Global Perspective or Local Knowledge: The Macro-information in the Sovereign CDS Market*

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Abstract

We find that sovereign CDS spreads can predict future stock index returns, sovereign bond yields, as well real macroeconomic variables such as GDP and PMI. The predictive power is almost entirely from the global, rather than country-specific, component of sovereign CDS spreads. This is consistent with the interpretation that the information advantage of sovereign CDS investors is derived from their "global perspective" rather than their local knowledge about individual countries. Stock and sovereign bond market indices gradually "catch up" with sovereign CDS spreads, mostly during the days surrounding credit rating or outlook changes, and especially for downgrades.

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I. Introduction

The sovereign CDS market has been developing rapidly since the early 2000s. By 2015, the market has an aggregate notional amount of around $2 trillion, and covers 91 countries.[1] What informational role does this market play? Does it aggregate new information, or merely repackage information in other financial markets, such as the stock and bond markets of the underlying countries? If it does aggregate new information, what is the nature of the information? Is it country-specific, or is it about global factors? Given the large and rapidly growing size of the sovereign debt markets and their systemic importance for the global economy, the answers to these questions are important in and of themselves. Moreover, the answers help improve our understanding of the interconnections among global financial markets and economies. Last but not least, the answers have direct implications for global investors' asset allocation, as well as capital flows across countries.

Our main finding is that sovereign CDS spreads possess information that has not been fully reflected in the stock and sovereign bond markets of the underlying countries, and that this information is about global factors, rather than country-specific variables. In other words, sovereign CDS spreads can predict future stock index returns and sovereign bond yields of the underlying countries, and the predictive power is almost entirely from the systematic, rather than country-specific, component of sovereign CDS spreads. This is consistent with the interpretation that the information advantage of sovereign CDS investors is derived from their "global perspective" rather than their local knowledge about individual countries.

Specifically, to examine whether sovereign CDS spreads can predict future stock index returns, we sort countries into 5 quintiles based on their past 3-month sovereign CDS performances. The sovereign creditworthiness of quintile-1 countries has improved the most according to the sovereign CDS market, while that of quintile-5 countries has deteriorated the most. Presumably, the sovereign CDS market indicates good news during the past 3 months for

[1] Based on the data from the Depository Trust & Clearing Corporation (DTCC) and Markit Inc.

quintile-1 countries, and bad news for quintile-5 ones. If this information is not fully reflected in stock prices, the stock indices of quintile-1 countries would outperform those of quintile 5 in the coming months.

This is indeed the case. For each quintile, we first form an equal-weighted portfolio of stock indices, and construct its dollar-denominated returns. During the month after the sorting, the quintile-1 portfolio outperforms the quintile-5 portfolio by 1.25% per month (t=3.80), or 15% per year. Similarly, the market-capitalization-weighted portfolio of quintile 1 outperforms that of quintile 5 by 1.10% per month (t=2.43). After accounting for the factors of international stock and currency markets, this return difference is still 1.00% per month (t= 2.83) for equal-weighted portfolios, and 0.89% (t=2.17) for value-weighted portfolios.

Similarly, if sovereign bond markets do not fully reflect the good news from the sovereign CDS market regarding quintile-1 countries, their bond prices will tend to go up in the coming months, i.e., their yields will fall. On the other hand, the bond yields of quintile-5 countries will tend go up. Indeed, during the month after the sorting, the average of 5-year sovereign bond yield indices of quintile-1 countries decreases by 7.04 basis points while that for quintile-5 countries increases by 4.90 basis points. The difference in the bond yield changes across these two quintiles is 11.87 basis points per month (t=3.15). After accounting for market and momentum factors in bond markets, this difference in yield changes is still 6.85 basis points per month (t=2.26). We also construct, for each portfolio, the average yield changes weighted by each country's GDP. The difference in this value-weighted average bond yield changes across the top and bottom quintiles is 6.42 basis points per month (t=2.37), and is 4.45 basis points per month (t=2.06) after accounting for market and momentum factors in bond markets.

Importantly, the above results are not all due to the small countries in our sample. In fact, we find qualitatively similar results for both stock and sovereign bond markets when we restrict our sample to G20 countries, which account for around 90% of the global GDP.[2] For example,

[2] See, e.g., http://www.oecd.org/g20/.

the long-short stock index return for the G20 sample is 1.01% (t=2.07) and 0.87% (t=2.04) per month for the equal and market-cap-weighted portfolios, respectively.

What is the nature of the information that is more efficiently aggregated by the sovereign CDS market? We conjecture that it is about global factors, rather than country-specific variables. This is because that the investors in the sovereign CDS market are mostly sophisticated financial institutions, while those in the stock and bond markets are predominately local investors, as is known in the international finance literature.[3] Sovereign CDS investors' advantage, over local stock and bond investors, is perhaps their superior capacity in gathering and analyzing global, rather than country-specific, information. For example, sovereign CDS investors may have advantages in predicting future risk tolerance of global investors and their capital flows to individual countries, which may have significant effects on the future prospects of those economies. Or, they may be better at analyzing the prospects of future global economy and their influences on individual countries. For example, they may be better at predicting the future of the monetary policies in the U.S. and their implications on the future individual economies. In contrast, sovereign CDS investors probably do not have advantage over local investors in obtaining country-specific information, such as local economic policy. In other words, our conjecture is that the sovereign CDS investors' advantage is due to their global perspective, rather than their superior local knowledge.

To test this conjecture, we decompose sovereign CDS spreads into a "systematic" component and an "idiosyncratic" component, and examine which one has predictive power for future stock returns and bond yields. Our evidence shows that the predictive power of sovereign CDS spreads is almost entirely from the systematic component.

Our interpretation of these results is that the sovereign CDS market is more efficient at aggregating global macro information, and its implications on countries around the world. Stock and bond markets only gradually "catch up" with the sovereign CDS market, i.e., the information

[3] See Karolyi and Stulz (2003) for a review.

in sovereign CDS spreads is gradually incorporated into stock and bond prices. This interpretation is further supported by the following evidence.

First, the cumulative alphas of the previously-described long-short strategies in both stock and bond markets increase with the holding period, and do not appear to mean revert. For instance, when the holding period increases to 6 months, the cumulative alphas are around 2% and 30 basis points for stock and bond markets, respectively. When we further increase the holding period, the cumulative alpha stabilizes and there is no sign of reversal. This is consistent with our interpretation that stock and bond markets gradually catch up with the information in sovereign CDS spreads, and that there is no overshooting and reversal.

Second, stock and bond prices appear to catch up with the sovereign CDS market "at the right time." Recall that our interpretation is that the sovereign CDS market contains some information that is not yet fully reflected in stock and bond prices. What is this information? A natural candidate is the sovereign creditworthiness. When should that information be incorporated into stock and bond prices? A conjecture is perhaps when that information becomes public, i.e., when credit rating or outlook changes are announced. Hence, our interpretation implies that the previous long-short strategies should be *more* profitable around the time when credit rating or outlook changes are announced.

Before testing this prediction, it is worth clarifying a potential confusion. One might think that credit rating and outlook changes are mostly *country specific* and hence there is some tension with our global-perspective interpretation. However, it is not the case that credit rating and outlook changes are mostly country specific. On the contrary, sovereign credit risks have a large systematic component. For example, Longstaff et al (2011) find that the first principal component of sovereign credit spreads explains 64% the credit spread variations in their sample.[4] This first principle component is highly correlated with the U.S. stock market return and volatility. This large systematic component can be due to the monetary policy in the U.S., which

[4] The global component for local currency sovereign credit spread is also substantial. For example, Du and Schreger (2016) find that the first principle component of local currency sovereign credit spreads explains 54% of the variation across countries.

drives both the global capital flows and demand, and hence significantly affects the creditworthiness of countries around the world. Another important driver for systematic variations of sovereign credit risks is perhaps the growth of the global economy, which significantly influences the balance sheets of countries around the world. Even the influence of natural disasters on sovereign credit risks has a strong systematic component. For example, rating agencies have long recognized the systematic nature of natural disasters due to climate changes.[5] Even idiosyncratic natural disaster may have systematic effect on global economies through the international trade network (see, e.g., Du et al. 2018).

To test the implication that long-short strategies should be more profitable around the time when credit rating or outlook changes are announced, we run a panel regression with an interaction term. Specifically, we regress the return of stock index of country i in month t on a return predictor, which is constructed from the sovereign CDS data during months $t-3$ to $t-1$, and a credit event dummy variable, which is 1 if country i has a credit rating or outlook change in month t and 0 otherwise. Our focus is on the coefficient of the interaction term of the predictor and this credit event dummy. Our estimates show that the interaction coefficient is twice as large as the coefficient of the predictor. That is, the sovereign CDS market's predictive power for stock returns is two times stronger during announcement months than during other periods. We also run similar regressions for bond markets and find that the sovereign CDS market's predictive power for future bond yield changes is 5 to 7 times stronger during announcement months than during other periods. Moreover, to conduct a more granular analysis of the timing of the information flow from the sovereign CDS market to stock and bond markets, we run similar regressions using daily data, and find that the long-short strategies are especially profitable during the several *days* around the announcements of credit rating or outlook changes. That is, stock and bond prices appear to catch up with the sovereign CDS market "at the right time."

Third, our interpretation implies asymmetry between positive and negative information. If stock and bond prices fail to reflect the information in the sovereign CDS market, arbitrageurs

[5] See, e.g., *Climate Risk: Rising Tides Raise the Stakes*, Standard and Poor's, *Insights*, December 2015.

can profit from trading stocks and bonds. Due to short sales constraints, however, it is more costly for arbitrageurs to exploit negative, rather than positive, information. Hence, less negative information is incorporated into stock and bond prices, and when it eventually becomes public, stock and bond prices will respond more strongly. Consistent with this prediction, we find that when a credit rating or outlook change is announced, stock and bond prices respond more strongly if the sovereign CDS market has been anticipating negative, rather than positive, news.

Fourth, the above logic also implies that the predictive power of the sovereign CDS market should be weaker if it is easier for arbitrageurs to trade in the stock and bond markets, for example, if there are stock or bond futures markets. Hence, we partition our sample based on whether there are futures markets for stock and sovereign bonds of the underlying countries, and examine the predictive power in both subsamples. Consistent with the interpretation, we find that the predictive power of the sovereign CDS market is indeed stronger for countries without futures markets for stock indices or sovereign bonds.[6]

Finally, in addition to the forecasting power for financial variables, sovereign CDS spreads can also forecast future real macroeconomic activities. Specifically, we run panel regressions of GDP growth and PMI index on the returns in stock, bond, and sovereign CDS markets during the previous quarter. Our evidence shows that the sovereign CDS market does possess unique predictive power for future GDP growth and PMI index. Interestingly, as in the case for predicting financial variables, the predictive power for future real economic activities is also mostly from the systematic component of sovereign CDS spreads.

Our paper adds to the growing literature on the sovereign CDS market. One prominent empirical fact in this literature is that there is a large global factor in sovereign CDS spreads (see, e.g., Pan and Singleton (2008) and Ang and Longstaff (2013), and Longstaff et al. (2011)). This

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leads to the conclusion in Longstaff et al. (2011) that "global investors play a predominant role" in the sovereign CDS market. Interestingly, the global factor explains little variation in sovereign CDS net notional amounts outstanding (Augustin et al. (2018)). Our study adds to this literature by showing that those global investors appear to be more capable of processing world-wide information whose implications for stock and bond markets are only gradually appreciated by local stock and bond investors.

Our paper also adds to the growing literature on slow information diffusion in financial markets. It demonstrates return predictability when financial markets are slow in incorporating subtle information implied by economic links (Cohen and Frazzini (2008), Menzly and Ozbas (2010)), trade credit (Albuquerque, Ramadorai and Watugala (2015)), complexity (Cohen and Lou (2012)), and incremental information (Da, Gurun and Warachka (2014)). While these studies focus on various aspects of firm level information, our paper demonstrates the slow diffusion of global macro information across countries and asset classes.

Our paper is also related to the literature on the informational role of derivative markets. These studies primarily focus on firm-level information,[7] and the evidence is often mixed. For example, a number of studies have examined the lead-lag relation between individual stock and option prices. While many studies (e.g., Chakravarty, Gulen, and Mayhew (2004)) conclude that option prices lead stock prices, Muravyev, Pearson, and Broussard (2013) reach the opposite conclusion using a different methodology. This literature often utilizes intra-day data to examine price discovery in order to address the asynchronous trading issue. At the monthly frequency, several studies show that individual options can predict future stock returns (e.g., Bali and Hovakimian (2009), Cremer and Weinbaum (2010), and An, Ang, Bali, and Cakici (2014)), and that options trading volume can predict future stock returns (e.g., Easley, O'Hara and Srinivas (1998) and Pan and Poteshman (2006)). But Goyal and Saretto (2009) find that underlying stock prices lead option prices. The direction of the information flow between the individual stocks

[7] Several exceptions analyze index futures and options, e.g., Kawaller, Koch, and Kock. (1987), Chan, Chan, and Karolyi (1991), and Chordia et al. (2016).

and corporate CDSs is also mixed. Acharya and Johnson (2007) find that the CDS market appears to be able to forecast future negative credit news. Lee, Naranjo, and Sirmans (2014) find that the corporate CDS market can improve the momentum trading strategy in the stock market. However, Hilscher, Pollet, and Wilson (2014) find that information flows from the equity to the CDS market. The lead-lag relations have also been analyzed between corporate CDSs and corporate bonds (Blanco et al. (2005)), CDOs versus stocks (Longstaff (2010)).

While these studies primarily focus on firm-level information, our paper adds to this literature by focusing on *macro* information. There might be important differences between aggregating micro and macro information. For the former, private information perhaps plays an important role. For the latter, however, since arguably most of the information is publicly available, investors' sophistication and information-processing capacity is likely to be more important. In fact, Paul Samuelson conjectured that there might be more informational inefficiency at the macro level than at the micro level.[8] Moreover, our setup also enables us to study the nature of the information that is better aggregated by sovereign CDSs, and their informational role for real macroeconomic activities.

II. Data

A sovereign CDS contract allows market participants to purchase or sell protection against the risk of default of a sovereign government. During the term of the contract, the buyer makes quarterly payments, which are called CDS coupons or spreads, to the seller in exchange for the seller's promise of protection. Sovereign CDS spreads are paid on the 20th day of March, June, September and December. If a credit event occurs, the protection buyer will be compensated by

[8] In a letter to John Campbell and Robert Shiller, as discussed in Shiller (2001, p. 243), Paul Samuelson states that "Modern markets show considerable micro efficiency … In no contradiction to the previous sentence, I had hypothesized considerable macro inefficiency, in the sense of long waves in the time series of aggregate indexes of security prices below and above various definitions of fundamental values."

the seller for the loss during the credit event.[9] The sovereign CDS market has been growing rapidly in the past decade, especially during the recent sovereign debt crisis. According to the Depository Trust & Clearing Corporation, the aggregate notional amount of sovereign CDS contracts was around $2 trillion in 2015, accounting for around 15% of all credit derivatives.

Our sovereign CDS data are from the Markit Group, which collects daily sovereign CDS quotation data from major dealers to publish the average CDS spread. Our sample is from January 2001 to September 2015. As shown in Figure 1, there are 29 countries in our sample in 2001. This number has been growing steadily and reaches 91 by 2015. The list of countries and the starting dates of the data for each country are listed in the appendix. We focus on US dollar denominated contracts with a five-year maturity with the default tier being senior unsecured debt, which are most actively traded and have the highest market liquidity.

Following Berndt and Obreja (2010), we construct the monthly sovereign "CDS returns," which effectively measure the sovereign CDS market implied excess returns from the exposure to the underlying sovereign debts. Specifically, the "return" of a CDS contract during a period of time is the ratio of the mark-to-the-market profit/loss during that period to the notional amount. The mark-to-the-market profit/loss is computed from the protection seller's perspective, and is estimated based on the widely used ISDA CDS model, which is standard in the industry and is described in detail in O'Kane (2008).[10] As pointed out in Longstaff et al (2011), sovereign CDS data have a number of advantages over sovereign bond data for the estimation of credit spreads and returns.

Several points are worth noting. First, a high sovereign CDS return is "good news," i.e., the sovereign CDS return increases when the underlying country's creditworthiness improves.

[9] The credit event includes failure to pay, moratorium, obligation acceleration, and restructuring, and is determined by the ISDA Determinations Committee. In most cases, the parties use "cash settlement" with an auction process, in which the CDS seller makes a cash payment based on an auction-generated market price of certain eligible debt obligation of the sovereign government. An alternative settlement is the "physical settlement," in which the protection buyers tender an eligible bond to the sellers and receive the par value of the bond.

[10] To implement this valuation model, we assume a constant hazard rate and a 40% recovery rate, and use the LIBOR term structure as the discount rates.

Second, we compute the monthly CDS returns based on the spreads on the 20th of a month and on the 19th of the next month to make sure that these two spreads are from two CDS contracts that expire on the same day. Specifically, there are four premium payment dates, the so-called IMM dates, each year: March 20, June 20, September 20 and December 20. All contracts initiated between two IMM dates expire on the same day. After each IMM date, contracts with a new maturity date start trading. These new contracts are said to be "on-the-run" until the next IMM date. Our sovereign CDS data are based on on-the-run contracts. Hence, a CDS contract on the 20th of a month and the contract on the 19th of the next month always expire on the same day. Third, there are two credit events in our analysis, one for Greece and one for Argentina. Both were auction-settled and the recovery rates are 21.5% and 39.5% for Greece and Argentina, respectively.[11] They led to two large negative monthly returns, which are included in our analysis. Due to our large sample size, these two observations have only a negligible influence on our estimates. Table 1 provides summary statistics of our sovereign CDS data from January 2001 to September 2015. The average CDS spread is 240 bps with a standard deviation of 557 bps. The monthly average SCDS return is 0.02%, with a standard deviation of 2.59%.

For each country, we obtain, from Bloomberg, the daily stock index returns, which are denominated in U.S. dollars and include dividends. As illustrated in Figure 1, the total number of countries for which we have both CDS and stock data is 28 in 2001 and 75 in 2015. The complete list of countries and stock indices is provided in the appendix. To be consistent with our CDS return data, we construct the monthly stock index return as the return from the 20th of a month to the 19th of the next month from daily stock index returns. As shown in Table 1, the average monthly stock index return is 1%, with a standard deviation of 7.99%.

We obtain daily yield to maturity of 5-year domestic-currency-denominated sovereign bond indices from Bloomberg. As illustrated in Figure 1, the number of countries with both bond yields and CDS data has grown from 17 in 2001 to 51 by 2015. The complete list of countries

[11] The credit event for Ecuador in 2008 is not in our sample due to the lack of data for its stock and bond indices.

and bond indices is provided in the appendix. The monthly yield changes are calculated based on the yield on the 20^{th} of a month and that on the 19^{th} of the next month. The average monthly yield change is -1.62 bps, with a standard deviation of 54 bps.

Finally, the rating and outlook of senior unsecured foreign currency debt are obtained from Standard and Poor's. They cover all the countries on which we have sovereign CDS data. The median rating for all the observations is BBB+.

III. Main Results

A. Using the sovereign CDS market to predict stock returns

We first examine whether sovereign CDS spreads contain information that can predict future stock returns. This is motivated by the fact that sovereign CDS investors are mostly sophisticated financial institutions, while stock and bond investors are predominately local. For firm-level variables, some local investors might have better access to private information, which can potentially overcome their disadvantage relative to sophisticated institutions. For macro variables, however, since arguably most of the information is publicly available, sophistication and information-processing capacity plays a more important role. Hence, the sovereign CDS market is expected to aggregate information more efficiently. In the presence of market frictions, stock prices may fail to fully reflect the information in sovereign CDS spreads. Hence, sovereign CDS spreads can predict future stock returns.

To test this conjecture, we sort countries into five quintiles based on their past 3-month sovereign CDS returns, and update the quintiles each month. The countries in quintile 1 have the highest CDS returns, i.e., according to the sovereign CDS market, their credit worthiness improved the most. Similarly, the credit worthiness of quintile-5 countries deteriorated the most. That is, the sovereign CDS market indicates that, during the prior three months, quintile-1 countries had "good news" while quintile-5 countries had "bad news." If stock markets do not fully reflect this information in sovereign CDS spreads, we would find that the stock markets in quintile 1 would, on average, outperform those in quintile 5 in the coming months.[12]

That is indeed the case. We first form an equal-weighted portfolio of stock indices for the countries in each quintile, and construct their dollar-denominated returns. Panel A of Table 2 reports the average excess return of each portfolio over the 1-month US Treasury yield. In our full sample, as shown in the first row, the excess return of the quintile-1 portfolio is 1.34% per month, while that of the quintile-5 portfolio is only 0.09%. The difference is 1.25% per month, or 15% per year, with a *t*-statistic of 3.80. We then obtain market capitalization data from the World Development Indicators database from the World Bank, and form a market-cap-weighted portfolio for each quintile, and find that quintile-1 portfolio outperforms quintile-5 portfolio by 1.10% per month (*t*=2.43).

To account for the risk premium, we construct a number of factors. We first compute the global stock market factor as the equal weighted return of all stock indices. Secondly, our long-short return should have a positive loading on the international momentum factor (Richards (1997), Rouwenhorst (1998)), because the good news in the sovereign CDS market about a country is likely accompanied by high stock returns in that country. Hence, we construct the stock index momentum strategy return factor, MOM_stock, as follows. We sort countries into five quintiles based on their past three-month stock index returns. MOM_stock is computed as the one-month return of the equal-weighted portfolio that is long in the winner quintile countries and short in the loser quintile ones. Finally, since our stock index returns are denominated in U.S dollars, foreign exchange exposures might have contributed to our long-short portfolio return. Hence, we obtain the two currency factors in Lustig, Roussanov and Verdelhan (2011), MKT_FX and HML_FX, which are currency market factor and the carry trade risk factor, respectively, from the author's website. We also construct the currency momentum return factor,

[12] One might be concerned that quintiles 1 and 5 might be dominated by emerging countries since their sovereign CDS returns are more volatile than those of developed countries. However, this is not the case. Every country in our sample has been sorted into each of the 5 quintiles at some point in time.

MOM_FX, based on a momentum trading strategy in the currency market with a 3-month formation period and a 1-month holding period.

We regress our long-short returns (i.e., quintile 1 minus quintile 5) on the above factors. The results based on the equal-weighted portfolios are reported in the first column of Panel B of Table 2. As expected, our long-short strategy return has a strong positive loading on the momentum factor. Nevertheless, the resulting alpha of our long-short strategy remains highly significant, and is 1.01% per month (t=2.89). In the second column, we include the global value and momentum factors in Asness, Moskowitz and Pederson (2013), VAL_global and MOM_global, which are obtained from AQR data library. Our long-short strategy alpha is 1.27% per month (t=3.50). The results based on the market-cap-weighted portfolios are reported in the third and fourth columns. The alphas are somewhat smaller, but remain statistically significant.

We conduct subsample analyses by partitioning our sample by time. The first half of the sample covers the data from January 2001 to December 2007, and the second half January 2008 to September 2015. The second and third rows of Panel A report the results based on equal weighted portfolios, showing that sovereign CDS spreads have predictive power in stock markets in both subsample periods. The long-short strategy return is 1.94% per month (t=3.51) for the first half of the sample, and 0.58% per month (t=2.10) for the second half.

Naturally, one might be concerned that the above results are entirely driven by countries with very small economies and stock markets. Our previous results based on market-cap-weighted portfolios partially alleviate this concern. More importantly, we repeat our analysis on the subsample of G20 countries, which overwhelmingly dominate the global economy.[13] As shown in Panel A, the long-short stock index return for G20 countries is 1.01% (t=2.07) and 0.87% (t=2.04) per month for the equal and value weighted portfolios, respectively. These are comparable to the results in the sample of non-G20 countries, where the long-short returns are

[13] According to the data from the Organisation for Economic Co-operation and Development (OECD), the G20 countries represent 90% of the global GDP in 2018.

0.92% (t=3.38) and 0.99% (t=2.69) for the equal and value weighted portfolios, respectively. Hence, our main results are not mostly driven by very small economies and stock markets.

The above analysis is based on a three-month sorting period and a one-month holding period. To examine the robustness of those results, we repeat the analysis by varying the sorting and holding periods. The upper part of Panel C reports the results based on equal-weighted portfolios. It shows that, for the one-month holding period, the long-short strategy alphas are significant when we vary the sorting period from one month to six months. For example, the long-short strategy alpha is 0.83% per month (t=2.71) when the sorting period is 6 months. Moreover, the long-short strategy return appears to decrease with the holding period. For example, when the sorting period is three months, the long-short strategy alpha is 1.01%, 0.45% and 0.32% per month when the holding period is 1, 3 and 6 months, respectively. The value-weighted results, reported in the lower part of Panel C, are smaller but show a similar pattern.

B. Using the sovereign CDS market to predict bond yields

We now examine whether sovereign CDS spreads contain information that can predict future bond returns. It is important to note that although there is a "no-arbitrage relation" between a sovereign CDS spread and the sovereign credit spread of the underlying country, it has been understood that the two variables do not track each other closely due to the costs and risks of arbitrage. As noted in Longstaff et al. (2011), sovereign CDSs and sovereign bonds have different embedded leverage and market liquidity and hence the prices in these two markets may contain different information.

Our bond data from Bloomberg provide the yields to maturity, but not returns, of the 5-year domestic sovereign bond index. Since the return of a bond is approximately the negative of yield change multiplied by its duration, we simply use yield changes to approximate bond returns.[14] To simplify our discussion, when there is no potential for confusion, we will refer to yield changes as if they are bond returns.

As in the previous section, we sort countries into 5 quintiles based on their past 3-month sovereign CDS returns, and update the quintiles each month. The sovereign CDS market implies that the creditworthiness of the quintile-1 countries improved the most, while that of quintile-5 countries deteriorated the most. If the good news about quintile-1 countries has not been fully reflected in the bond markets, we would expect the borrowing costs of the governments in those countries to go down in the future. Similarly, we would expect the future borrowing costs of the governments of quintile-5 countries to go up.

This conjecture is confirmed by our evidence. Specifically, we compute the equal-weighted average of bond yield changes for the countries in each quintile. As shown in the first row of Panel A in Table 3, on average, the bond yield of quintile-1 countries decreases by 7.04 basis points, while that of quintile-5 countries increases by 4.90 basis points. The difference between the two yield changes is 11.87 basis points (t=3.15). Due to the difficulty to obtain sovereign bond market sizes for a large cross section of countries, we construct GDP-weighted average of yield changes instead. The value weighted results are qualitatively similar but smaller in magnitude. The difference in weighted average yield changes between quintiles 1 and 5 is 6.42 basis points (t=2.37).

In order to control for the factors that might have contributed to the yield change difference, we regress it on a market factor, MKT_bond, which is computed as the equal weighted yield changes across all countries, and the momentum factor, MOM_bond, which is the counterpart of the momentum return in sovereign bond markets, with a 3-month formation period and a 1-month holding period, whereby we use yield changes as if they are bond returns.

[14] As a robustness check, we obtain monthly excess returns of U.S. dollar-denominated sovereign bonds of developing countries from Borri and Verdelhan (2015). The analysis based on this smaller sample leads to similar results.

As shown in the first column of Panel B of Table 3, the market and momentum factors cannot account for the difference in bond yield changes between quintiles 1 and 5. The estimated "alpha" is 6.85 basis points (t=2.26). That is, if the duration of the five-year bonds is 4 years, then the alpha from the long-short strategy in the sovereign bond markets is roughly 27.4 (=6.85×4) basis points per month. In the second column, we find that the global value and momentum factors in Asness, Moskowitz, and Pedersen (2013) cannot explain the difference in yield changes either. The estimated alpha is 11.16 basis points (t=2.47). The value-weighted results, reported in the last two columns of Panel B, are weaker but qualitatively similar.

We repeat our analysis for the two subsample periods, January 2001 to December 2007 and January 2008 to September 2015. The second and third rows of Panel A of Table 3 show that the sovereign CDS market has predictive power in the sovereign bond markets for both periods. The yield change difference between the top and bottom quintiles is 7.75 basis points per month (t=1.75) for the first half of the sample, and 15.63 basis points per month (t=2.82) for the second half. The value-weighted results are reported in the last two rows of the Panel A, and are weaker but qualitatively similar.

To address the concern that the above results are entirely driven by countries with very small economies and sovereign bond markets, we repeat our analysis on the subsample of G20 countries. As shown in Panel A of Table 3, the yield change difference for G20 countries is 6.76 basis point (t=2.69) and 5.39 basis points (t=1.96) per month for the equal and value weighted portfolios, respectively. Hence, our main results also hold for the major economies of G20 countries. In comparison, the results for the subsample of non-G20 countries are much stronger. The yield change difference is 16.36 (t=2.67) and 18.68 (t=2.59) for the equal and value weighted portfolios, respectively.

We repeat our analysis by varying the sorting period n and holding period h. The results, reported in Panel C, remain quite similar. For example, as shown in upper half of Panel C, which reports the results based on equal-weighted portfolios, for the case of n=3 months, the long-short strategy alpha is 5.33 basis points (t=2.49) for h=3 months, and 4.54 basis points (t=2.19) for

h=6 months. The results based on value-weighted portfolios, reported in the lower half of Panel C, remain similar.

C. The direction of information flow

Our previous evidence shows that the sovereign CDS market appears to contain information that can predict future stock index and sovereign bond returns. A natural question is whether there is information dissemination in the opposite direction. That is, can stock or bond markets predict future returns in the sovereign CDS market?

Note that there is momentum in all three markets. To examine if market A has marginal predictive power for market B, it is important to control for the past return in market B. Hence, to examine the direction of information flow, we conduct the following sequential sorting. We first sort countries into 5 quintiles based on their past 3-month stock index returns. Then, for each quintile, we sort countries into 2 halves based on their past 3-month sovereign CDS returns, and compute the return from the equal-weighted long-short portfolio that buys stock indices of countries with high past CDS returns and sells those of countries with low past CDS returns. We then equally weight these 5 long-short portfolios. That is, the return from this strategy reflects sovereign CDS markets' marginal predictive power for future stock returns, after controlling for the past stock returns. As shown in Panel A of Table 4, for our full sample, the strategy return is 51 basis points per month (t=3.17). After controlling for the market factor, the alpha remains at 49 basis points per month (t=2.75). This is consistent with our evidence in Table 2 that the sovereign CDS market can predict future stock returns. Columns two and three report the strategy returns for the first and second half of our sample, and demonstrate that the predictive power of Sovereign CDS spreads is present in both subsamples.

We now examine whether there is information flowing along the opposite direction, that is, if stock returns can predict future sovereign CDS returns after controlling for past CDS returns. We conduct similar 5 by 2 sequential sorting, first based on the past 3-month CDS returns and then based on the past 3-month stock returns. As we can see from the last three columns of Panel A, the average strategy returns are very close to zero, for both the full sample and the two subsamples. The largest *t*-statistic is merely 0.55. Hence, we don't find any evidence that stock markets have marginal predictive power for future sovereign CDS returns.

Our analysis of the direction of the information flow between sovereign CDS markets and bond markets is based on similar 5-by-2 sequential sorting. As shown in Panel B of Table 4, the sovereign CDS market has strong predictive power for future bond yield changes, after controlling for past bond yield changes. The alpha for our full sample is 5.73 basis points per month (*t*=2.88). On the other hand, the predictive power of bond yields for sovereign CDS returns is marginal. The *t*-statistic for the alpha is 1.68 for the full sample, and the predictive power is mostly concentrated in the second half of the sample.

D. Global perspective vs. local knowledge

What is the nature of the information that is more efficiently aggregated by the sovereign CDS market than local stock and bond markets? Is it about country-specific variables, or is it about global factors? We conjecture that it is mostly about global factors, rather than country-specific variables. This is because sovereign CDS investors' advantage, over local stock and bond investors, is perhaps their superior capacity in gathering and analyzing global, rather than country-specific, information. For example, sovereign CDS investors may have advantages in predicting future risk tolerance of global investors and their capital flows to individual countries, which may have significant effects on the future prospects of those economies. Or, they may be better at analyzing the prospects of future global economy and their influences on individual countries. For example, they may be better at predicting the future of the monetary policies in the U.S. and their implications on the future individual economies. In other words, our conjecture is that the sovereign CDS investors' advantage is due to their global perspective, rather than their superior local knowledge.

To test this conjecture, we decompose the monthly sovereign CDS returns into a "systematic" component and an "idiosyncratic" component, and examine which component has predictive power for future stock and bond returns. Specifically, we regress sovereign CDS returns on the average sovereign CDS returns across all countries in our sample. The regression residual is classified as the idiosyncratic component of a sovereign CDS return, which captures country-specific information. The remaining portion of the CDS return is the systematic component, which reflects global information. Which component has predictive power for future stock and bond returns? To answer this, we repeat our analyses in Tables 2 and 3, using the two components as predictors. The results are summarized in Table 5.

As shown in the first row of Panel A, the systematic component of the CDS returns can predict future stock returns. The long-short strategy sorted by the systematic component generates 81 basis points per month (t=3.20). Adjusting for risk factors leads to an alpha of 69 basis points per month (t=2.75). In contrast, there is no evidence that the idiosyncratic component has predictive power for future stock index returns. As shown in the second row of Panel A, the long-short strategy sorted by the idiosyncratic component has a return of -7 basis points per month (t=0.21), and an alpha of 4 basis points per month (t=0.12). As a comparison, we report in the third row the returns of the portfolios sorted by total CDS returns for the same sample period. It shows that both the long-short return and alpha are virtually the same as those from the sorting based on the systematic components. In other words, the predictive power of sovereign CDS returns is almost entirely from the systematic, rather than country-specific, component.

Similar results hold for bond markets. As shown in Panel B of Table 5, if we sort countries based on the systematic component of CDS returns, the difference in bond yield changes between the top and bottom quintiles is 11.61 basis points per month (t=2.78), and is 7.77 basis points (t=2.84) after accounting for risk factors. In contrast, this difference in bond yield changes is 6.11 basis points (t=1.71), and is 3.28 basis points (t=1.06) after adjusting for risk factors, if the countries are sorted based on the idiosyncratic component of the CDS returns. As a comparison, we report in the third row the results from total-CDS-return-based sorting.

Similar to the results for stock returns, the comparison shows that the predictive power of the sovereign CDS return is almost entirely from its systematic component.

Our previous evidence suggests that the predictive power of the sovereign CDS market is mostly from its advantage in world-wide information. This interpretation further implies that the predictive power of the sovereign CDS market should come mostly from its ability to predict the "systematic" component, rather than the "idiosyncratic" component, of future stock and bond returns. To test this, we decompose stock and bond returns using a simple market model. Specifically, we regress excess stock index returns on the excess returns of the global stock index, which are obtained from Kenneth French's website. The idiosyncratic component is the regression residual and the remaining portion of the stock index return is the systematic component. Similarly, the bond yield change decomposition is based on a regression of bond yield changes on the bond yield changes in the U.S., which serves as a proxy for the global market factor.[15] Consistent with our interpretation, the bottom two rows of Panels A and B show that the predictive power of the sovereign CDS returns comes almost entirely from their ability to forecast the systematic components of future stock and bond returns.

To examine the robustness, we repeat the above analysis by constructing value-weighted portfolios, and the results are very similar. Moreover, the decomposition in the above analysis is based on 12-month rolling window regressions. We also repeat our analysis based on decompositions from 24-month rolling window regressions. The results remain very similar.

The above evidence is consistent with the view in Longstaff, Pan, Pedersen, and Singleton (2011) that "global investors play a predominant role" in the sovereign CDS market. Our results suggest that those global investors appear to be more capable of processing world-wide information, whose implications on local stock and bond markets are only gradually appreciated by local investors.

[15] We also explored alternative market factors in our decomposition. For example, we used the equal weighted average return of all stock indices in our sample as the market factor for our stock regressions, and the average bond yield change across all countries in our sample as the market factor for our bond regressions. The results based on the alternative decompositions remain very similar.

E. Interpretation

Our interpretation of the above results is as follows. Relative to stock and bond markets, the sovereign CDS market is better at aggregating certain information about its underlying countries. When this information gradually becomes public, stock and bond prices catch up with the sovereign CDS market. This interpretation is motivated by the fact that the investors in the sovereign CDS market are mostly sophisticated financial institutions, while those in the stock and bond markets are predominately local investors, as is known in the international finance literature.[16] For firm-level variables, some local investors might have better access to private information, which can potentially overcome their disadvantage relative to sophisticated investors. This may explain the mixed results in the literature on whether local investors know more.[17] For macro variables, however, sophistication and information-processing capacity plays a more important role, since arguably most of the information is publicly available. Hence, in our macro information setup, the sovereign CDS market should aggregate information more efficiently. Moreover, our interpretation is also motivated by the insight in Black (1975) that derivatives often have embedded leverage, allowing investors to trade on their information more aggressively. Shen, Yan and Zhang (2014) show that due to collateral netting frictions, optimal derivative contracts are designed such that they are the most efficient in facilitating investors' speculation or hedging. This provides a foundation for the conjecture that the sovereign CDS market might be more efficient in aggregating certain macro information than stock and bond markets. We have the following four pieces of evidence that further supports this interpretation.

E.1 Persistence

Our interpretation suggests that the sovereign CDS market contains information that is only gradually incorporated into stock and bond prices over time. That is, stock and bond markets gradually "catch up" with the sovereign CDS market. This interpretation implies that when we

[16] See Karolyi and Stulz (2003) for a review.
[17] See, for example, Bae, Stulz, and Tan (2008) and its references.

increase the holding period of the long-short portfolios in Tables 2 and 3, the cumulative alphas should increase and stabilize, but not revert back to zero.

This is indeed the case. We repeat the analysis in Table 2 by extending the holding period, and the results are summarized in Panel A of Figure 2. It shows that the cumulative alpha of the long-short strategy in stock markets gradually increases when the holding period increases to around 6 months. The cumulative alpha stabilizes when the holding period increases further, and does not revert back to zero. Similarly, we repeat the bond market analysis in Table 3 by extending the holding period. As shown in Panel B of Figure 2, the cumulative yield change difference gradually increases when the holding period increases to around 6 months, and then stays roughly there when we further increase the holding period.

E.2 Timing of the predictability

Our interpretation is that the sovereign CDS market contains some information that is later transmitted into stock and bond markets. What kind of information? A natural candidate is perhaps the sovereign creditworthiness. When should that information be incorporated into stock and bond prices? A natural conjecture is perhaps when that information becomes public, e.g., when credit rating or outlook changes are announced.

This conjecture implies that that sovereign CDS spreads have a stronger predictive power for stock and bond returns around the announcements of credit rating or outlook changes. That is, the previously described long-short strategies in stock and bond markets should be *more* profitable around those announcements. Intuitively, one reason that our long-short strategies in stock and bond markets are profitable is that the sovereign CDS market can anticipate future rating or outlook changes and position the portfolios in advance, which reap profits when those events eventually become public.

Before testing this prediction, it is worth clarifying a potential confusion. One might think that credit rating and outlook changes are mostly *country specific*, and hence the above prediction seems to imply that the country specific component of sovereign CDS spreads should have strong predictive power for stock and bond returns, which appears inconsistent with our interpretation that the advantage of the sovereign CDS market is aggregating *global* macro information. However, it is *not* the case that credit rating and outlook changes are mostly country specific. On the contrary, sovereign credit risks have a large systematic component. For example, Longstaff et al (2011) find that the first principal component of sovereign credit spreads explains 64% the credit spread variations in their sample. This first principle component is highly correlated with the U.S. market, and has a correlation of −74% with U.S. stock market returns, and a correlation of 61% with changes in the VIX index. Intuitively, this large systematic component can be due to the monetary policy in the U.S., which drives both the global capital flows and demand, and hence significantly affects the creditworthiness of countries around the world. Another important driver for systematic variations of sovereign credit risks is perhaps the growth of the global economy, which significantly influences the balance sheets of countries around the world. Even the influence of natural disasters on sovereign credit risks has a strong systematic component. For example, rating agencies have long recognized the systematic nature of natural disasters due to the climate changes.[18]

To test the prediction that sovereign CDS spreads have a stronger predictive power for stock returns around announcements, we run a panel regression of the stock index return of country *i* in month *t* on an indicator variable, I_CDS_{it}, a dummy variable D_{it}, and their interaction term. The indicator variable I_CDS_{it} is set to 1 if country *i* is in quintile 1 according to the sorting by sovereign CDS returns during months *t-3* to *t-1* (i.e., the CDS market indicates that the creditworthiness of country *i* improved the most during the *previous* 3 months), is set to *-1* if country *i* is in quintile 5, and is set to 0 if country *i* is in the other three quintiles. The dummy variable D_{it} is 1 if there is a credit rating or outlook change by Standard & Poor's on country *i* in month *t*, and is 0 otherwise. Our prediction that sovereign CDS spreads have a stronger predictive power for stock returns in announcement months implies that the coefficient of the interaction term should be positive.

[18] See, e.g., *Climate Risk: Rising Tides Raise the Stakes,* Standard and Poor's, *Insights*, December 2015.

This is indeed the case. As shown in the first column of Panel A Table 6, the coefficient of I_CDS_{it} is 0.38 (t=2.81). The coefficient of the interaction term $I\_CDS_{it} \times D_{it}$ is 0.84 ($t=1.70$), which is more than twice the coefficient for I_CDS_{it}. That is, the CDS market's predictive power is more than two times stronger during announcement months than during other periods. In column two, we control for the stock momentum by including a momentum indicator variable I_MOM_{it}, which is 1 if country *i* is in the top quintile based on the stock returns in the past 3 months, is -1 if country *i* is in the bottom quintile, and is 0 otherwise. The interaction coefficient is still twice as large as the coefficient for I_CDS_{it}.[19]

We run similar panel regressions for bond yield changes. Since yield change and bond return are negatively related, our interpretation implies that the coefficient of the interaction term should be negative. Indeed, as shown in the third column, the coefficient for $I\_CDS_{it} \times D_{it}$ is -29.28 (t=2.36) and that for I_CDS_{it} is -4.11 (t=1.51). That is, the sovereign CDS market's predictive power for future bond yield changes is 7 times stronger during announcement months than other periods. The last column shows that the results remain similar after controlling for the bond market momentum.

The above evidence has been based on monthly data, which do not allow for detailed analysis on the timing of the responses of stock and bond prices. We now utilize daily data to conduct more granular analysis on the timing of stock and bond markets catching up with the sovereign CDS market. Specifically, we run the regressions in Panel A of Table 6 at daily frequency. The indicator variable $\mathrm{I\_CDS}_{it}$ and the dummy variable D_{it} are now replaced by their daily-frequency counterparts, $\mathrm{I\_CDS}_{it}^{d}$ and D_{it}^{n}. For country *i* on day *t*, we have $\mathrm{I\_CDS}_{it}^{d} = \mathrm{I\_CDS}_{im}$, if day *t* is in month *m*. For *n=0,1,2…*, the dummy variable D_{it}^{n} is 1 if country *i* has an S&P credit rating change or outlook change during the (2*n*+1)-day window, from day *t-n* to day *t+n*, and is 0 otherwise.

[19] The interaction coefficient is statistically insignificant. This is perhaps because, as will be shown in Panel B of Table 6, the sovereign CDS market's predictive power in stock markets appears to be mostly from bad news. Moreover, as will be shown in Panel A of Table 7, the interaction coefficient becomes significant when we focus on a shorter event window.

The idea is to examine whether stock and bond prices catch up with the sovereign CDS market during the (2n+1)-day window around the credit event day. In the case of n=10, for example, the coefficient of the interaction term $\mathrm{I\_CDS}_{it}^{d} \times D_{it}^{n}$ captures the effect during the 21-day window around credit event days. When we decrease the value of n, the event window gets shorter. In the case of $n=0$, the interaction coefficient captures the effect on credit event days only. Hence, by varying the value of n from 20 to 0, we can "zoom in" to examine the timing of the stock and bond markets catching up with the sovereign CDS market. If stock and bond markets catch up quickly with the sovereign CDS market around the announcements of credit rating or outlook changes, the interaction coefficient should be large for narrow event windows surrounding announcement days (i.e., when n is small), but decays towards zero when the event window expands (i.e., when n increases).

This is exactly what we find. For the case n=0 in stock return regressions, as shown in Panel A of Table 7, the coefficients of $\mathrm{I\_CDS}_{it}^{d}$ and the interaction term $\mathrm{I\_CDS}_{it}^{d} \times D_{it}^{n}$ are 1.11 (t=2.37) and 22.91 (t=1.69), respectively. That is, the sovereign CDS market's predictive power for stock returns is over 20 times stronger on credit event days than on other days. This extra predictive power decays quickly when we expand the event window. For example, during the 3-day window around the credit event day (i.e., $n=1$), the interaction coefficient is 12.04 basis points (t=1.76), suggesting that the sovereign CDS market's predictive power is around 12 times stronger during the 3-day window relative to other periods. For the case of n=5, for example, the interaction coefficient is only 2.60, and is insignificantly different from zero. A similar pattern exists for bond markets. Since yield change and return are negatively related, the interaction coefficient is negative, and converges to zero when n increases. For example, as shown in Panel B, the interaction coefficient is -4.74 (t=2.77) for the case of $n=0$, is -2.58 (t=2.58) for the case of n=1, and is only -1.01 (t=1.46) for the case of n=5.

In summary, the above evidence lends further support to our interpretation by showing that the predictability is concentrated around the days surrounding the announcements of rating or outlook changes. That is, stock and bond markets appear to catch up with the sovereign CDS market at the "right time"—when credit-related information becomes public.

E.3 Asymmetry in predictability

Our interpretation implies asymmetry between catching up with positive and negative news. If stock and bond prices fail to reflect the information in sovereign CDS spreads, arbitrageurs can profit from trading stocks and bonds. In the presence of short sales constraints, however, it is more costly to exploit negative information than positive. Hence, less negative information is incorporated into stock and bond prices, and when it eventually becomes public, stock and bond prices should respond more strongly. In other words, catchup should be stronger around announcements of negative information.

To test this implication, we decompose the indicator I_CDS_{it} into two variables. The first one, $Good\_CDS_{it}$, is set to 1 if the sovereign CDS market indicates "good news" for country *i* in the *previous* three months. That is, $Good\_CDS_{it}$ is 1 if country *i* is in quintile 1 in month *t* according to the sorting based on sovereign CDS returns during the prior three months, and is 0 otherwise. The second variable, Bad_CDS_{it}, is set to -1 if country *i* is in quintile 5, and is 0 otherwise. Note that I_CDS_{it} is the sum of $Good\_CDS_{it}$ and Bad_CDS_{it}. Hence, one can view our earlier regressions in Table 6 Panel A as restricted regressions where the coefficients for $Good\_CDS_{it}$ and Bad_CDS_{it} are restricted to be the same; and the coefficients for $Bad\_CDS_{it} \times D_{it}$ and $Good\_CDS_{it} \times D_{it}$ are also restricted to be the same. We now allow these coefficients to be different. Our interpretation that catchup to bad news is stronger implies that the coefficient for $Bad\_CDS_{it} \times D_{it}$ should be larger than that for $Good\_CDS_{it} \times D_{it}$.

Our evidence is consistent with this implication. For stock markets, as shown in the first column of Panel B of Table 6, the coefficient of $Bad\_CDS_{it} \times D_{it}$ is 2.46 (t=2.48), while that of $Good\_CDS_{it} \times D_{it}$ is -0.82 (t=1.08). This is consistent with the interpretation that stock markets catch up with bad news more strongly. A similar pattern exists for the bond markets. Since yield change and bond return are negatively related, our interpretation implies that the two interaction coefficients should be negative and that the coefficient of $Bad\_CDS_{it} \times D_{it}$ should be larger in absolute value. Indeed, as shown in the column three, the coefficient of $Bad\_CDS_{it} \times D_{it}$ is -50.47 (t=2.25) while that of $Good\_CDS_{it} \times D_{it}$ is -4.26 (t=0.47). Finally, we control for momentum in the regressions, and the results, reported in columns two and four, remain very similar.

We also run daily regressions to conduct more granular analysis on the timing of the catchup to the sovereign CDS market. Specifically, we rerun the above regressions at daily frequency. The indicator $Good\_CDS_{it}$ and Bad_CDS_{it} are now replaced by their daily-frequency counterparts, Good_CDS_{it}^{d} and Bad_CDS_{it}^{d}. For country i on day t, we have $\text{Good\_CDS}_{it}^{d} = \text{Good\_CDS}_{im}$ and $\text{Bad\_CDS}_{it}^{d} = \text{Bad\_CDS}_{im}$ if day t is in month m.

Our evidence shows that the stronger catchup to bad news is also concentrated during the days surrounding the credit events. As shown in Panel C of Table 7, the coefficient for $\text{Bad\_CDS}_{it}^{d} \times D_{it}^{n}$ is 37.97 (t=1.53) for the case of $n=0$. For the case of n=2, for example, the interactive coefficient is 21.06 basis points (t=2.50). For the case of n=20, the interactive coefficient is only 5.32 basis points per day (t=2.04). In contrast to these results, the catching up with good news is not detectable: the coefficient estimates for $\text{Good\_CDS}_{it}^{d} \times D_{it}^{n}$ are insignificantly different from 0. Similar patterns hold for bond markets. As shown in Panel D, the coefficients for the interaction term $\text{Bad\_CDS}_{it}^{d} \times D_{it}^{n}$ are highly significant and they decay towards zero when n increases. In contrast, the coefficients for $\text{Good\_CDS}_{it}^{d} \times D_{it}^{n}$ are insignificantly different from zero.

The above evidence suggests that, perhaps due to short sales constraint, stock and bond markets are less effective in incorporating negative information from the sovereign CDS market. If the sovereign CDS market was anticipating negative information, when it eventually arrives (i.e., a credit event is announced), stock and bond markets respond strongly since they have not yet fully incorporated it. In contrast, if the sovereign CDS market was anticipating positive information, when it eventually arrives, stock and bond markets barely respond since they have already incorporated the positive information in the sovereign CDS market.

E.4 Futures markets

Following the logic in the previous section, our interpretation also implies that the predictive power of the sovereign CDS market should be weaker if it is easier for investors to trade in the stock and bond markets, for example, if there are stock or bond futures markets. We expect that futures markets would alleviate the predictive power of the sovereign CDS market, but may not fully eliminate it due to the costs and risks arbitrageurs face when exploiting this predictability.

From Datastream, we obtain information on whether there exist stock index futures markets for each country during our sample period. At the beginning of our sample, there are 9 countries with stock index futures markets and 7 countries with sovereign bond or interest rate futures markets. In 2015, the end of our sample, there are 33 countries with stock index futures markets and 27 countries with sovereign bond or interest rate futures markets.

We partition our stock index return sample according to whether there exists a stock index futures market for the country's main stock index. Then, we repeat our analysis in Panel A of Table 2 for each of the two subsamples, and report the results in Panel A of Table 8. As shown in the first row, the equal-weighted long-short portfolio return is 0.58% per month (t=2.06) in the subsample of countries with stock index futures markets. In contrast, in the second row, where the sample includes countries without stock index futures markets, the long-short return is almost twice as large, and is 1.26% per month (t=2.61). As shown in the last two rows, the results based on value-weighted portfolios are qualitatively similar. We conduct similar analysis for sovereign bond yields, and the results are similar. For the subsample of countries without sovereign bond or interest rate futures markets, as shown in Panel B of Table 8, the difference in bond yield changes between the top and bottom quintiles is 19.38 basis points (t=2.98) for equal-weighted portfolios and 25.45 basis points (t=2.86) for value-weighted portfolios. In contrast, for the subsample of countries with sovereign bond or interest rate futures markets, the difference in bond yield changes between the top and bottom quintiles is only 2.42 (t=0.92) basis points for equal-weighted portfolios and 4.23 basis points (t=1.68) for value-weighted portfolios. These results are consistent with the interpretation that predictive power of the sovereign CDS market is weaker in the presence futures markets for stock and bond indices.

F. Using the sovereign CDS market to predict real economic activities

In this section, we examine whether the sovereign CDS market can predict future real economic activities. Specifically, we run panel regressions of quarterly year over year GDP growth on the returns in the stock, bond, and sovereign CDS markets during the previous quarter, after controlling for the GDP growth in the previous quarter. As shown in Table 9, despite the short sample period for quarterly observations, the estimates are still statistically significant. In the first column of Panel A, the coefficient for CDS return is -1.18 (t=2.03), suggesting that sovereign CDS returns have marginal predictive power for future GDP growth. Interestingly, the coefficients for stock return and yield change are 0.97 (t=2.05) and -13.66 (t=1.12). That is, the stock markets possess additional information that is relevant for predicting future GDP growth, but the information in bond markets barely has additional predictive power.

Following the analysis in Section III.D, we decompose sovereign CDS returns into systematic and idiosyncratic components. Under the hypothesis that sovereign CDS investors have an advantage in analyzing world-wide information and its implications on individual countries, the marginal predictive power of sovereign CDS returns should come mostly from their systematic component. This implication is confirmed by the results in the second column. It shows that the coefficients for the systematic and idiosyncratic components of the sovereign CDS return are -4.98 (t=1.71) and 1.58 (t=0.91), respectively. That is, the unique information in the sovereign CDS return is mostly embedded in its systematic component.

We run similar regressions for the Purchasing Managers' Index (PMI), which is a monthly indicator of the manufacturing activity in private sectors. Perhaps due to the higher frequency of the observations, the statistical significance of our evidence is much stronger. As shown in column one of Panel B, the coefficient for the CDS return is -6.10 (t=3.55) and the coefficients of both stock and bond returns are insignificant. It suggests that sovereign CDS returns contain unique information that has predictive power for future PMI index. The deterioration of the creditworthiness in the sovereign CDS market predicts that the manufacturing activity will slow down in the future. Column two shows that the coefficients for the systematic and idiosyncratic components of the sovereign CDS return are -14.23 (t=2.18) and -2.29 (t=1.01), respectively. That is, once again, the unique information in the sovereign CDS return that can predict future PMI is mostly from its global component.

IV. Conclusion

We have shown that sovereign CDS spreads can predict future stock index returns, government bond yields, as well we real macroeconomic activities. This predictive power is almost entirely from the global, rather than country-specific, component of sovereign CDS spreads. Our evidence is consistent with the interpretation that the sovereign CDS market contains information, especially global information, which is only gradually reflected in stock and bond markets, especially during the a few days around credit rating or outlook changes.

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Figure 1. Number of countries

This figure plots the number of countries in our sovereign CDS sample, the sample with both sovereign CDSs and stock indices, and the sample for both sovereign CDSs and sovereign bond indices.

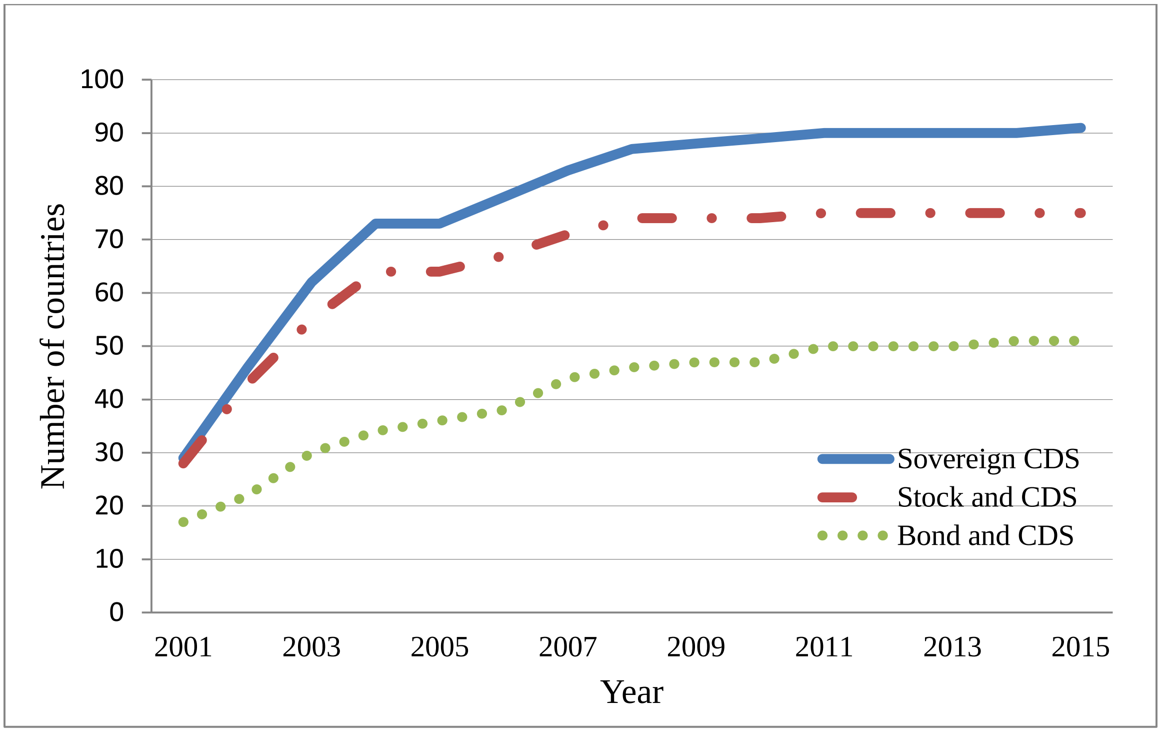
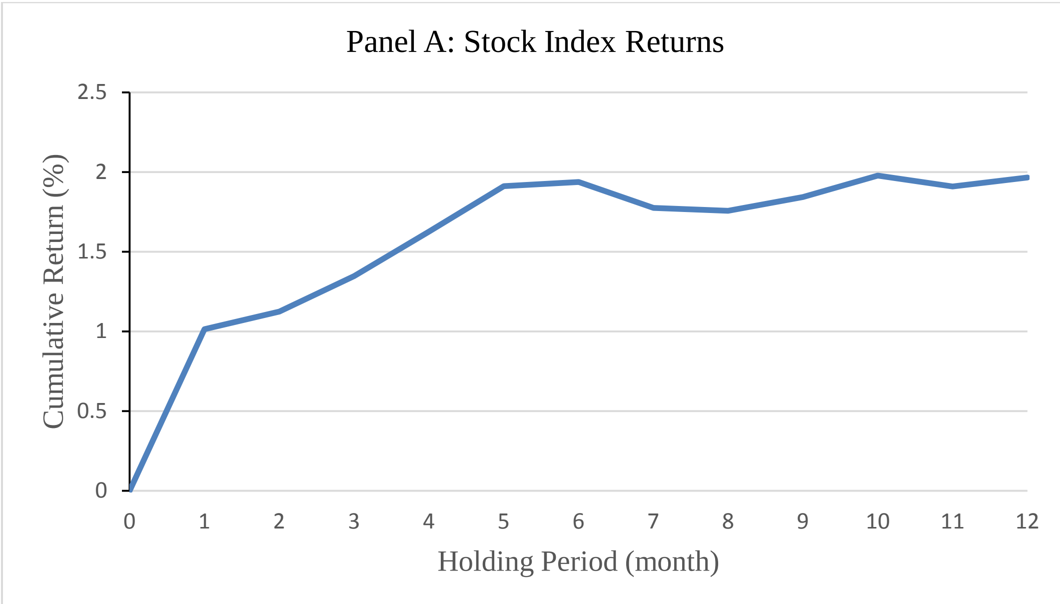


Figure 2. Cumulative alphas

Panel A plots the cumulative alphas of the long-short strategy in stock markets, after controlling for MKT_stock, MOM_stock, MKT_FX, HML_FX, and MOM_FX. Panel B plots the cumulative yield changes in sovereign bond markets, after controlling for MKT_bond and MOM_bond. All factors are described in Table 2.



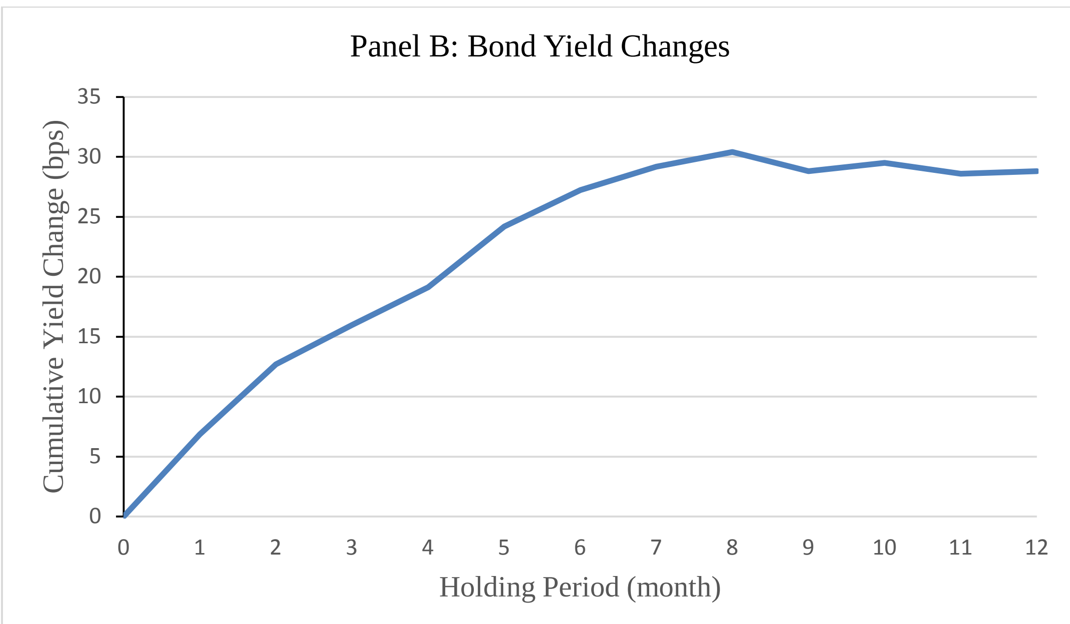


Table 1. Summary statistics

This table presents the summary statistics of main variables in the paper. *CDS spread* is the sovereign CDS spread, and is from Markit. Following Berndt and Obreja (2010), we compute the monthly *CDS return* from the *CDS spreads* on the 20th of a month and on the 19th of the next month. *Stock index return* is the monthly US-dollar denominated return of the main stock index of a country, from the 20th of a month to the 19th of the next month, and is from Bloomberg. *Bond yield change* is the monthly yield change, from the 20th of a month to the 19th of the next month, of 5-year local currency denominated sovereign bond index, which is constructed by Bloomberg. The quarterly year-over-year GDP growth data are from the IMF World Economic Outlook Database. The seasonally adjusted Product Manager Index (PMI) data are from Markit Group. The list of stock indices and bond yield indices is reported in the appendix. The sample period is from January 2001 to September 2015.

	Mean	**Std Dev**	**1st**	**25th**	**50th**	**75th**	**99th**	**Obs**
CDS spread (bps)	240.40	556.66	1.74	36.45	118.79	276.17	1975.68	12193
CDS return (%)	0.02	2.59	-7.83	-0.22	-0.01	0.37	6.64	12065
Stock index return (%)	1.00	7.99	-21.70	-3.01	1.12	5.18	22.14	11196
Bond yield change (bps)	-1.62	54.01	-130.00	-17.00	-2.40	13.30	140.00	6375
PMI	52.57	6.38	31.88	49.41	52.88	56.40	67.59	5051
GDP growth (%)	3.12	4.13	-9.11	1.19	3.09	5.43	12.55	3559

Table 2. Using sovereign CDSs to predict stock returns

Countries are sorted into 5 quintiles based on their past 3-month sovereign CDS returns. Those in quintile 1 (5) have the highest (lowest) CDS returns, i.e., their credit worthiness improved (deteriorated) the most, according to the sovereign CDS market. Then, for each quintile, we form portfolios of stock indices, one equal weighted and one market-cap weighted. Panel A reports the average excess return over the 1-month US Treasury yield for each of the 5 portfolios, and the long-short portfolio that is long in quintile 1 and short in quintile 5. The first 5 rows are for the equal weighted results. The first row is for the full sample, from January 2001 to September 2015. The second and third rows are based on subsamples partitioned by time. The first half is from January 2001 to December 2007 and the second half is from January 2008 to September 2015. The fourth row reports the results for the subsample of G20 countries while the fifth row reports the results for the subsample of non-G20 countries. Rows six through ten report the market-cap weight results. Panel B reports the results from the regression of the monthly returns of the long-short portfolio on various factors for the full sample, from January 2001 to September 2015. MKT_stock is the monthly return of the equal-weighted portfolio of all stock indices. MOM_stock is the momentum return for stock indices, with a 3-month portfolio formation period and a 1-month holding period. MOM_FX is the momentum return in the currency market, with a 3-month portfolio formation period and a 1-month holding period. MKT_FX and HML_FX are the two currency factors in Lustig, Roussanov and Verdelhan (2011), and are obtained from the authors' website. VAL_global and MOM_global are the global value and momentum factors in Asness, Moskowitz and Pederson (2013), and are obtained from the AQR data library. Panel C reports the alphas from the long-short strategies for the full sample, from January 2001 to September 2015. Portfolios are sorted based on the data from the prior *n* months and have a holding period of *h* months, for various values of *n* and *h*. All *t*-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Returns of stock index portfolios (%)

		1 (good)	2	3	4	5 (bad)	1-5
Equal weight	Full sample	1.34**	1.41**	0.89*	0.76	0.09	1.25***
		(2.34)	(2.46)	(1.73)	(1.53)	(0.15)	(3.80)
	2001-2007	2.56***	2.82***	1.54***	1.73***	0.62	1.94***
		(4.27)	(6.04)	(3.01)	(4.04)	(0.63)	(3.51)
	2008-2015	0.27	0.22	0.38	-0.07	-0.31	0.58**
		(0.36)	(0.30)	(0.47)	(0.10)	(0.40)	(2.10)
	G20	1.48**	0.86*	0.65	0.52	0.47	1.01**
		(2.22)	(1.67)	(1.23)	(0.99)	(0.82)	(2.07)
	Other	1.39**	1.46**	1.12**	0.67	0.48	0.92***
		(2.38)	(2.43)	(2.10)	(1.30)	(0.84)	(3.38)
Value weight	Full sample	1.14**	0.82*	0.54	0.82	0.04	1.10**
		(2.15)	(1.77)	(1.22)	(1.85)	(0.06)	(2.43)
	2001-2007	2.12***	1.68***	0.92	1.10**	0.44	1.68**
		(2.94)	(2.73)	(1.39)	(2.12)	(0.43)	(1.96)
	2008-2015	0.28	0.15	0.26	0.56	-0.22	0.51*
		(0.33)	(0.21)	(0.31)	(0.9)	(0.28)	(1.77)
	G20	1.30**	0.80	0.53	0.54	0.43	0.87**
		(1.96)	(1.49)	(1.01)	(1.09)	(0.74)	(2.04)
	Other	1.23**	1.12**	0.70	0.79	0.26	0.99***
		(1.98)	(2.10)	(1.20)	(1.59)	(0.50)	(2.69)

Panel B: Dependent variable: return of quintile 1 – quintile 5 (%)

	Equal weight		Value weight	
Alpha	1.01***	1.27***	0.90**	0.99**
	(2.89)	(3.50)	(2.17)	(2.23)
MKT_stock (%)	-0.048	-0.063	0.018	-0.10
	(0.53)	(0.57)	(0.20)	(1.17)
MOM_stock (%)	0.263**		0.32***	
	(2.30)		(4.08)	
MKT_FX (%)	-0.10		-0.30	
	(0.57)		(1.06)	
HML_FX (%)	0.40***		0.060	
	(2.61)		(0.30)	
MOM_FX (%)	-0.155		0.26	
	(1.34)		(1.11)	
VAL_global (%)		0.31		0.66
		(0.69)		(1.23)
MOM_global (%)		-0.040		0.18
		(0.21)		(0.61)
Observations	175	175	175	175
R-Square	0.12	0.02	0.13	0.02

Panel C: Long-short strategy alpha (%). n: sorting period, h: holding period (months)

		h=1	*h*=3	*h*=6
Equal weight	*n*=1	0.59**	0.36*	0.27
		(2.17)	(1.74)	(1.47)
	n=3	1.01***	0.45**	0.32*
		(2.89)	(2.25)	(1.81)
	n=6	0.83***	0.43**	0.32
		(2.71)	(2.00)	(1.51)
Value weight	*n*=1	1.12**	0.66**	0.22
		(2.49)	(2.53)	(1.34)
	n=3	0.90**	0.36	0.11
		(2.17)	(1.54)	(0.38)
	n=6	0.11	-0.23	-0.06
		(0.24)	(0.68)	(0.21)

Table 3 Using sovereign CDSs to predict bond yield changes

Countries are sorted into 5 quintiles based on their past 3-month sovereign CDS returns. Those in quintile 1 (5) have the highest (lowest) CDS returns, i.e., their credit worthiness improved (deteriorated) the most, according to the sovereign CDS market. Then, for each quintile, we compute equal-weighted and GDP-weighted averages of bond yield changes, ΔYield. Panel A reports ΔYield for each of the 5 quintiles and the difference in ΔYield between quintiles 1 and 5. The first 5 rows are for the equal weighted results. The first row is for the full sample, from January 2001 to September 2015. The second and third rows are based on subsamples partitioned by time. The first half is from January 2001 to December 2007 and the second half is from January 2008 to September 2015. The fourth row reports the results for the subsample of G20 countries while the fifth row reports the results for the subsample of non-G20 countries. Rows six through ten report the GDP-weighted results. Panel B reports the results from the regression of monthly difference in ΔYield between quintiles 1 and 5 on various factors for the full sample, from January 2001 to September 2015. MKT_bond is the monthly equal-weighted yield changes across all countries. MOM_bond is equivalent to the momentum return in the sovereign bond market, with a 3-month portfolio formation period and a 1-month holding period, with yield changes as proxies for bond returns. VAL_global and MOM_global are the global value and momentum factors in Asness, Moskowitz and Pederson (2013), and are obtained from the AQR data library. Panel C reports the alphas from the long-short strategies for the full sample, from January 2001 to September 2015. Portfolios are sorted based on the data from the prior *n* months and have a holding period of *h* months, for various values of *n* and *h*. All *t*-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Yield changes of bond index portfolios (bps)

		1 (good)	2	3	4	5 (bad)	5-1
Equal weight	Full sample	-7.04***	-3.85***	-2.28	-3.38*	4.90	11.87***
		(2.76)	(2.59)	(1.61)	(1.87)	(1.46)	(3.15)
	2001-2007	-8.24*	-3.04	-0.42	-1.39	-0.30	7.75*
		(1.78)	(1.26)	(0.20)	(0.58)	(0.15)	(1.75)
	2008-2015	-5.81**	-4.36**	-3.7**	-4.59*	9.82*	15.63***
		(2.32)	(2.32)	(2.10)	(1.77)	(1.73)	(2.82)
	G20	-5.16*	-4.44**	-2.64*	-1.44	1.03	6.76***
		(1.92)	(2.30)	(1.81)	(0.69)	(0.64)	(2.69)
	Other	-7.01**	-2.60	-2.09	-2.31	9.36*	16.36***
		(2.36)	(1.58)	(1.32)	(1.28)	(1.79)	(2.67)
Value weight	Full sample	-6.12**	-4.40***	-1.71	-3.15	0.31	6.42**
		(2.38)	(3.01)	(1.26)	(1.44)	(0.14)	(2.37)
	2001-2007	-8.48**	-3.07	-0.38	-1.25	-3.10	5.39*
		(1.96)	(1.49)	(0.18)	(0.45)	(1.02)	(1.72)
	2008-2015	-4.02	-4.68**	-2.38	-4.33	3.73	7.75**
		(1.40)	(2.65)	(1.31)	(1.34)	(1.32)	(2.59)
	G20	-4.57*	-4.01**	-1.95	-1.31	0.56	5.39**
		(1.76)	(2.23)	(1.44)	(0.56)	(0.36)	(1.96)
	Other	-7.36**	-1.80	-2.51*	-3.88*	11.32	18.69**
		(2.22)	(1.28)	(1.73)	(1.83)	(1.79)	(2.59)

Panel B: Dependent variable: ΔYield of quintile 5 – ΔYield of quintile 1 (bps)

	Equal weight		Value weight	
Alpha	6.85**	11.16**	4.45**	6.14**
	(2.26)	(2.47)	(2.06)	(2.40)
MKT_bond (%)	14.36	79.51**	18.11	7.99
	0.74	(2.06)	(0.78)	(0.45)
MOM_bond (%)	69.81***		59.67***	
	(6.60)		(8.19)	
VAL_global (%)		6.69***		5.82**
		(2.79)		(1.98)
MOM_global (%)		3.88**		2.18
		(2.32)		(1.19)
Observations	175	175	175	175
R-Square	0.42	0.10	0.32	0.02

Panel C: Long-short strategy alpha (bps) *n*: sorting period, *h*: holding period (months)

		h=1	*h*=3	*h*=6
Equal weight	*n*=1	4.35	3.17*	2.45**
		(1.52)	(1.84)	(2.04)
	n=3	6.85**	5.33**	4.54**
		(2.26)	(2.49)	(2.19)
	n=6	4.76**	4.27**	3.71**
		(2.08)	(2.36)	(2.04)
Value weight	*n*=1	1.36	3.23**	2.16
		(0.69)	(2.29)	(1.61)
	n=3	4.45**	3.60**	3.08*
		(2.06)	(2.15)	(1.80)
	n=6	5.66***	4.59*	3.56
		(2.66)	(1.92)	(1.43)

Table 4. The direction of information flow

Panel A reports the sequential sort results for stock and sovereign CDS markets. In the first 3 columns, we first sort countries into 5 quintiles by their past 3-month stock index returns. Then, for each quintile, we sort countries into 2 halves based on their past 3-month sovereign CDS returns, and compute the return from the equal-weighted stock portfolio that is long in countries with high past CDS returns and short in countries with low past CDS returns. Finally, we compute the equal-weighted average return across the five long-short stock portfolios. The first 3 columns report the average returns and alphas for the full sample, from January 2001 to September 2015, and the two subsamples. The first half is from January 2001 to December 2007 and the second half is from January 2008 to September 2015. The results in the last 3 columns are based on similar 5-by-2 sequential sorting for CDS returns, first based on the past 3-month CDS returns and then based on the past 3-month stock returns. The analysis in Panel B is similar to that in Panel A, where bond yield changes replace stock returns. T-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Sovereign CDSs vs. Stocks

	CDSs to Stocks (%)			Stocks to CDSs (%)		
	Full	First	Second	Full	First	Second
Mean	0.51***	0.77***	0.32**	0.01	0.04	-0.02
	(3.17)	(2.82)	(2.08)	(0.15)	(0.46)	(0.20)
Alpha	0.49***	1.03***	0.31**	0.01	0.05	-0.02
	(2.75)	(3.77)	(1.99)	(0.1)	(0.55)	(0.28)

Panel B: Sovereign CDSs vs. Bond yields

	CDSs to Bond Yields (bps)			Bond Yields to CDSs (%)		
	Full	First	Second	Full	First	Second
Mean	5.46***	4.28*	6.59**	0.21*	0.02	0.38*
	(2.96)	(1.68)	(2.53)	(1.72)	(0.8)	(1.74)
Alpha	5.73***	3.55*	7.12***	0.21*	0.02	0.38*
	(2.88)	(1.73)	(2.65)	(1.68)	(0.83)	(1.67)

Table 5. Systematic vs. Idiosyncratic

Countries are sorted into 5 quintiles based on their past 3-month sovereign CDS returns, their systematic or idiosyncratic component (denoted as "Sys" and "Idio", respectively). The CDS return decomposition is based on a regression of CDS return on the average CDS return across all countries. The idiosyncratic component is the regression residual and the remaining portion of the CDS return is the systematic component. Quintile-1 (-5) countries have the highest (lowest) returns. In Panel A, for each quintile, we form an equal-weighted portfolio of stock indices. It reports the average excess return of the portfolio over the 1-month US Treasury yield (Total), the average of the systematic and idiosyncratic components of the stock index returns (Sys and Idio) for each of the 5 portfolios, and for the long-short portfolio that is long in quintile 1 and short in quintile 5. The stock index return decomposition is based on a 12-month rolling window regression of excess stock index returns on the excess returns of the global stock index, which are obtained from Kenneth French's website. The idiosyncratic component is the regression residual and the remaining portion of the stock index return is the systematic component. The "alpha" column reports the alpha of the long-short strategy after adjusting for MKT_stock, MOM_stock, MOM_FX, MKT_FX and HML_FX, all of which are defined in Table 2. Similarly, Panel B reports the analysis on bond yield changes. The bond yield change decomposition is based on a 12-month rolling window regression of bond yield changes on the U.S. yield changes. The idiosyncratic component is the regression residual and the remaining portion of the yield change is the systematic component. The "alpha" column reports the estimates of the constant term from the regression of the monthly difference in yield changes between quintiles 1 and 5 on MKT_bond and MOM_bond, both of which are defined in Table 3. Since we need 12-month data to estimate the decomposition regressions, the sample period of the portfolio returns is from January 2002 to September 2015. T-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Using CDS returns to predict stock returns (%)

Sorting var. CDS return	Predicted var. Stock return	1 (good)	2	3	4	5 (bad)	1 - 5	alpha
Sys	Total	1.51**	1.25**	0.70	0.68	0.69	0.81***	0.69***
		(2.20)	(2.10)	(1.42)	(1.23)	(1.13)	(3.20)	(2.75)
Idio	Total	1.07	0.85	0.82	0.95	1.14	-0.07	0.04
		(1.61)	(1.73)	(1.51)	(1.63)	(1.58)	(0.21)	(0.12)
Total	Total	1.36**	1.42**	0.96*	0.79	0.54	0.81***	0.69**
		(2.23)	(2.34)	(1.77)	(1.50)	(0.97)	(3.82)	(2.37)
Total	Sys	1.65***	1.37***	1.18***	1.03**	0.57	1.08***	0.96***
		(3.08)	(2.76)	(2.83)	(2.27)	(1.07)	(6.83)	(5.15)
Total	Idio	-0.27	0.03	-0.20	-0.26	-0.04	-0.23	-0.26
		(1.26)	(0.16)	(1.03)	(1.44)	(0.15)	(0.84)	(0.82)

Panel B: Using CDS returns to predict bond yield changes (bps)

Sorting var. CDS return	Predicted var. Yield change	1 (good)	2	3	4	5 (bad)	5 - 1	alpha
Sys	Total	-5.35**	-3.68**	-2.64*	-3.42*	6.08	11.61***	7.77***
		(2.41)	(2.45)	(1.71)	(1.76)	(1.48)	(2.78)	(2.84)
Idio	Total	-3.19	-3.65**	-2.20	-3.20**	2.92	6.11*	3.28
		(0.92)	(2.35)	(1.52)	(2.00)	(0.90)	(1.71)	(1.06)
Total	Total	-7.31***	-3.16**	-2.46*	-2.67	6.23*	13.54***	8.51***
		(2.88)	(2.25)	(1.69)	(1.45)	(1.81)	(3.54)	(2.88)
Total	Sys	-5.79***	-3.69***	-1.73*	-1.39	4.42*	10.18***	8.82***
		(3.39)	(4.58)	(1.89)	(1.54)	(1.69)	(4.54)	(5.18)
Total	Idio	-0.87	0.59	-0.69	-1.69	2.33	3.24	-0.60
		(0.37)	(0.46)	(0.67)	(1.10)	(0.84)	(0.88)	(0.19)

Table 6. The timing of predictability

This table reports results from panel regressions of monthly excess stock index returns and changes in 5-year bond yields for the full sample, from January 2001 to September 2015. In Panel A, I_CDS_{it} is 1, if country *i* is in quintile 1 in month *t* according to the sorting based on sovereign CDS returns during the *previous* three months *t*-3 to *t*-1, i.e., its creditworthiness improved the most. Similarly, I_CDS_{it} is set to -1 if country *i* is in quintile 5, and is set to 0 if country *i* is in the other three quintiles. D_{it} is 1 if there is a credit rating change or outlook change for country *i* in month *t* according to Standard & Poor's, and is 0 otherwise. I_MOM_{it} is an indicator for momentum. For the second column, I_MOM_{it} is 1 if the excess return of country *i*'s stock index is in the top quintile portfolio during months *t-3* to *t-1*, is -1 if country *i* is in the bottom quintile, and is 0 otherwise. For the last column, I_MOM_{it} is similarly constructed, with yield changes replacing stock returns. In Panel B, $Good\_CDS_{it}$ is 1 if country *i* is in the top quintile based on sovereign CDS returns during months *t-3* to *t-1* (i.e., for country *i* had "good news"), and is 0 otherwise. Bad_CDS_{it} is -1 if country *i* is in the bottom quintile based on sovereign CDS returns during months *t-3* to *t-1*, and is 0 otherwise. $Winner_{it}$ is a dummy variable, which is 1 if country *i* is in the top quintile based on the performance of the dependent variable (i.e., stock index return in the second column, and yield change in the last column) during months *t-3* to *t-1*, and is 0 otherwise. Similarly, $Loser_{it}$ is a dummy variable, which is 1 if country *i* is in the bottom quintile based on the performance of the dependent variable during months *t-3* to *t-1*, and is 0 otherwise. T-statistics, in parentheses, are based on standard errors that are clustered by month. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A

	Return (%)	Return (%)	ΔYield (bps)	ΔYield (bps)
I_CDS_{it}	0.38***	0.31**	-4.11	-3.57
	(2.81)	(2.23)	(-1.51)	(-1.49)
$I\_CDS_{it} \times D_{it}$	0.84*	0.59	-29.28**	-20.33**
	(1.70)	(1.10)	(-2.36)	(-1.98)
I_MOM_{it}		0.35*		1.70
		(1.93)		(0.93)
$I\_MOM_{it} \times D_{it}$		0.87		18.55**
		(1.47)		(2.40)
D_{it}	-0.26	-0.19	10.33	8.31
	(0.77)	(0.53)	(1.52)	(1.32)
Country Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	10,161	10,161	5,696	5,696
R-squared	0.4056	0.4071	0.162	0.164

Panel B

	Return (%)	Return (%)	ΔYield (bps)	ΔYield (bps)
	(1)	(2)	(3)	(4)
Bad_CDS_{it}	0.43**	0.35*	-5.73*	-5.30*
	(2.22)	(1.80)	(1.80)	(1.71)
$Bad\_CDS_{it} \times D_{it}$	2.46**	2.12**	-50.47**	-38.40**
	(2.48)	(2.17)	(2.25)	(1.98)
$Good\_CDS_{it}$	0.33	0.27	-2.29	-1.57
	(1.58)	(1.29)	(0.65)	(0.46)
$Good\_CDS_{it} \times D_{it}$	-0.82	-1.00	-4.26	-3.39
	(1.08)	(1.30)	(0.47)	(0.41)
$Winner_{it}$		0.45*		1.33
		(1.85)		(0.38)
$Winner \times D_{it}$		0.76		33.45**
		(0.77)		(2.46)
$Loser_{it}$		-0.24		-2.15
		(1.01)		(1.18)
$Loser_{it} \times D_{it}$		-0.83		2.58
		(0.94)		(0.33)
D_{it}	0.59	0.63	1.18	-7.69
	(1.48)	(1.43)	(0.21)	(1.25)
Country Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes
Observations	10,161	10,161	5,696	5,696
R-squared	0.406	0.408	0.164	0.167

Table 7. Daily regressions

This table repeats the analysis in columns 2 and 4 of both panels of Table 6, but using daily data. The sample period is from January 2001 to September 2015. The dependent variable is daily stock index returns in Panels A and C, and is changes in 5-year bond yield indices in Panels B and D. The dummy variable in Table 6, D_{it}, is now replaced by its daily-frequency counterpart, D_{it}^{n}, which is 1 if there is an S&P credit rating change or outlook change for country *i* during day *t*-*n* to *t*+*n*, and is 0 otherwise. We adjust all other independent variables in Table 6 (I_CDS_{it}, Bad_CDS_{it}, Good_CDS_{it}, Winner_{it} and Loser_{it}) into daily frequency to obtain I_CDS_{it}^{d}, Bad_CDS_{it}^{d}, Good_CDS_{it}^{d}, Winner_{it}^{d} and Loser_{it}^{d}, respectively For example, for country *i* on day *t*, we set $\text{I\_CDS}_{it}^{d} = \text{I\_CDS}_{im}$, if day *t* is in month *m*. Bad_CDS_{it}^{d}, Good_CDS_{it}^{d}, Winner_{it}^{d} and Loser_{it}^{d} are defined similarly. The table only reports the estimated coefficients of I_CDS_{it}^{d}, Bad_CDS_{it}^{d}, Good_CDS_{it}^{d}, and the interaction terms for various values of *n*. T-statistics are based on standard errors that are clustered by day. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Dependent variable: daily stock index return (bps)

	***n*=0**	***n*=1**	***n*=2**	***n*=5**	***n*=10**	***n*=20**
I_CDS_{it}^{d}	1.11**	1.07**	1.07**	1.11**	1.01**	0.96**
	(2.37)	(2.29)	(2.28)	(2.36)	(2.16)	(2.03)
$\text{I\_CDS}_{it}^{d} \times D_{it}^{n}$	22.91*	12.04*	7.93*	2.60	3.47	2.06
	(1.69)	(1.76)	(1.65)	(0.84)	(1.55)	(1.32)

Panel B: Dependent variable: daily yield change (bps)

	***n*=0**	***n*=1**	***n*=2**	***n*=5**	***n*=10**	***n*=20**
I_CDS_{it}^{d}	-0.15***	-0.15***	-0.14***	-0.14***	-0.12**	-0.13**
	(-2.88)	(-2.74)	(-2.70)	(-2.61)	(-2.32)	(-2.53)
$\text{I\_CDS}_{it}^{d} \times D_{it}^{n}$	-4.74***	-2.58**	-1.57*	-1.01	-0.82*	-0.34
	(-2.77)	(-2.58)	(-1.80)	(-1.46)	(-1.88)	(-1.05)

Panel C: Dependent variable: daily stock index return (bps)

	***n*=0**	***n*=1**	***n*=2**	***n*=5**	***n*=10**	***n*=20**
Bad_CDS_{it}^{d}	1.48**	1.41**	1.34**	1.32*	1.12*	1.09
	(2.16)	(2.06)	(1.96)	(1.93)	(1.64)	(1.60)
$\text{Bad\_CDS}_{it}^{d} \times D_{it}^{n}$	37.97	23.11*	21.06**	11.17**	10.35***	5.32**
	(1.53)	(1.89)	(2.50)	(2.08)	(2.65)	(2.04)
Good_CDS_{it}^{d}	0.74	0.74	0.79	0.89	0.90	0.83
	(1.04)	(1.04)	(1.11)	(1.23)	(1.25)	(1.13)
$\text{Good\_CDS}_{it}^{d} \times D_{it}^{n}$	8.55	1.13	-5.14	-5.93	-3.33	-1.21
	(0.52)	(0.13)	(-0.81)	(-1.4)	(-1.06)	(-0.54)

Panel D: Dependent variable: daily yield change (bps)

	***n*=0**	***n*=1**	***n*=2**	***n*=5**	***n*=10**	***n*=20**
Bad_CDS_{it}^{d}	-0.30***	-0.29***	-0.28***	-0.26***	-0.22**	-0.23***
	(-3.35)	(-3.20)	(-3.15)	(-2.88)	(-2.54)	(-2.82)
$\text{Bad\_CDS}_{it}^{d} \times D_{it}^{n}$	-10.42***	-5.55***	-3.52**	-2.94***	-2.27***	-1.13*
	(-2.83)	(-2.85)	(-2.28)	(-2.66)	(-3.05)	(-1.83)
Good_CDS_{it}^{d}	0.01	0.01	0.00	0.01	0.01	0.02
	(0.07)	(0.08)	(0.07)	(-0.12)	(-0.17)	(-0.29)
$\text{Good\_CDS}_{it}^{d} \times D_{it}^{n}$	1.35	0.37	0.30	0.90	0.64	0.48
	(0.55)	(0.33)	(0.30)	(1.10)	(1.32)	(1.38)

Table 8. Futures markets

In Panel A, the stock index return sample is partitioned according to whether there exists a stock index futures market for the country's main stock index. Then, for each of the two subsamples, countries are sorted into 5 quintiles based on their past 3-month sovereign CDS returns. Those in quintile 1 (5) have the lowest (highest) CDS returns, i.e., their credit worthiness improved (deteriorated) the most, according to the sovereign CDS market. Then, for each quintile, we form portfolios of stock indices, one equal weighted and one market-cap weighted. The panel reports the average excess return over the 1-month US Treasury yield for each of the 5 portfolios, and the long-short portfolio that is long in quintile 1 and short in quintile 5. Panel B is constructed similarly, where the bond yield index sample is partitioned according to whether there exists a bond futures market or interest rate futures market for the country's sovereign bonds. The sample period is from January 2001 to September 2015. All *t*-statistics are based on standard errors that are Newey-West (1987) adjusted with 12 lags, and are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: Returns of stock index portfolios (%)

		1 (good)	2	3	4	5 (bad)	1-5
Equal weight	With futures	1.07*	0.88	0.91*	0.80	0.50	0.58**
		(1.78)	(1.51)	(1.92)	(1.53)	(0.80)	(2.06)
	Without futures	1.59**	1.40**	1.00*	0.95	0.33	1.26***
		(2.45)	(2.27)	(1.89)	(1.63)	(0.50)	(2.61)
Value weight	With futures	1.13**	0.80	0.74	0.71	0.34	0.79**
		(1.97)	(1.22)	(1.57)	(1.39)	(0.59)	(2.03)
	Without futures	1.57**	0.84	0.89*	0.69	0.42	1.15*
		(2.08)	(1.34)	(1.72)	(1.21)	(0.57)	(1.77)

Panel B: Yield changes of bond index portfolios (bps)

		1 (good)	2	3	4	5 (bad)	5-1
Equal weight	With futures	-4.61**	-3.07*	-2.24	-3.16*	-2.77	2.42
		(2.25)	(1.93)	(0.97)	(1.84)	(1.34)	(0.92)
	Without futures	-8.32**	-3.94**	-2.34	-1.00	10.88*	19.38***
		(2.64)	(2.40)	(1.59)	(1.28)	(1.82)	(2.98)
Value weight	With futures	-6.11***	-3.99**	-3.46*	-2.95	-2.38	4.23*
		(2.85)	(2.43)	(1.92)	(1.28)	(1.10)	(1.68)
	Without futures	-8.99**	-1.63	-2.71*	-1.44	16.15**	25.45***
		(2.64)	(1.15)	(1.74)	(1.55)	(1.97)	(2.86)

Table 9. Predicting real economic activities

This table reports the results from panel regressions for the full sample, from January 2001 to September 2015. In Panel A, the dependent variable is the quarterly GDP year over year growth rate. CDS return$_{t-1}$, Stock return$_{i,t-1}$, ΔYield$_{i,t-1}$ and GDP$_{i,t-1}$ are country *i*'s sovereign CDS return, stock index return, 5-year bond yield index change, and GDP growth rate respectively, during the previous quarter. Sys. CDS return$_{i,t-1}$ and Idio. CDS return$_{i,t-1}$ are the systematic and idiosyncratic components of country *i*'s CDS returns in the previous quarter, respectively. The CDS return decomposition is described in Table 5. In Panel B, the dependent variable is the monthly PMI index on output. CDS return$_{i,t-3,t-1}$, Stock return$_{i,t-3,t-1}$, ΔYield$_{i,t-3,t-1}$ are country *i*'s sovereign CDS return, stock index return, and change in 5-year bond yield index, respectively, during the previous three months. PMI$_{i,t-1}$ is country *i*'s PMI index in the previous month. Sys. CDS return$_{i,t-3,t-1}$ and Idio. CDS return$_{i,t-3,t-1}$ are country *i*'s systematic and idiosyncratic components of its CDS returns during the previous three months. The CDS return decomposition is described in Table 5. T-statistics, in parentheses, are based on standard errors that are clustered by country. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.

Panel A: GDP Growth Rate

CDS return$_{i,t-1}$	-1.18**	
	(-2.03)	
Sys. CDS return$_{i,t-1}$		-4.98*
		(-1.71)
Idio. CDS return$_{t,t-1}$		1.58
		(0.91)
ΔYield$_{i,t-1}$	-13.66	-9.57
	(-1.12)	(-0.47)
Stock return$_{i,t-1}$	0.97**	0.79
	(2.05)	(1.50)
GDP$_{i,t-1}$	0.822***	0.83***
	(18.83)	(17.56)
Constant	13.49	10.36
	(1.10)	(0.51)
Country fixed effects	Yes	Yes
Quarter fixed effects	Yes	Yes
Observations	1,891	1,702
R-squared	0.866	0.872

Panel B: PMI

CDS return$_{i,t-3,t-1}$	-6.10***	
	(-3.55)	
Sys. CDS return$_{i,t-3,t-1}$		-14.23**
		(-2.18)
Idio. CDS return$_{i,t-3,t-1}$		-2.29
		(-1.01)
ΔYield $_{i,t-3,t-1}$	-6.33	-2.03
	(-1.05)	(-0.38)
Stock return $_{i,t-3,t-1}$	0.83	0.97
	(1.06)	(1.13)
PMI $_{i,t-1}$	0.61***	0.59***
	(7.84)	(7.81)
Constant	27.53***	27.85***
	(6.72)	(4.91)
Country fixed effects	Yes	Yes
Month fixed effects	Yes	Yes
Observations	3,538	3,215
R-squared	0.754	0.759

Appendix: List of countries and indices

Country	CDS	Stock		Bond		PMI	GDP
		Index name	Start	Index name	Start		
Algeria	Sep-2008						2008Q1
Angola	Oct-2009						2009Q1
Argentina	Apr-2001	MERVAL	Apr-2001				2001Q1
Austria	Jul-2001	ATX	Jul-2001	GAGB5YR	Jul-2001	Jul-2001	2001Q1
Australia	Oct-2003	AS51	Oct-2003	GACGB5	Oct-2003	Oct-2003	2003Q1
Barbados	Jul-2006						2006Q1
Belgium	Mar-2001	BEL20	Mar-2001	GBGB5YR	Mar-2001		2001Q1
Bulgaria	May-2001	SOFIX	May-2001	GBBP05	Aug-2008		2001Q1
Bahrain	Aug-2004	BHSEASI	Aug-2004				2004Q1
Belize	Jan-2010						2010Q1
Brazil	Feb-2001	IBOV	Feb-2001	GEBR5Y	Feb-2007	Feb-2001	2001Q1
Tunisia	Dec-2003	TUSISE	Dec-2003				2003Q1
Canada	Oct-2003	SPTSX	Oct-2003	GCAN5YR	Oct-2003	Oct-2003	2003Q1
Chile	Mar-2002	IGPA	Mar-2002	CLGB5Y	Jul-2014		2002Q1
China	Feb-2001	SHSZ300	Feb-2001	GCNY5YR	Jul-2005	Feb-2001	2001Q1
Hong Kong	Sep-2004	HSCI	Sep-2004	HKGG5Y	Sep-2004	Sep-2004	2004Q1
Colombia	Apr-2001	COLCAP	Apr-2001	COGR5Y	Dec-2009		2001Q1
Costa Rica	Sep-2003	CRSMBCT	Sep-2003				2003Q1
Croatia	Feb-2001	CRO	Feb-2001	HRKGGR05	Aug-2008		2001Q1
Cyprus	Aug-2002	CYSMMAPA	Aug-2002				2002Q1
Czech	Apr-2001	PX	Apr-2001	CZGB5YR	Apr-2001	Apr-2001	2001Q1
Germany	Nov-2002	DAX	Nov-2002	GDBR5	Nov-2002	Nov-2002	2002Q1
Denmark	Dec-2002	KFX	Dec-2002	GDGB5YR	Dec-2002	Dec-2002	2002Q1
Dominica	Aug-2003						2003Q1
Ecuador	Jul-2003						2003Q1
Egypt	Apr-2002	HERMES	Apr-2002			Apr-2002	2002Q1
El Salvador	Jul-2003						2003Q1
Estonia	Jul-2004	TALSE	Jul-2004				2004Q1
Fiji	Jul-2007						2007Q1
Finland	Aug-2002	HEX	Aug-2002	GFIN5YR	Aug-2002		2002Q1
France	May-2002	CAC	May-2002	GFRN5	May-2002	May-2002	2002Q1
Greece	Feb-2001	ASE	Feb-2001	GGGB5YR	Feb-2001	Feb-2001	2001Q1
Guatemala	Sep-2003						2003Q1
Iceland	Apr-2004						2004Q1
India	Aug-2003	SENSEX	Aug-2003	GIND5YR	Aug-2003	Aug-2003	2003Q1
Indonesia	Jan-2002	JCI	Jan-2002	GIDN5YR	Feb-2003	Jan-2002	2002Q1
Iraq	Mar-2006						2006Q1
Ireland	Feb-2003	ISEQ	Feb-2003	GIGB5YR	Feb-2003	Feb-2003	2003Q1
Israel	May-2001	TA-25	May-2001	GISR5YR	Jul-2001	May-2001	2001Q1
Italy	Mar-2001	FTSEMIB	Mar-2001	GBTPGR5	Mar-2001	Mar-2001	2001Q1
Jamaica	Oct-2003	JMSMX	Oct-2003				2003Q1
Japan	Feb-2001	TPX	Feb-2001	GJGB5	Feb-2001	Feb-2001	2001Q1
Jordan	Oct-2003	JOSMGNFF	Oct-2003				2003Q1
Kazakhstan	Feb-2004	KZKAK	Feb-2004				2004Q1
South Korea	May-2001	KRX100	May-2001	GVSK5YR	May-2001	May-2001	2001Q1

Latvia	Sep-2004	RIGSE	Sep-2004				2004Q1
Lebanon	Apr-2003	BLOM	Apr-2003			Apr-2003	2003Q1
Lithuania	May-2002	VILSE	May-2002				2002Q1
Malaysia	May-2001	FBMKLCI	May-2001	MGIY5Y	Aug-2005	May-2001	2001Q1
Malta	Aug-2004	MALTEX	Aug-2004				2004Q1
Macedonia	Oct-2011	MCTSTAT	Oct-2011				
Mexico	Feb-2001	MEXBOL	Feb-2001	GMXN05YR	Jun-2001	Feb-2001	2001Q1
Morocco	May-2001	MCSINDEX	May-2001				2001Q1
Netherlands	Sep-2003	AEX	Sep-2003	GNTH5YR	Sep-2003	Sep-2003	2003Q1
Nigeria	Jan-2007	NGSEINDX	Jan-2007			Jan-2007	2007Q1
Norway	Nov-2003	OBX	Nov-2003	GNOR5YR	Nov-2003		2003Q1
New Zealand	Jan-2004	NZSE50FG	Jan-2004	GNZGB5	Jan-2004	Jan-2004	2004Q1
Oman	Dec-2008	MSM30	Dec-2008				2008Q1
Pakistan	Aug-2004	KSE100	Aug-2004	PKRF/5Y	Aug-2004		2004Q1
Panama	Mar-2002	BVPSBVPS	Mar-2002				2002Q1
Peru	Mar-2002	SPBLPGPT	Mar-2002	GRPE5Y	Nov-2007		2002Q1
Philippines	Apr-2001	PCOMP	Apr-2001	PDSR5YR	Apr-2001	Apr-2001	2001Q1
Poland	Feb-2001	WIG	Feb-2001	POGB5YR	Feb-2001	Feb-2001	2001Q1
Portugal	Mar-2002	BVLX	Mar-2002	GSPT5YR	Mar-2002		2002Q1
Qatar	Oct-2001	DSM	Oct-2001				2001Q1
Hungary	Apr-2001	BUX	Apr-2001	GHGB5YR	Apr-2001		2001Q1
Georgia	Jul-2015						2015Q1
Romania	Apr-2002	BET	Apr-2002	ROMGGR05	Aug-2011		2002Q1
Ghana	Jun-2008	GGSECI	Jun-2008				2008Q1
Russia	Oct-2001	INDEXCF	Oct-2001	RUGE7Y	Oct-2001	Oct-2001	2001Q1
Saudi Arabia	Mar-2007	SASEIDX	Mar-2007			Mar-2007	2007Q1
Singapore	Aug-2003	STI	Aug-2003	MASB5Y	Aug-2003	Aug-2003	2003Q1
Slovakia	Jun-2001	SKSM	Jun-2001	GRSK5Y	Sep-2007		2001Q1
Slovenia	Mar-2002						2002Q1
South Africa	Feb-2001	TOP40	Feb-2001	GSAB5YR	Feb-2001	Feb-2001	2001Q1
Spain	Mar-2001	IBEX	Mar-2001	GSPG5YR	Mar-2001	Mar-2001	2001Q1
Serbia	Jul-2006	BELEXLN	Jul-2006				2006Q1
Sri Lanka	Jan-2008	CSEALL	Jan-2008	GGRSL5Y NTBA	Aug-2011		2008Q1
Sweden	Jul-2001	OMX	Jul-2001	GSGB5YR	Jul-2001		2001Q1
Switzerland	Jul-2007	SMI	Jul-2007	GSWISS05	Jul-2007	Jul-2007	2007Q1
Taiwan	Sep-2006	TWSE	Sep-2006	GVTW5YR	Sep-2006	Sep-2006	2006Q1
Thailand	Apr-2001	SET	Apr-2001	GVTL5YR	Apr-2001	Apr-2001	2001Q1
Trinidad and Tobago	Dec-2004						2004Q1
Turkey	Feb-2001	XU100	Feb-2001	IECM5Y	Aug-2007	Feb-2001	2001Q1
UAE	Mar-2007	DFMGI	Mar-2007			Mar-2007	2007Q1
United Kingdom	Apr-2006	UKX	Apr-2006	GUKG5	Apr-2006	Apr-2006	2006Q1
Ukraine	Oct-2002	UX	Oct-2002	GUAU5YR	Apr-2011		2002Q1
Uruguay	Jun-2002						2002Q1
US	Jan-2004	SPX	Jan-2004	USGG5YR	Jan-2004	Jan-2004	2004Q1
Venezuela	Mar-2001						2001Q1
Vietnam	Sep-2002	VNINDEX	Sep-2002	GGVF5YR BIDV	Feb-2007	Sep-2002	2002Q1