	0.49	1		
rule_law	0.39	0.48	0.39	0.37	1	
Corruption (F)	0.62	0.26	0.53	0.62	0.48	1

Appendix 8

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