Short-term Drivers of Sovereign CDS spreads*

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Abstract

This paper comes up with different underlying structures of explanatory variables, one for each country, which drive changes in Sovereign CDS (Credit Default Swap) spreads by means of a time series analysis and a subsequent cluster analysis. The set of explanatory variables comprises indicators for the states of the global and local economies, proxies of risk premia, and other financial variables such as exchange rates and interest rates. We develop this study for a selected set of 33 investable markets, including developed as well as emerging markets. Empirical results for emerging countries are markedly different from developed countries both in terms of sensitivity to some global factors and forecast accuracy of the estimations.

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1. Introduction

As the market of sovereign CDS (Credit Default Swap) is increasing in size and importance, so is the interest in further the understanding of what drives the variation in CDS spreads. CDS's are particularly useful to a wide range of investors, either for hedging existing exposures or for more speculative activities, as they don't need to have the reference obligation in its books.

As investors are increasingly focused on international diversification, they may be willing to broaden their understanding on issues that impact the sovereign debt and CDS markets (see Alsakka and Gwilym, 2010). This may be even more the case now, in the wake of a sovereign bond crisis which in October 2009 engulfed Greece, one year later embraced Ireland and in May 2011 reached Portugal. Since the financial bailout of the Greek government in May 2010, investors have been putting pressure on countries with high indebtedness and low growth prospects. As investors demand higher yields for buying their sovereign bonds, their sovereign CDS spreads increase in tandem. Then, funding costs have been driven up to the point of making borrowing from the market very difficult for some governments. This is the case of governments of Greece, Ireland and Portugal, which ended up asking for financial assistance from IMF and European Union.

The objective of this paper is to assess the impact of global and local market-related factors on changes in Sovereign CDS spreads. We develop this study for a selected set of 33 investable markets, including developed as well as emerging markets[1]. For this purpose, we use econometric of time series analysis and a cluster analysis. In the cluster analysis, countries are sorted into groups where the members of each group are as similar as possible. It is important to emphasize, however, that we don't aim to provide any framework for predicting crisis, but to suggest a useful approach for short-term horizon investment decisions. Our paper is more related to Longstaff et al. (2010), but differentiates from theirs in some important aspects: i) as our focus is on asset allocation, an extensive set of investable sovereigns are included in our analysis; ii) the data frequency is weekly; and iii) we compare results of developed against emerging market sovereigns.

The paper is organized as follows: Section 2 revises the related literature; Section 3 presents a short description of the CDS market; on Section 4 we describe the data; Section 5 provides the empirical strategy and results; and finally Section 6 concludes the paper.

2. Related Literature

This paper relates more closely to Longstaff et al. (2010)[2]. They find that sovereign credit is primarily driven by global macroeconomic forces external to the country and that the risk premium represents about a third of the credit spread. 64% of the variations in sovereign credit spreads are accounted by a single principal component and those variations are more significantly explained by U.S. stock, high-yield markets and volatility risk premium (embedded in the VIX index) than by local economic variables. Our paper, on the other hand, investigates the underlying structure of explanatory variables for a sample of investable sovereigns with a focus on the short-term horizon.

[1] See Table 1.

[2] Longstaff, Francis A., Pan, Jun, Pedersen, Lasse Heje and Singleton, Kenneth J. (2010), "How Sovereign is Sovereign Credit Risk?". American Economic Journal, forthcoming.

While our focus is on the short-term determinants of sovereign risk, Remolona et al. (2008) are concerned on pricing mechanisms for sovereign risk and propose a framework for distinguishing market-assessed sovereign risk from its risk premia. They use a dynamic panel data model with a sample covering 24 emerging countries' sovereign CDS spreads. We believe we can provide a more comprehensive understanding of recent developments as our sample covers a period during which Sovereign CDS turned into a more mature and liquid market and our sample covers not only emerging countries, but also developed countries, summing up 33 countries. Moreover, we assume that variation in risk premia component of spreads is partially, if not fully, captured by the explanatory variables (local stock exchange index, local short term yield or local term premium).

3. Description of CDS market

Sovereign CDS's are a growing part of the CDS market. The Sovereign CDS market grew[3] in fast pace since December 2004, from $0.17 trillion to almost $2.4 trillion in terms of notional amounts outstanding[4] in July 2010, while the increase of the whole market of credit derivatives was from $6 trillion to $30 trillion in the same period. Figure 1 shows that positions in sovereign contracts have been increasing since December 2004, while for the credit derivatives market as a whole, total notional amounts outstanding declined in the last five periods. According to BIS, these declines are largely due to terminations of existing contracts, by netting gross notional outstanding through portfolio compression and clearing.

Calculated as a percentage of the notional value of the reference obligation, CDS spreads are the cost of benefiting from an insurance-like contract against default of a reference entity. The protection buyer pays a premium or spread on a periodic basis and in exchange, upon the occurrence of a credit event (defined within the terms of a CDS contract) has the right to sell the bond to the protection seller at face value. Then, it is considered an efficient and liquid instrument for market participants to mitigate the concentration of credit risk and to enable credit providers to diversify exposure and expand lending capacity. The protection seller, on the other hand, can take credit exposure over a customised term and earn the premium without having to fund the position. The required premium is related to the expected loss of the bond; the higher the expected loss is, the higher the premium is expected to be. Moreover, CDS spreads may be useful for gauging the market perception of credit conditions of specific names, as they provide timelier assessments than rating agencies.

A Sovereign CDS contract has some specificity regarding the triggering credit event and the reference obligation. The credit event may be a failure-to-pay, a moratorium or a restructuring. A failure-to-pay occurs when a government fails to pay more of its obligations in an amount at least as large as the payment requirement after any applicable grace period. A moratorium occurs when an authorized officer of the reference entity disclaims, repudiates, rejects or challenges the validity of one or more obligations and, after a pre-defined time lapse, there is effectively a failure-to-pay event or a restructuring. The restructuring occurs when there is a reduction, postponement or deferral of obligation principal; when contractually agreed interest payments are not permitted by the original terms of the obligation; when there is a change in priority ranking causing subordination to another obligation; or when there is a change in currency or composition of interest or principal payments to any currency which is not a permitted currency.

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[3] OTC Derivatives Market Activity at end-June 2010, BIS.

[4] Notional amounts outstanding are defined as the gross nominal or notional value of all deals concluded and not yet settled on the reporting date. These amounts provide a measure of market size and a reference from which contractual payments are determined in derivatives markets.

Upon default, there are two types of settlement: physical settlement and cash settlement. Both of them cause the termination of the contract. In case of physical settlement, the protection buyer delivers to the protection seller one of a list of bonds with equivalent seniority rights and the protection seller pays to the protection buyer the face value of the debt. In case of cash settlement, the protection seller pays to the protection buyer the difference between the face value of the debt and its current market value.

4. Data

The data sample comprises a set of time series of 33 investment-class markets[5]. The dependent variable of the estimation for each country is the change in its CDS spreads. The characteristics of the CDS's are the following: the maturity is 5-year and the reference obligation is a deliverable senior dollar-denominated external debt of the sovereign. In Table 2, we show descriptive statistics for the sovereign CDS spreads.

On the explanatory variables, we select a set of market-sensitive ones, to the extent that they embed economic reasoning for investors taking short-term decisions on sovereign debt allocation. We classify them as global factors and local factors. Their description, economic reasoning and data source are thoroughly informed in Table 3. It is worth mentioning that we are not concerned on disentangling and assigning the specific effects one variable can convey and, instead, consider that in the end we choose a sub-set of variables that expresses views on debt, tax revenue and risk premium in aggregate. U.S. Term Premium and Local Term Premium, for example, not only provide indirect assessment on future tax revenues, as they are related to growth prospects through the business cycle, but also capture risk premia embedded in long term yields. The global factors inform the state of the global economy on growth prospects, risk aversion, perception of counterparty risk within the banking system and business cycle: log difference of S&P 500 index, log difference of VIX index, first difference of TED spread, first difference of U.S. term premium and log difference of oil price. The acronyms for these factors are, respectively: $sp500$, vix, ted, TP and oil. The local factors should each provide, in theory, information on specific aspects related to debt, tax revenue and risk premium: lagged dependent variable (first difference of CDS spreads), log difference of local stock index, log difference of exchange rate, first difference of local short term yield, first difference of local term premium and log difference of foreign reserves. The acronyms for these factors are, respectively: $spread_i$, $stock_i$, xr_i, $localTY_i$, $localTP_i$ and fr_i.

The dependent and explanatory variables are sampled as weekly changes from July 2005 to July 2010. All observations refer to end-of-the-day quoted prices. The use of weekly data, however, prevents us to use other related sovereign credit-related factors, like deficit/GDP and debt/GDP ratios, which are available only on a quarterly basis. We estimate the econometric models for a time period encompassing the pre-2007 crisis and crisis periods. The pre-crisis period is from July 2005 to November 2007, the crisis period, from December 2007 to June 2009 and the post-crisis period is from July 2009 to July 2010. The end of in-sample period is based on the NBER's (National Bureau of Economic Research) Committee announcement[6], in which it states that the recession that began in December 2007 ended in

[5] See Table 1.

[6] Business Cycle Dating Committee, National Bureau of Economic Research, September 20th, 2010.

June 2009. Then, the estimation period is from July 2005 to June 2009. We use the post-crisis period as an out-of-sample period for calculating goodness-of-fit statistics.

Variable transformations are such that "interest rate" variables are transformed into percentage values, i.e., CDS spreads, originally in basis points, are divided by 100; the other "interest rate" variables are already in percentage format (TED spread, U.S. Term Premium, Local Short-Term Yield and Local Term Premium). Then, we transform these variables into first differences. Moreover, "price" variables are transformed into $\Delta\log(.)$: S&P 500 index, VIX index, Oil price, Local Stock Index, Exchange Rate and Foreign Reserves.

5. Empirical Strategy and Results

Our empirical strategy is to first select a set of eligible factors for each country. Secondly, we choose the best model for each country according to pre-defined set of criteria.

In order to obtain the "best" model specification for each country, we first choose the sub-set of eligible factors for each country. The focus on a smaller set of testable variables is paramount for reducing the processing time. Then, we resort to the Granger-causality test (Granger, 1969) not only for assessing weak endogeneity, but mostly for limiting the sub-set of eligible local explanatory variables to endogenous and exogenous variables. When estimating models with all the variables in contemporaneous form, one primary concern is endogeneity. For example, in the case of exchange rate, changes in this factor may anticipate changes in CDS spreads. On the other hand, currency devaluation may be consequence of deteriorating economic fundamentals, i.e., if the public debt is perceived to be unsustainable in the short term, the government may pursue currency depreciation in order to soften the burden of servicing the debt. Then, in order to circumvent endogeneity issues, we run GMM estimations with instrumental variables for the endogenous variables. When the variable is considered exogenous, we simply use it as instrument for itself; for the endogenous ones, we use their first lags as instruments. Non-exogenous and non-endogenous variables are not considered in the model specification. Therefore, by restricting the testable model specifications to combinations of only endogenous and exogenous variables, we can filter out some model specifications and save computational cost. Table 5 summarizes Table 4 showing the sub-set of eligible variables for each country, marked with labels "(*)", "*" and "&". Parts A and B of Table 4 show chi-squared statistics for testing, respectively: i) whether local variables anticipate changes in CDS spreads, and ii) whether the opposite holds true. A variable is deemed eligible when it is weakly exogenous or endogenous. When the statistic is non-significant at 10% in Part A, then the corresponding variable is not eligible. Weak exogeneity is attributed to a variable when the chi-squared statistic is 10% significant in Part A, but not in Part B. A variable is considered endogenous in case the chi-squared statistic is 10% significant both in Part A and Part B. In order to provide a clear view of the set of eligible variables, the weakly exogenous and endogenous variables are marked with label "*" and "&", respectively, in Table 5. When there is no label, the corresponding variable is not considered as eligible. Variables labelled "(*)" in Table 5 are considered exogenous by assumption, i.e., the global variables and the first lag of the dependent variable are not due to be affected by the dependent variable in any sense for any country in the sample.

In the second step, we select[7] the model specification for each country, according to the following criteria: i) expected signs according to Table 3, ii) at least two 10%-significant parameters, iii) highest possible number of parameters, iv) highest Adjusted R^2 and v) superior[8] to all possible nested[9] models; or vi) which satisfies conditions i) and ii) and with Adjusted R^2 higher than model's satisfying conditions i), ii), iii), iv) and v). Blank cells in Table 6 mean that models including the corresponding factor are superseded by the prevailing model specification; or that the corresponding factor is just non-eligible.

We also perform a cluster analysis, in which countries are sorted into groups where the members of each group are as similar as possible[10]. At the same time, the algorithm attempts to form the groups to be as dissimilar from one another as possible. In effect, the algorithm tries to create groupings in a way that maximizes the average distance between countries in the same group, while minimizing the average distance between countries of different groups.

Finally, we assess the goodness-of-fit of the estimations and their forecast accuracy.

5.1 Results

The most striking result of Table 6 is that the global variables $sp500$ and oil not only show up as significant estimators for most of the countries, but also that there is a difference in sensitivity to these global factors between emerging markets and developing countries. Even for countries for which those global variables don't show up (Austria, India and Hong Kong), we find that the estimators for vix and $stock_i$ (which are highly correlated[11] to $sp500$) are significant. The other four countries significantly sensitive to $stock_i$ are: Japan, Belgium, Mexico and Thailand. This is also in line with the perception that government debt riskiness of these countries are linked to the dynamics of the general state of the local economy and that the local stock exchange is a very important driver for these local economies. Besides, no local variable shows up as significant for more than half[12] (19) of the sample of countries. Moreover, for 17 out of 19 of these countries (exceptions are New Zealand and Poland), only $sp500$ and oil are significant. One can argue that for these sovereigns (one third of them are developed European countries and the remaining is mostly comprised of investment-grade[13] European and Asian countries – except for Greece and Indonesia), the main driver is the general state of the global economy. The pervasiveness of global factors is consistent with the results obtained by other authors (Longstaff et al. 2010; Pan and Singleton, 2008).

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[7] The total number of models tested comprises all possible combinations of factors labelled with "(*)", "*" or "&" in Table 5 with minimum of three factors. For example, in case of Japan, we have a set of 8 eligible factors (see table 5): $sp500$, vix, ted, TP, oil, $spread_i$, $stock_i$ and xr_i. Then, we test $\binom{8}{3}+\binom{8}{4}+\binom{8}{5}+\binom{8}{6}+\binom{8}{7}+\binom{8}{8}=219$ models.

[8] We use F-test (see Greene, 2007) for testing the null hypothesis that the more comprehensive model does not contribute additional information. When we reject this hypothesis at 5% significance level, then the more comprehensive model is not rejected to be superior to the nested one.

[9] A model nests another one when the first contains the same terms as the second and at least one additional term.

[10] See Annex.

[11] Correlation with vix is -70% and is between 50% and 77% with $stock_i$ for Austria, India, Hong Kong, Japan, Belgium, Mexico and Thailand.

[12] Italy, Spain, Netherlands, Greece, Portugal, Ireland, Russia, Chile, China, Korea, Indonesia, Denmark, Sweden, New Zealand, Poland, Malaysia, Hungary, Peru and Slovakia.

[13] See Table 1.

Remarkably, the results also confirm the intuition that spreads of emerging market sovereigns are much more sensitive to global factors than spreads of developed countries. Tables 6 shows that estimators for $sp500$ and oil are higher in absolute terms for emerging market countries. Taking estimator values for $sp500$ and clustering the non-null values into two groups leads us to results in Table 7. Statistics in Table 8 just supports the choice of the number of clusters, as the two-group solution with a Calinski-Harabasz (1974) pseudo-F value[14] of 59.21 is the largest, indicating that this grouping solution is the most distinct compared with three-group and four-group solutions. Moreover, as expected, we observe a clear-cut separation between emerging market and developed countries. The results are similar for non-null estimator values of oil, in the sense that a group of emerging market countries cluster together distinctively as well.

Another interesting finding is that Brazil and Turkey appear in Table 6 with $sp500$ and local short term yield being significant drivers of riskiness perception of their debts. One common characteristic of these countries is that they are used to figure in the top list of countries with high nominal interest rates. Therefore, any move in the policy rate, which is tracked very closely by short term yields, can cause a relevant impact on the domestic bond and stock markets and non-domestic derivative markets, like the sovereign CDS market. If a history of high indebtedness and debt restructurings is any guide, this conciliates with the view that an increasingly high short term yield signals that the sovereign may be struggling to attract investors to fund its fiscal deficit. This is due to lead protection sellers to charge higher premiums on CDS contracts with those debts as reference obligations. Moreover, both countries share a history of struggle against inflation. According to Blanchard (2005), for example, in 2002 and 2003, fiscal dominance regime prevailed within the Brazilian economy, where the monetary policy turned to be ineffective for inflation control and, even worse, a raise of the policy rate was signaling high riskiness of exchange rate devaluation. In this case, the realization of currency depreciation led to a reduction in value of local currency denominated public debt in dollar terms to the detriment of debtholders. Still consistent with the positive sign for the estimators, the opposite seems to hold true recently, i.e., short term yields have been declining in those countries and CDS spreads have also been declining accordingly.

The fact that ted doesn't show up as significant may be due to the general assessment that, mainly for countries within the Euro zone and other developed countries, the transmission of distress from the banking sector to sovereign credit deterioration may occur more like a structural break than continuously in time. When the ted increases, banks may be not even relying on each other that short term loan will be repaid in full. Our ex-ante expectation was that increases in ted, as a stress indicator[15] of the banking sector, could have, from some moment, continuously contaminated risk perception of sovereign bonds. It is worth mentioning that ted effects are not captured by other global variables, like $sp500$ or oil, as their pair-wise correlations are not high: -12% and -15%, respectively. Thus, the underpricing of the spillover effect from the financial stability stance to the sovereign debt risk during the period leading to the 2007-2009 crisis can be tentatively explained by a reliance that governments would: i) monetize their debts (this may be more the case of United States, but less the case of Euro-zone country members), ii) wipe out defaulted bank's shareholders and subordinated debtholders, or iii) be simply rescued by economically stronger sovereigns. Anyway, sovereign risk may deteriorate abruptly, once none of those issues are appropriately addressed. In Iceland and Ireland, for example, problems in the banking sector

[14] See Annex.

[15] See Table 3.

brought down market assessment of their debt sustainability in a couple of days, but only after a prolonged period during which those problems in their respective financial systems were well-known. In the case of the non-Euro zone member Iceland, although their citizens voted against repaying depositors in United Kingdom and Netherlands, there was no sovereign debt restructuring as far as it is concerned. In the end, the IMF and the European Union provided financial assistance to Iceland and Ireland and CDS spreads referencing their debts receded as a result.

Colombia is one of a few countries showing significant positive estimator of xr_i and this evidence stands as supportive to the hypothesis that the currency channel plays a role in determining market perception of sovereign credit risk. Colombia is a special case, because it suffered a recession in 1999, in the wake of the currency crisis in Russia and Brazil, which threatened debtholders with a possibility of debt restructuring. According to Clavijo (2004), over the years 1999-2002, the exchange rate depreciated by about 20% in real effective terms. It is argued that the stability of real exchange rate and the inflation control were achieved by the implementation of monetary and exchange rate policies during this period. More recently, imports, exports, and the overall balance of trade are at significant levels, and the inflow of export dollars has resulted in a substantial re-valuation of the Colombian peso. Its sovereign credit risk is being priced at lower levels, accordingly.

$localTP_i$ and fr_i don't show up as significant for any country. The evidence that TP also shows up as barely significant (only for Thailand) suggests that business cycle effects are more broadly captured by $sp500$, oil and $stock_i$, while credit risk signals embedded in term premium and foreign reserves may be encompassed by changes in xr_i and $localTY_i$. Moreover, our time series of foreign reserves are obtained as interpolation of the original data available only on a monthly basis. Then, this treatment of missing values for foreign reserves may be one reason why we don't obtain significant estimators for this variable.

Next, we follow through a goodness-of-fit analysis by identifying clusters and by comparing estimation results of models with lagged explanatory variables and ARMA structural models.

5.2 Robustness Check

We assess the goodness-of-fit of the estimations by means of Adjusted R^2, PMAD (Percent Mean Absolute Deviation) and PHM (Percent Hit Misses). Adjusted R^2's are calculated for the in-sample period, whereas PMAD and PHM, for out-of-sample period. As a test of forecast accuracy, we believe that the assessment using PMAD is more intuitive than squared errors (SE), since it is the average value of the error in absolute terms as percentage of the average value of the realized value also in absolute terms. PHM, on the other hand, stands as an assessment of whether the direction of the prediction is accurate or not, i.e.:

$$PHM = {\#HitMisses}/{N}.$$

where $\#HitMisses$ = number of times the prediction does not have the same sign as the realized value and N = total number of observations.

While for Adjusted R^2, the higher it is, the better, for PMAD and PHM, we should expect low values.

Clustering results of Table 9 suggest that changes in CDS spreads for emerging market countries as a class, especially for those within clusters in the lower part of table, show more potential for prediction than spreads of developed countries. Data in Table 9 are essentially a rearrangement of goodness-of-fit measures of Table 6, but with each column sorted in ascending or descending order depending on the measure. Countries in the lowest part of the table are associated to better goodness-of-fit measures. Then, we define the number of clusters and their members by means of Calinski-Harabasz (1974) stopping rule[16]. The numbers of groups are robust to Calinski-Harabasz pseudo-F index stopping rule, according to Table 10. For Adjusted R^2, the highest index value is assigned to three as the number of clusters. For both PMAD and PHM, we parsimoniously choose four as the number of clusters. Results show that the best performing clusters at the three goodness-of-fit measures (those at the lowest part of the Table 9) are essentially comprised of emerging market countries (except for Japan in the PMAD clustering). Their adjusted R^2's are relatively high and their PHM's are low. Their PMAD's, however, are not low in absolute terms, but still lower than PMAD's of developed countries. Moreover, Colombia stands out as the common country across those best performing clusters.

When we estimate the models for each country with exactly the same explanatory variables as in Table 6, but with these variables in lags, the results are less robust in terms of significance of parameters and goodness-of-fit as expected. Taking results of $sp500$ and oil in Table 11, we observe that much less estimators show up as significant. Statistically significant local variables are even less numerous in comparison to Table 6. Besides, except for a few cases (five out of 97), all the the goodness-of-fit metrics are comprehensively better for models in Table 6.

As a benchmark for our GMM estimations with lagged explanatory variables, we model change in CDS spreads as an ARMA (Autoregressive Moving Average) process.

We proceed with ARMA modelling according to Box-Jenkins (1994) and Enders (2004). The ARMA(p,q) process is estimated by FIMLE (Full-Information Maximum Likelihood Estimation). The best model is selected if: i) the AR and MA terms are 10% significant; ii) the residuals behave as a white-noise process (in which all autocorrelations should be zero), iii) it has the lowest BIC (Bayesian Information Criteria) statistic, iv) it is non-degenerate, i.e., there are no gaps within AR or MA terms and v) when i) and ii) don't hold, then only criteria iii) and iv) are taken into consideration. We use Ljung-Box (1978) Q-statistic in equation (2) at 10% significance level for testing the ii) hypothesis.

$$Q = T(T+2)\sum_{k=1}^{s} r_k^2 \Big/ (T-k) \tag{2}$$

If Q exceeds the critical value of χ^2 with $s-p-q$ degrees of freedom, then at least one value of r_k, which is the sample autocorrelation coefficient or order k, is statistically different from zero. We set s as 10.

Results of Table 12 don't allow us to affirm that pure time series-based models are consistently better than fundamental-based models or whether the opposite holds true. While adjusted R^2's and PHM's are, respectively, better for 70% and 55% of the countries in comparison with the same statistics as reported in Table 11, PMAD's are higher only for 36% of the countries.

6. Conclusion

Results provide useful insights and a promising framework for supporting short-term investment decisions.

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[16] See Annex.

The empirical evidence is strongly supportive of the models presented in Table 6. The estimators of important global variables (S&P500 and Oil price) are comprehensively significant, whereas Local Stock Exchange, Exchange Rate and Local Short Term Yield show up with significant estimators and with correct signs for selected important investable emerging market countries. Moreover, goodness-of-fit and forecasting accuracy are much better for a sub-set of emerging markets than for developed countries. As we expected, models with contemporaneous variables are consistently better than with lagged variables, both in terms of significance of estimators and goodness-of-fit. Nonetheless, when analysing models with lagged variables, one cannot affirm that goodness-of-fit and forecasting accuracy are better for fundamental-based models than for ARMA structural models.

If the past is any guide (so far we believe it is!) and investment decisions are due to be taken on a weekly basis, one may consider choosing specific sovereigns for trading credit default swaps with their bonds as reference obligations and pursuing the proposed econometric-based framework for forecasting their spreads. In order to use this framework in practice, however, one must consider some caveats. Models with contemporaneous variables need one-week-ahead predictions as inputs. In this case, results of Table 6 suggest that forecasting efforts should be focused on global variables in the first stage, particularly S&P500 and Oil price. Moreover, the same caveat mentioned by Longstaff et al. (2010) applies here: the period of analysis is “characterized by excess global liquidity, prevalence of carry trades and reaching for yield in the sovereign market”.

For future research, one may consider testing other banking sector-related factors or models with dummy variables. The well-functioning of the banking sector is essential to fostering the economic development of any country, while the opposite holds true as well: banking crisis can lead to economic recession. Therefore, distresses in the banking sector, when pervasive and reaching too-systemic-to-fail firms, like the one that happened during the 2007-2009 crisis, may lead to negative views on the debt sustainability of the corresponding sovereign. In this sense, whether for paving the way for economic growth or where having a specific mandate of guaranteeing financial stability, central banks, as lenders of last resort, have an incentive for recuing the banking sector. In our paper, we use ted as a proxy for distress in the banking sector, but it doesn’t show up as significant. We conjecture that Sovereign CDS spreads may not have captured distress from the banking sector, as its transmission to sovereign credit deterioration may occur more like a structural break than continuously in time. This hypothesis should be more rigorously tested by including a dummy variable or other banking-related variables.

As an additional robustness check, we recommend undertaking randomization tests on selected set of explanatory variables and compare the forecast accuracy ex-post. For example, if 60% of predictions of changes in S&P500 had been correct, what would have been the value for PHM (Percent Hit Misses)?

Reference

Alsakka, R., O. Gwilym. 2010. “Leads and Lags in Sovereign Credit Ratings”, Journal of Banking & Finance 34: 2614-2626.

Blanchard, Olivier. 2005. “Fiscal Dominance and Inflation Targeting: Lessons from Brazil”, in G. Giavazzi, I. Goldfajn and S. Herrera (eds.) “Inflation Targeting, Debt and the Brazilian Experience, 1999 to 2003”, Cambridge, MA: MIT Press, pp. 49-80.

Box, George, G. Jenkins, G. Reinsel. 1994. “Time Series Analysis: Forecast and Control”. John Wiley.& Sons.

Baum, Christopher. 2003. “An Introduction to Modern Econometrics using Stata”.

Calinski, T. and J. Harabasz .1974. “A dendrite method for cluster analysis”, Communications in Statistics 3: 1-27.

Clavijo, Sergio. 2004. “Monetary and Exchange Rate Policies in Colombia: Progress and Challenges”, IMF Working paper.

Enders, Walter. 2004. “Applied Econometric Time Series”. John Wiley.& Sons.

Granger, Clive, 1969. "Investigating causal relations by econometric models and cross-spectral methods". Econometrica 37 (3), 424–438.

Greene, William. 2007. “Econometric Analysis”. Prentice Hall.

Longstaff, Francis A., J. Pan, L. H. Pedersen, K. Singleton. 2010. “How Sovereign is Sovereign Credit Risk?”. American Economic Journal, forthcoming.

Longstaff, Francis, S. Mithal and E. Neis. 2005. “Corporate Yield Spreads: Default Risk or Liquidity? New Evidence from the Credit Default Swap Market”. The Journal of Finance 40(5): 221-53.

Ljung, Greta; G. E. P. Box. 1978. "On a Measure of a Lack of Fit in Time Series Models". Biometrika 65: 297–303

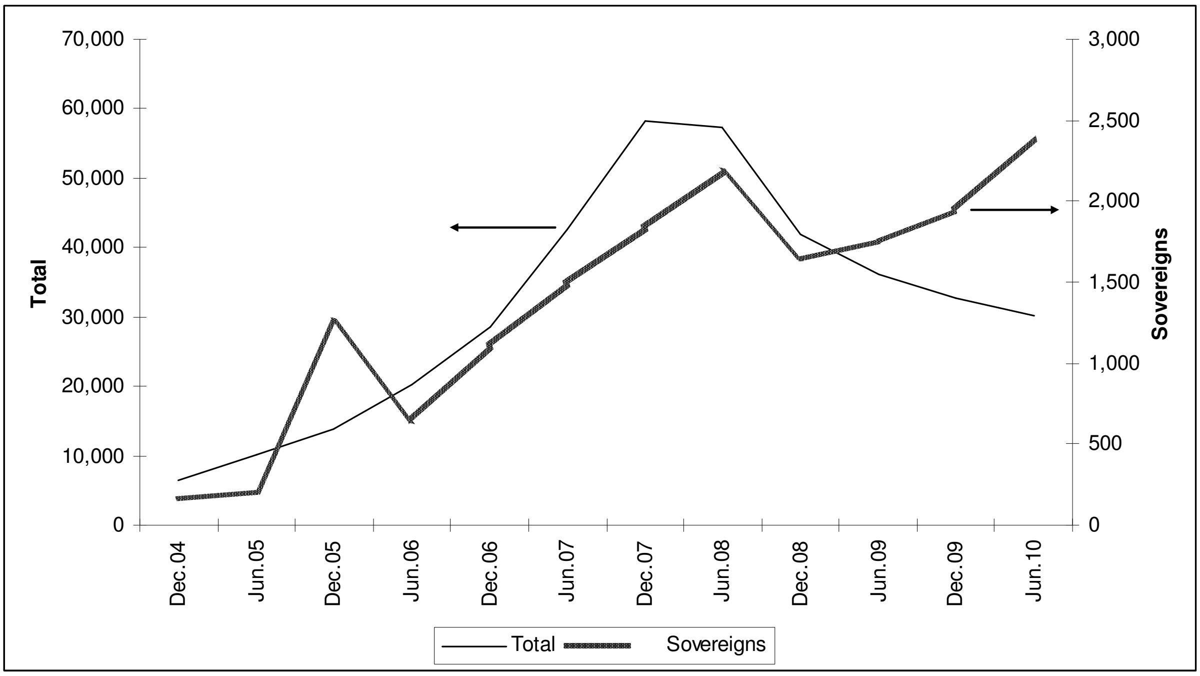
Milligan, G. W., and M. C. Cooper. 1985. “An examination of procedures for determining the number of clusters in a dataset”, Psychometrika 50: 159-179.

Pan, Jun, K. Singleton. 2008. “Default and Recovery Implicit in the Term Structure of Sovereign CDS Spreads”, Journal of Finance 63(5): 2345-2384.

Remolona, Eli, M. Scatigna, and E. Wu. 2008. “The Dynamic Pricing of Sovereign Risk in Emerging Markets: Fundamentals and Risk Aversion”, The Journal of Fixed Income 17(4): 57-71.

White, Halbert. 1980. “A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity”. Econometrica 48(4): 817-838.

Figure 1 – Notional Amount of CDS Contracts Outstanding (US$ Billions): Total vs. Sovereigns



Source: Bank for International Settlement

Table 1 – Classification of Sovereigns according to Investment Class

Investment Class	Countries	Rating*
SDR (Special Drawing Right) basket	Japan Germany Italy France Spain Belgium Netherlands Greece Austria Portugal Ireland Finland	AA AAA A+ AAA AA AA+ AAA BB+ AAA A- AA AAA
Commodity exporting countries	Mexico Russia Chile	A BBB+ A+
Other G20 countries	China Korea India Brazil Turkey Indonesia	AA A+ BBB- BBB+ BB+ BB+
Other highly rated countries	Denmark Sweden New Zealand Hong Kong	AAA AAA AAA AA+
Other emerging markets	Poland Malaysia Thailand Colombia Czech Republic Hungary Peru Slovakia	A A+ A- BBB+ A+ BBB- BBB+ A+

*Source: Standard & Poor’s, Aug/2010

Table 2 – Descriptive Statistics for CDS Spreads

	Mean	Standard Deviation	Minimum	Median	Maximum	# obs
Japan	21.26	22.88	2.38	10.17	114.23	451
Germany	11.20	14.78	1.45	4.00	87.76	421
Italy	33.63	46.90	5.54	9.50	226.56	451
France	13.40	19.50	1.45	4.00	93.67	433
Spain	29.09	48.10	2.25	5.65	259.31	451
Belgium	18.47	29.13	1.86	5.02	147.75	451
Netherlands	15.14	23.69	1.08	3.60	120.99	365
Greece	68.77	142.21	4.54	13.91	956.66	451
Austria	22.39	40.59	1.43	4.55	254.21	451
Portugal	32.93	58.33	3.75	7.72	363.46	442
Ireland	47.16	79.16	1.65	3.95	364.37	395
Finland	10.54	14.69	1.17	3.72	87.33	421
Mexico	139.00	89.66	27.16	115.93	454.81	451
Russia	214.31	175.44	35.31	169.45	972.82	451
Chile	76.11	69.36	11.95	52.94	311.02	443
China	47.54	41.37	8.68	34.27	247.25	451
Korea	78.45	79.64	13.60	56.32	561.80	451
India	114.58	100.21	28.18	77.69	457.92	320
Brazil	504.30	666.74	57.66	279.23	3540.24	451
Turkey	365.38	259.71	116.64	256.47	1235.44	451
Indonesia	289.96	144.12	87.55	258.44	938.63	450
Denmark	15.29	26.00	1.14	3.21	135.20	400
Sweden	15.53	26.95	1.25	3.71	150.16	451
New Zealand	26.30	40.58	2.06	4.80	233.71	365
Hong Kong	30.90	29.61	3.51	19.51	145.00	361
Poland	59.83	65.41	7.58	38.98	393.81	451
Malaysia	74.48	58.61	11.32	57.67	364.33	451
Thailand	77.30	56.98	22.77	55.55	361.39	451
Colombia	328.03	249.10	62.01	245.95	1305.65	451
Czech Republic	38.10	49.93	4.59	22.89	331.08	451
Hungary	93.39	120.78	9.63	33.65	562.29	451
Peru	273.96	205.81	57.29	190.11	1012.13	443
Slovakia	44.18	44.56	5.20	24.37	250.05	451

Table 3 – Description of Explanatory Variables

Variable acronym	Description and Economic Reasoning	Expected Sign	Source
$spread_i$	First difference of CDS spread of country i : These spreads are the last price for five-year senior dollar-denominated CDS contracts. This is the dependent variable in the estimation and its lag is also included as explanatory variable in the estimation.	Negative/ Positive	Markit
$sp500$	Δlog of Standard & Poor's 500 Index: it is a gauge of the general state of the global economy.	Negative	Bloomberg Ticker: SPX
vix	Δlog of VIX Index: VIX is a measure of market's expectation of stock market volatility. The positive variation of this index is associated with higher uncertainty and risk aversion among investors.	Positive	Bloomberg Ticker: VIX
ted	First difference of TED spreads: this spread is the difference between the three-month interest rates on interbank loans (LIBOR) and three-month U.S. government debt (OIS – Overnight Indexed Swap). The higher is the positive change of this spread, the less willing banks are to lend to each other.	Positive	Bloomberg Tickers: US0003M and USSOC
TP	First difference of U.S. Term Premium: term premium is the difference between the interest rates on 10-year U.S. Treasury Bond and three-month U.S. Treasury Bills. It provides prospective information on the business cycle of the global economy. U.S. term premium is influenced positively by economic growth and by inflationary expectations; it is influenced negatively by risk aversion.	Negative	Bloomberg Tickers: H15T10Y and H15T3M
oil	Δlog of Oil Price: Oil price is last quoted price of the day of the London Brent Crude Oil Index. In general, increasing oil prices reflects both the surging of global economic activity or the impact of production shortfalls. Focusing on the demand side, when the pace of economic expansion picks up, so are expected to increase world demand in general for energy and for oil in particular. In this sense, changes in oil prices may be considered a better indicator for the state of the global economy than changes in S&P 500 or VIX indices	Negative	Datastream Mnemonic: LCRINDX
$stock_i$	Δlog of Local Stock Exchange Index: this index is expected to rise or remain stable when companies and the economy in general show signs of stability and growth. It is expected to decrease in periods of crisis. Then, it is an indicator generally used to gauge the health of an economy.	Negative	Bloomberg
xr_i	Δlog of Exchange Rate: the last-price-of-the-day exchange rates are expressed in units of local currency per U.S. dollar. One may argue that currency devaluation may lead to additional charges for dollar-denominated indebted countries and for countries with negative balance of trade and highly dependent on import of manufactured products. On the other hand, as an indicator of relative international price competitiveness, currency devaluation may lead to high benefits derived from international trade.	Positive/ Negative	Bloomberg
$localTY_i$	First difference of the One-To-Three-Year Local Bond Yield: the yield refers to the local currency denominated fixed rate government debt. All bond prices are mid rates and are taken at the close of business in the local office for all markets. In general, high short term yields negatively impact growth prospects in the near future. Moreover, an increasingly high short term yield signals that the country may be struggling to attract investors to fund its expenses.	Positive	Morgan Markets
$localTP_i$	First difference of Local Term Premium: local term premium is the difference between the interest rates on Seven-To-Ten-Year and One-To-Three-Year Local Bond Yields. It provides prospective information on the business cycle of the local economy. When the premium becomes small or negative, it indicates a slowdown in economic activity in the foreseeable future. On the other hand, higher term premium suggests expectations of increasing economic growth or that investors may be requiring additional discount on long term bonds to account for liquidity risk.	Negative/ Positive	Morgan Markets
fr_i	Δlog of Foreign Reserves: foreign reserves are the dollar values of foreign currency holdings. Weekly values are calculated by linear interpolation of monthly values. It is considered a protection against withdrawal of foreign funding.	Negative	IMF - international financial statistics

Table 4 – Granger Causality Test

Each column in Part A shows the chi-squared statistics with n degrees of freedom (χ^2_n) for the hypothesis test that the corresponding factor f_t does not "Granger cause" the first difference of CDS spreads of the country in the corresponding row. The Granger causality test is a Wald test on the restrictions that the β_l's are jointly zero at the estimation of equation: $spread_{i,t} = \alpha_0 + \sum_{k=1}^{5} \alpha_k spread_{t-k} + \sum_{l=1}^{5} \beta_l f_{t-l} + \varepsilon_t$. 'N' accounts for the number of countries in each column for which the chi-squared statistic is 10% significant. Part B shows the chi-squared statistics for whether the opposite holds true, i.e., for the hypothesis test that the first difference of CDS spreads of the country in the corresponding row does not "Granger cause" the corresponding factor f_t. The Granger causality test is a Wald test on the restrictions that the δ_l's are jointly zero at the estimation of equation:

$$f_t = \gamma_0 + \sum_{k=1}^{5} \gamma_k f_{t-k} + \sum_{l=1}^{5} \delta_l spread_{t-l} + \eta_t.$$

	Part A					**Part B**				
	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localTP_{i,t}$	$fr_{i,t}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localTP_{i,t}$	$fr_{i,t}$
Japan	9.4*	10.9*	5.6	1.0	6.1	7.0	6.6	4.2	5.5	13.7**
Germany	15.2***	19.3***	24.7***	18.5***	26.6***	15.3***	9.2	7.2	4.1	15.2***
Italy	5.1	17.6***	11.8**	23.4***	2.5	19.7***	15.1***	24.0***	15.0**	1.9
France	15.7***	14.5**	11.1**	17.1***	9.4*	17.6***	5.6	9.7*	12.9**	5.1
Spain	4.2	15.9***	6.9	14.5**	3.9	20.3***	11.8**	20.0***	28.6***	4.1
Belgium	11.5**	15.9***	4.8	19.6***	3.3	5.3	9.8*	14.3**	24.9***	0.5
Netherlands	13.4**	26.4***	19.6***	15.7***	1.9	3.3	11.3**	18.6***	18.4***	1.3
Greece	10.1*	9.7*	10.8*	10.2*	15.2***	10.3*	9.4*	33.7***	50.2***	7.0
Austria	16.9***	18.1***	8.7	32.7***	2.9	5.6	7.5	15.4***	15.7***	4.6
Portugal	2.7	9.3*	8.0	10.2*	2.1	7.6	12.4**	23.3***	21.3***	0.7
Ireland	14.4**	9.1	10.6*	53.8***	1.6	11.9**	13.7**	10.0*	11.5**	1.5
Finland	2.2	9.9*	11.8**	19.0***	0.6	7.0	5.4	10.1*	6.9	2.7
Mexico	26.0***	58.4***	3.7	45.5***	31.4***	5.1	13.8**	8.3	16.2***	27.1***
Russia	38.0***	13.0**	43.3***		30.4***	9.7*	12.8**	16.8***		4.9
Chile	15.5***	19.6***	1.6	7.7	12.8**	11.1*	1.9	11.0*	21.8***	3.5
China	9.3*	2.7	26.4***	1.6	27.1***	10.7*	8.9	10.9*	6.3	15.4***
Korea	0.4	66.5***	3.5	8.3	134.7***	11.7**	24.8***	13.5**	5.0	30.2***
India	8.6	18.7***	26.4***	25.0***	52.3***	12.8**	29.9***	6.2	9.7*	4.2
Brazil	7.2	28.4***	16.5***	19.2***	1.8	10.3*	10.5*	5.2	28.9***	2.0
Turkey	11.6**	42.5***	16.3***		21.8***	12.0**	21.5***	4.7		4.7
Indonesia	19.3***	41.8***	35.9***	3.4	24.8***	15.2***	73.5***	19.4***	3.1	6.3
Denmark	27.9***	30.3***	5.7	26.3***	32.6***	11.4**	11.6**	24.0***	20.8***	15.9***
Sweden	20.1***	53.2***	27.5***	30.3***	22.3***	4.1	19.5***	8.2	10.6*	14.0**
New Zealand	9.4*	16.2***	13.5**	7.9	7.2	8.0	12.4**	18.0***	16.2***	5.6
Hong Kong	16.7***	6.9	8.3	7.6	17.8***	6.5	5.2	6.1	6.0	27.0***
Poland	13.0**	19.2***	60.6***	63.0***	13.6**	17.8***	9.9*	14.6**	5.6	4.2
Malaysia	3.5	12.5**	12.5**	3.8	20.6***	8.2	6.1	4.3	4.5	4.4
Thailand	15.9***	10.4*	10.1*	9.7*	3.3	8.2	3.3	16.7***	2.0	12.9**
Colombia	9.7*	12.2**	10.9*	5.9	5.3	3.7	3.6	2.4	10.2*	9.2
Czech Rep.	20.3***	35.8***	20.2***	13.4**	28.6***	16.1***	14.2**	52.5***	7.2	16.1***
Hungary	6.9	17.7***	6.8	35.9***	18.9***	20.9***	52.0***	11.7**	42.1***	71.3***
Peru	6.4	22.9***	7.7	9.6*	6.5	10.1*	12.5**	3.8	11.9**	6.8
Slovakia	11.5**	7.1	8.2	0.9	65.3***	36.3***	11.7**	20.9***	6.9	22.1***
N	**23**	**29**	**20**	**23**	**19**	**20**	**22**	**22**	**21**	**12**

* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Table 5 – Set of Eligible Explanatory Variables

	Global Variables					Local Variables					
	$sp500_t$	vix_t	ted_t	TP_t	oil_t	$spread_{i,t-1}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	$localTP_{i,t}$	$fr_{i,t}$
Japan	(*)	(*)	(*)	(*)	(*)	(*)	*	*			
Germany	(*)	(*)	(*)	(*)	(*)	(*)	&	*	*	*	&
Italy	(*)	(*)	(*)	(*)	(*)	(*)		&	&	&	
France	(*)	(*)	(*)	(*)	(*)	(*)	&	*	&	&	*
Spain	(*)	(*)	(*)	(*)	(*)	(*)		&		&	
Belgium	(*)	(*)	(*)	(*)	(*)	(*)	*	&		&	
Netherlands	(*)	(*)	(*)	(*)	(*)	(*)	*	&	&	&	
Greece	(*)	(*)	(*)	(*)	(*)	(*)	&	&	&	&	*
Austria	(*)	(*)	(*)	(*)	(*)	(*)	*	*		&	
Portugal	(*)	(*)	(*)	(*)	(*)	(*)		&		&	
Ireland	(*)	(*)	(*)	(*)	(*)	(*)	&		&	&	
Finland	(*)	(*)	(*)	(*)	(*)	(*)		*	&	*	
Mexico	(*)	(*)	(*)	(*)	(*)	(*)	*	&		&	&
Russia	(*)	(*)	(*)	(*)	(*)	(*)	&	&	&		*
Chile	(*)	(*)	(*)	(*)	(*)	(*)	&	*			*
China	(*)	(*)	(*)	(*)	(*)	(*)	&		&		&
Korea	(*)	(*)	(*)	(*)	(*)	(*)		&			&
India	(*)	(*)	(*)	(*)	(*)	(*)		&	*	&	*
Brazil	(*)	(*)	(*)	(*)	(*)	(*)		&	*		
Turkey	(*)	(*)	(*)	(*)	(*)	(*)	&	&	*		*
Indonesia	(*)	(*)	(*)	(*)	(*)	(*)	&	&	&		*
Denmark	(*)	(*)	(*)	(*)	(*)	(*)	&	&		&	&
Sweden	(*)	(*)	(*)	(*)	(*)	(*)	*	&	*	&	&
New Zealand	(*)	(*)	(*)	(*)	(*)	(*)	*	&	&		
Hong Kong	(*)	(*)	(*)	(*)	(*)	(*)	*				&
Poland	(*)	(*)	(*)	(*)	(*)	(*)	&	&	&	*	*
Malaysia	(*)	(*)	(*)	(*)	(*)	(*)		*	*		*
Thailand	(*)	(*)	(*)	(*)	(*)	(*)	*	*	&	*	
Colombia	(*)	(*)	(*)	(*)	(*)	(*)	*	*	*		
Czech Rep.	(*)	(*)	(*)	(*)	(*)	(*)	&	&	&	*	&
Hungary	(*)	(*)	(*)	(*)	(*)	(*)		&		&	&
Peru	(*)	(*)	(*)	(*)	(*)	(*)		&		&	
Slovakia	(*)	(*)	(*)	(*)	(*)	(*)	&				&

(*) stands for Exogeneity by Assumption
* and & stand for Weak Exogeneity and Non-Weak Exogeneity at 10% significance level, respectively
Blank accounts for non-significance at 10% significance level, in this case, the corresponding variable is not part of any estimation model for the respective country

Table 6 – GMM Results

This table reports, for each country, statistical results of models: i) with expected signs according to Table 3, ii) with at least two 10%-significant parameters, iii) with the highest number of parameters, iv) with highest Adjusted R^2 and v) superior to all possible nested models; or vi): which satisfies conditions i) and ii) and with Adjusted R^2 higher than model's satisfying conditions i), ii), iii), iv) and v). The dependent variable is the first difference of CDS spreads. All the global and local variables are considered for the estimation. Goodness-of-fit statistics are calculated for estimation sample (July 2005 to June 2009) and out-of-sample periods (July 2009 to July 2010). Only combinations of explanatory variables labelled with "(*)", "*" and "&" in Table 5 are considered as possible estimation models. The first lag of local variable is used as instrument for the corresponding local variable labelled with "&" in Table 5. Variables transformations are such that we apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, Exchange Rate and Foreign Reserves) and Δ(.) to "interest rate" variables (TED spread, U.S. Term Premium, CDS spreads, Local Short-Term Yield and Local Term Premium). The variance-covariance matrices are estimated according to White (1980) robust estimation. Local Term Premium and Foreign Reserves don't show up as significant for any country.

		Global Variables					Local Variables						
	$cons$	$sp500_t$	vix_t	ted_t	TP_t	oil_t	$spread_{i,t-1}$	$stock_{i,t}$	$xr_{i,t}$	$localTY_{i,t}$	**Adj.R$^{2[c]}$**	**PMAD[a,d]**	**PHM[b,d]**
Japan	0.0019					-0.1**	-0.15	-0.4***			16%	81%	27%
Germany	0.0006	-0.3**				-0.2***	0.22				25%	95%	38%
Italy	0.0021	-0.8***				-0.5***	0.12				27%	91%	29%
France	0.0008	-0.4***					0.25		0.3**		26%	91%	29%
Spain	0.0029	-0.8**			-0.02	-0.3***					20%	91%	33%
Belgium	0.0016				-0.03	-0.3**		-0.6***			19%	92%	40%
Netherlands	0.0009	-0.7**				-0.2*	0.07				20%	98%	29%
Greece	0.0031	-1.4***				-0.5**	0.10				24%	99%	40%
Austria	0.0024						0.19	-0.9***	1.1**		24%	90%	31%
Portugal	0.0021	-0.8***			-0.02	-0.2**					24%	97%	38%
Ireland	0.0062	-2.2*	-0.1			-0.5*					16%	86%	33%
Finland	0.0006	-0.6***	-0.04				0.27*		0.3*		28%	87%	33%
Mexico	0.0136			0.20		-0.9**		-3.0***			40%	70%	31%
Russia	0.0044	-7.6***				-2.8***	-0.09				24%	109%	20%
Chile	0.0030	-1.8***			-0.04	-0.5*					25%	86%	27%
China	0.0008	-1.8***			-0.06	-0.5**					26%	80%	20%
Korea	0.0014	-4.7***		0.12		-1.1*					23%	94%	25%
India	0.0126		0.4*		0.22	-1.2	-0.16**				12%	-	-
Brazil	-0.0048	-4.3***		0.18						0.26***	39%	79%	33%
Turkey	0.0016	-4.6***					-0.14			0.35***	57%	95%	29%
Indonesia	-0.0073	-7.8***		0.58		-1.5*					28%	109%	18%
Denmark	0.0010	-0.5**				-0.3**	0.23				22%	95%	38%
Sweden	0.0022	-0.5*				-0.5***	0.15			0.03	21%	111%	42%
New Zealand	0.0027		0.1**		0.07	-0.5*					10%	87%	29%
Hong Kong	0.0038					-0.3	-0.21**	-0.6**			24%	70%	24%
Poland	0.0059		0.2*	-0.05		-1.0***				0.51	23%	91%	31%
Malaysia	0.0012	-2.8***		0.07		-0.8*	-0.19				23%	97%	29%
Thailand	0.0049				-0.23**			-3.2***	0.9		32%	103%	27%
Colombia	-0.0052	-3.7***		0.14				-0.9*	2.5***		41%	70%	24%
Czech Rep.	0.0019	-1.7***				-0.4**	0.14				21%	94%	27%
Hungary	0.0095	-4.2***				-1.3***	0.07				28%	87%	22%
Peru	-0.0055	-4.1***		0.21		-1.1**					34%	91%	25%
Slovakia	0.0015	-1.3***				-0.5***	0.12				21%	91%	33%

[a] and [b] stand for Percent Mean Absolute Deviation and Percent Hit Misses, respectively
[c] and [d] stand for in-sample and out-of-sample calculations, respectively
* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Table 7 – Clusters according to estimators for $sp500_t$ and oil_t

This table shows clusters according to non-null estimator values for $sp500_t$ and oil_t values reported in Table 6. Groups are separated by a thin solid horizontal line and are defined according to Calinski-Harabasz indices reported in Table 8.

$sp500_t$		oil_t	
Country	**Parameter**	**Country**	**Parameter**
Germany	-0.3	Japan	-0.1
France	-0.4	Germany	-0.2
Sweden	-0.5	Netherlands	-0.2
Denmark	-0.5	Portugal	-0.2
Finland	-0.6	Denmark	-0.3
Netherlands	-0.7	Belgium	-0.3
Portugal	-0.8	Spain	-0.3
Spain	-0.8	Czech Rep.	-0.4
Italy	-0.8	Slovakia	-0.5
Slovakia	-1.3	New Zealand	-0.5
Greece	-1.4	Greece	-0.5
Czech Rep.	-1.7	Italy	-0.5
China	-1.8	Chile	-0.5
Chile	-1.8	Sweden	-0.5
Ireland	-2.2	Ireland	-0.5
Malaysia	-2.8	China	-0.5
Colombia	-3.7	Malaysia	-0.8
Peru	-4.1	Mexico	-0.9
Hungary	-4.2	Poland	-1.0
Brazil	-4.3	Peru	-1.1
Turkey	-4.6	Korea	-1.1
Korea	-4.7	Hungary	-1.3
Russia	-7.6	Indonesia	-1.5
Indonesia	-7.8	Russia	-2.8

Table 8 – Calinski-Harabasz pseudo-F Statistic for Clusters for $sp500_t$ and oil_t

The formula of the index is in the Annex. Large values of the index indicate distinct clustering.

Number of clusters	$sp500_t$	oil_t
2	**59.21**	**39.91**
3	42.35	25.29
4	28.67	16.29

Table 9 – Clusters according to Goodness-of-Fit

This table shows clusters according to goodness-of-fit statistics reported in Table 6. Groups are separated by a thin solid horizontal line and are defined according to Calinski-Harabasz indices reported in Table 10. PMAD and PHM statistics are not reported for India, because the time series of its CDS spread is not available for the out-of-sample period.

Adj.R^2 [c]		PMAD [a,d]		PHM [b,d]	
Country	**Value**	**Country**	**Value**	**Country**	**Value**
New Zealand	10%	Sweden	111%	Sweden	42%
India	12%	Indonesia	109%	Greece	40%
Ireland	16%	Russia	109%	Belgium	40%
Japan	16%	Thailand	103%	Portugal	38%
Belgium	19%	Greece	99%	Denmark	38%
Spain	20%	Netherlands	98%	Germany	38%
Netherlands	20%	Malaysia	97%	Spain	33%
Czech Rep.	21%	Portugal	97%	Slovakia	33%
Sweden	21%	Denmark	95%	Finland	33%
Slovakia	21%	Germany	95%	Ireland	33%
Denmark	22%	Turkey	95%	Brazil	33%
Malaysia	23%	Czech Rep.	94%	Poland	31%
Poland	23%	Korea	94%	Austria	31%
Korea	23%	Belgium	92%	Mexico	31%
Hong Kong	24%	Spain	91%	Netherlands	29%
Portugal	24%	Italy	91%	Malaysia	29%
Greece	24%	Peru	91%	Turkey	29%
Russia	24%	France	91%	Italy	29%
Austria	24%	Slovakia	91%	France	29%
Chile	25%	Poland	91%	New Zealand	29%
Germany	25%	Austria	90%	Thailand	27%
China	26%	Finland	87%	Czech Rep.	27%
France	26%	Hungary	87%	Chile	27%
Italy	27%	New Zealand	87%	Japan	27%
Hungary	28%	Chile	86%	Korea	25%
Finland	28%	Ireland	86%	Peru	25%
Indonesia	28%	Japan	81%	Colombia	24%
Thailand	32%	China	80%	Hong Kong	24%
Peru	34%	Brazil	79%	Hungary	22%
Brazil	39%	Colombia	70%	Russia	20%
Mexico	40%	Mexico	70%	China	20%
Colombia	41%	Hong Kong	70%	Indonesia	18%
Turkey	57%				

[a] and [b] stand for Percent Mean Absolute Deviation and Percent Hit Misses, respectively
[c] and [d] stand for in-sample and out-of-sample calculations, respectively

Table 10 – Calinski-Harabasz pseudo-F Statistic for Goodness-of-Fit Clusters

The formula of the index is in the Annex. Large values of the index indicate distinct clustering.

Number of clusters	**Adj.**$R^{2[c]}$	**PMAD**[a,d]	**PHM**[b,d]
2	54.79	40.70	50.40
3	**56.27**	76.43	65.81
4	48.32	**100.53**	**158.65**
5	49.78	85.70	134.32

Table 11 – GMM Results with Lagged Explanatory Variables

This table reports, for each country, statistical results of models with the same explanatory variables as in Table 6, but in lags. The dependent variable is the first difference of CDS spreads. Goodness-of-fit statistics are calculated for estimation sample (July 2005 to June 2009) and out-of-sample periods (July 2009 to July 2010). The explanatory variable itself is used as instrument for the GMM estimation. Variables transformations are such that we apply Δlog(.) to "price" variables (S&P 500 index, VIX index, Oil price, Local Stock Index, Exchange Rate and Foreign Reserves) and Δ(.) to "interest rate" variables (TED spread, U.S. Term Premium, CDS spreads, Local Short-Term Yield and Local Term Premium). The variance-covariance matrices are estimated according to White (1980) robust estimation.

		Global Variables					Local Variables						
	$cons$	$sp500_{t-1}$	vix_{t-1}	ted_{t-1}	TP_{t-1}	oil_{t-1}	$spread_{i,t-1}$	$stock_{i,t-1}$	$xr_{i,t-1}$	$localTY_{i,t-1}$	Adj.R[2[c]]	PMAD[a,d]	PHM[b,d]
Japan	0.0019					0.03	-0.175	-0.14			1%	100%	51%
Germany	0.0005	-0.3**				0.03	0.205				11%	106%	45%
Italy	0.0022	-0.7**				0.05	0.011				6%	99%	53%
France	0.0010	-0.2*					0.142		0.18		10%	99%	38%
Spain	0.0029	-0.5*			-0.03	0.13					5%	100%	45%
Belgium	0.0019				-0.04**	0.07		-0.31**			3%	102%	51%
Netherlands	0.0013	-0.5**				-0.10	-0.103				7%	110%	49%
Greece	0.0038	-1.0**				0.04	-0.017				6%	100%	45%
Austria	0.0037						0.116	-0.24	0.98*		6%	103%	44%
Portugal	0.0024	-0.4			-0.03	0.12					3%	100%	38%
Ireland	0.0065	-1.4	-0.10			0.18					2%	100%	53%
Finland	0.0008	-0.2	-0.03				0.221		0.03		8%	106%	47%
Mexico	0.0046			0.17		-0.09		-0.04			0%	101%	49%
Russia	0.0056	-5.9**				-0.24	-0.269				7%	118%	47%
Chile	0.0043	-0.6			-0.04	-0.16					2%	110%	49%
China	0.0013	-0.8**			-0.04	0.03					3%	99%	45%
Korea	0.0034	-1.8*		0.15		0.55					2%	100%	47%
India	0.0202		0.05		-0.41	-0.30	-0.150*				12%	-	-
Brazil	-0.0143	-1.2		0.16						-0.16	4%	121%	58%
Turkey	-0.0048	-2.5					-0.193			-0.07	5%	111%	53%
Indonesia	-0.0064	-5.1**		0.24		1.22					7%	115%	47%
Denmark	0.0009	-0.6***				-0.08	0.136				17%	129%	58%
Sweden	0.0010	-0.6**				0.15	0.084			-0.15**	15%	129%	45%
New Zealand	0.0055		0.01		-0.13*	-0.41*					12%	107%	44%
Hong Kong	0.0032					-0.03	-0.254**	-0.18			4%	101%	51%
Poland	0.0066		0.09	0.03		0.05				-0.13	1%	99%	49%
Malaysia	0.0016	-2.1*		0.01		0.19	-0.326				9%	105%	49%
Thailand	0.0052				-0.15			0.83	-0.71		3%	111%	62%
Colombia	-0.0091	-1.7*		0.08				0.72	-0.71		2%	107%	51%
Czech Rep.	0.0033	-0.3				0.08	0.138				1%	104%	44%
Hungary	0.0113	-2.3**				0.45	0.002				4%	102%	47%
Peru	-0.0024	-1.1		0.11		-0.12					1%	110%	56%
Slovakia	0.0022	-0.6				-0.005	0.063				2%	104%	45%

[a] and [b] stand for Percent Mean Absolute Deviation and Percent Hit Misses, respectively
[c] and [d] stand for in-sample and out-of-sample calculations, respectively
* Significant at the 10 percent level
** Significant at the 5 percent level
*** Significant at the 1 percent level

Table 12 – ARMA Results

		AR Terms					MA Terms							
	cons	α_1	α_2	α_3	α_4	α_5	β_1	β_2	β_3	β_4	β_5	**Adj.R^2[c]**	**PMAD[a,d]**	**PHM[b,d]**
Japan		0.3*	-0.7***				-0.4***	0.9***				7%	104%	51%
Germany		-0.5***					0.8***					10%	110%	56%
Italy		-2.0***	-2.1***	-1.9***	-1.4***	-0.5***	2.3***	2.6***	2.5***	2.2***	0.9***	24%	156%	55%
France		-1.2***	-0.3**	0.4***			1.8***	1.0***				29%	120%	44%
Spain		-0.6***					0.6***					-1%	100%	38%
Belgium		-1.6***	-0.7***				1.8***	1.0***				10%	114%	51%
Netherlands		-1.0***					1.0***					0%	104%	56%
Greece		-1.6***	-0.8***				1.8***	1.0***				9%	98%	47%
Austria		-0.6***	-0.9***				0.8***	1.2***	0.3*			9%	136%	40%
Portugal		-1.6***	-0.8***				1.8***	1.0***				6%	104%	45%
Ireland		1.0***					-1.0***					-1%	100%	47%
Finland		0.8***	-0.9***				-0.6***	0.9***				15%	137%	53%
Mexico		1.0***					-1.0***					0%	100%	49%
Russia		0.5					-0.8***	-0.2	0.4***			17%	131%	60%
Chile							0.1	-0.1	0.4**			14%	114%	45%
China		-0.6***					0.8***					7%	102%	47%
Korea		-0.8***	-0.4				0.7***					16%	105%	42%
India		-1.1***	-0.3***				1.0***					11%	-	-
Brazil		-0.9***	-0.8***				0.9***	0.6***				9%	101%	42%
Turkey		-0.2	-0.3									8%	98%	42%
Indonesia		-0.5***	-0.4*				0.5*					14%	106%	45%
Denmark		-0.9***	-0.5**	-0.4*	-0.2	0.4***	1.3***	1.0***	1.3***	1.0***		38%	206%	56%
Sweden		0.5***	-0.8***				-0.4***	1.0***				11%	140%	55%
New Zealand	0.005***	1.0***					-1.0***					-1%	105%	55%
Hong Kong		-0.6***	-0.4***				0.4**					15%	104%	53%
Poland							0.3*	-0.3**				9%	126%	47%
Malaysia		-0.8***	-0.5*				0.6**					20%	105%	47%
Thailand		-0.9***	-0.4				0.7***					14%	103%	44%
Colombia		1.0***					-1.0***					-12%	126%	53%
Czech Rep.		-0.5*					0.7***					3%	107%	49%
Hungary		-0.3*	-0.4**				0.6***					19%	124%	45%
Peru		-0.7***					0.8***					2%	102%	47%
Slovakia							0.2					1%	105%	51%

The equation estimated by FIMLE is: $spread_{t,i} = cons + \sum_{i=1}^{p} \alpha_i spread_{t-i} + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i}$

Dependent Variable: % Weekly Change in CDS spreads

[a] and [b] stand for Percent Mean Absolute Deviation and Percent Hit Misses, respectively

[c] and [d] stand for in-sample and out-of-sample calculations, respectively

***, ** and * stand for significance at the 1%, 5% and 10% level, respectively.

ANNEX

Determination of the Number of Clusters

'k' is the number of clusters to be tested. For determining the clusters, we define the absolute-value as the distance measure. i.e., countries within a cluster should have low distances among them and high distances between countries of different clusters. We apply the absolute-value to two metrics, depending on the partition: one based on medians (for $sp500$ and oil parameters – Table 7) and the other, on means (for goodness-of-fit measures – Table 9). Arbitrary values for the metrics are initially set for each cluster. Then, each observation is assigned to the cluster whose metric is closest, and then based on that classification, new cluster metrics are determined. These steps continue until no observations change clusters. Finally, we need to compare the fitness of formed clusters. According to Milligan and Cooper (1985), Calinski-Harabasz (1974) index is one of the best stopping rules for the determination of the number of clusters. The formula of the index is:

$$\frac{trace(B)/(g-1)}{trace(W)/(N-g)}$$

where g is the number of clusters, N is total number of observations, B is the between-cluster sum of squares and cross-products matrix, and W is the within-cluster sum of squares and cross-products matrix.

Large values of the index indicate distinct clustering.