Institut de Recerca en Economia Aplicada Regional i Pública
Research Institute of Applied Economics

Document de Treball 2021/18 1/33 pág.
Working Paper 2021/18 1/33 pag.

"Risk Spillovers between Global Corporations and Latin American Sovereigns: Global Factors Matter"

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Abstract

We study volatility spillovers between the corporate sector's and Latin American countries' CDS. Daily data from October 14 2006 to August 23 2021 are employed. Spillovers are computed both for the raw data and for filtered series which factor out the effect of global common factors on the various CDS series. Results indicate that most spillovers occur within groups, i.e., within countries and within global corporations. However, considerable spillovers are also registered from LAC sovereigns to corporations and vice versa. Interesting differences are encountered between filtered and unfiltered data. Specifically, spillovers from countries to corporations are overestimated (in about 4.3 percentage points) and spillovers from corporations to sovereigns are underestimated (in about 5.8 percentage points) when unfiltered data is used. This result calls for a revision of results obtained from studies that do not consider the role of global common factors on system spillovers. Like in most related studies, spillovers show considerable time-variation, being larger during times of financial or economic distress. When looking at total system spillovers over time, those corresponding to unfiltered series are always larger than those corresponding to filtered series. The difference between the two time-series is largest in times of distress, indicating that global factors play a major role in times of crises. Similar conclusions are derived from network analysis.

JEL classification: G01, G12, C22.

Keywords: Volatility spillovers, Corporate debt, Latin American countries, Filtered and unfiltered data, Factor models.

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1. Introduction

International financial market integration has importantly increased over the last two decades. Different factors have contributed to this observed globalization, including the implementation of policies favoring financial market deregulation, the development of new trading technologies, and the interest of global investors in diversifying their financial portfolios in world asset markets. Financial integration can potentially yield many benefits for market participants and even for countries. The former obtain larger investment opportunities and better chances for risk sharing, while the latter benefit from the effects that deeper financial markets have on their economic stability and resilience.

Risk sharing is a key channel through which financial integration improves the resilience of the global financial system. Financial openness has proven effective in increasing consumption opportunities and income risk sharing, and in reducing the volatility of consumption growth (Bekaert et al. 2006; Uribe and Chuliá, 2021). Similarly, integration promotes new investment opportunities and new sources for funding investment plans. Hence, financial integration is beneficial for allocative efficiency and economic diversification. However, the benefits of financial integration are not cost-free. In a more financially integrated world, national policies and relevant financial events may have important cross-border effects. Over the past two decades crises have propagated more rapidly than in the past and have proven to be more persistent and disruptive. It is in this sense that understanding and quantifying the financial linkages between global sovereign and corporate debt markets, along the lines proposed in this study, has become an absolute priority in political and academic circles, which perceive such linkages as a potential source of global financial instability.

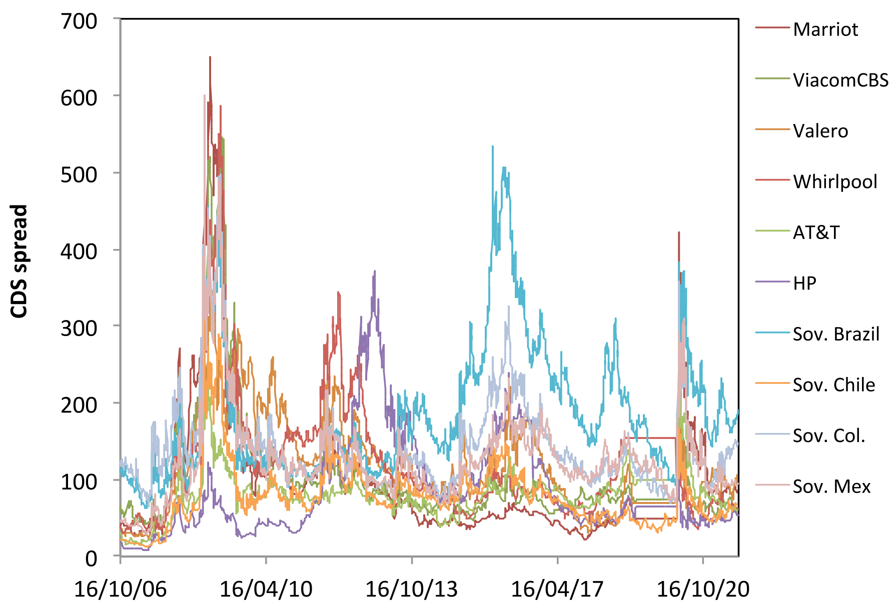
Those fears are grounded in fact. The European sovereign debt crisis that peaked around 2010-2012, particularly in Greece and Ireland, showed the rapid and strong impact that widening sovereign spreads have on funding costs and external finance available for corporations (e.g. Augistin et al. 2018). Second, historical records in the level of corporate and sovereign debt on a global scale have been reached in 2020-2021, due in part to the devastating effects of the Covid-19 disease and the public health measures necessary contain it, but also, as a consequence of the increasing trend in leverage on the side of emerging economies and non-financial corporates, observed since the end of the Global Financial Crisis (Facundo et al., 2020). These unprecedented heights of private and corporate debt, which have been referred to as a "mountain of debt" by some authors (Kose et al. 2021), have been consistently pointed out by several economic analysts as the main source of fiscal and financial vulnerability for the global economy in recent times (Financial Times, 2017; UN, 2019; IMF, 2019, 2021; Bloomberg, 2019; The Guardian, 2019).

Corporate and sovereign defaults are costly. During default episodes, the defaulting entity loses access to debt financing. When sovereign defaults occur, the government temporarily loses the ability to issue bailouts. Consequently, banks' credit to the private sector declines, and eventually output and consumption fall. While defaults have some benefits, for instance the fact that all existing debt is wiped out, relaxing the government's budget constraint, and allowing it to reduce distortionary taxes, its costs can be so high that preventing default events is a main concern of macroeconomic policy in large.

Bernanke (2005), on a related point, drew the attention of the profession almost two decades ago to the complex relationship that exists between debt committed by global corporations and both, debt issuances and government debt portfolio holdings of emerging economies' governments. Bernanke points out that, in emerging countries, the government may act as a kind of financial intermediary between the citizens of these countries and the international private debt markets that global corporations use to fund their operations. Hence, following Bernanke's reasoning we hypothesize on the existence of a close relationship between emerging public and global private debt markets, allowing the emergence of risk spillovers in the two directions, from corporates to emerging sovereigns and from emerging sovereigns to global corporations. The empirical study of this double relationship, with possible causal arrows in the two directions, has been mainly overlooked by extant literature.

Our main motivation comes from the fact that since Bernanke's speech, the relationship between global public and private debt markets only appears to have gained traction. Figure 1 shows recent Credit Default Swaps (CDS) trajectories, since 2006, for five large corporations and four emerging economies in Latin America, which is currently one of the most indebted regions in the world and shares strong historical commercial and financial ties with the United States, where most of these global corporations operate. CDS spreads are timely indicators of the dynamics of corporate and sovereign debt markets, which offer the possibility to track risk spillovers in real time, which is not possible via traditional analyses that focus on financial statements and national account statistics.

Figure 1. CDS Oct-16 to Aug-21 for selected corporations and emerging economy governments



Note: Selected CDS series for five corporations and four emerging sovereigns in Latin America.
Source: Bloomberg

After observing Figure 1, it becomes clear that the two markets (i.e. emerging sovereigns in LA and corporate global) are closely linked. Series coming from the corporate sector and from sovereign markets are practically indistinguishable, as they all peak around the same events, the Global Financial Crisis, European Crisis and Covid19, albeit with different intensities. Many questions arose after observing the figure: What part of this close relationship is due to global factors that simultaneously affect both markets? What part is due to cross-spillovers between these specific markets? How strong is the relationship between and within these two markets? Where do shocks originate, in the emerging sovereign debt market or in the corporate global market? Have the strength and shape of the relationship changed over the last decades, especially in times of crisis? By answering these questions we contribute to the aforementioned literature on international finance that is concerned with financial vulnerability and financial stability arising from the complex relationship between public and private global debt markets. We also contribute to the corporate finance literature that emphasizes on the unique features of CDS contracts to extract market information and timely signals about the price of risk in debt markets[4]. In a more general sense, we add to the large and growing literature on financial contagion and volatility transmission in financial markets (e.g., Forbes and Rigobon 2002; Bradley and Taqqu 2004; Diebold and Yilmaz 2009; Caccioli et al.2014; Aït-Sahalia et al. 2015; Gamba-Santamaria et al., 2017; Chuliá et al. 2018), but unlike most of this literature we focus on debt markets.

We analyze more than 600 daily series of corporate CDS and 48 series of sovereign CDS from October 14 2006 to August 23 2021. We follow the proposal of Josee and Husson (2013) to construct time varying indices of the price of risk in sovereign and corporate debt markets, and the popular methodology advanced by Diebold and Yilmaz (2009, 2012) to estimate risk spillovers and connectedness indicators. Many recent studies have followed Diebold and Yilmaz's approach for estimating volatility spillovers within many different markets. However, some recent studies have challenged the construction of spillover indices using "raw" data without considering the role that common factors may have in spillover transmission (see, for instance Guerello and Tronzano, 2020; Ha et al., 2020, among others). According to these authors, omitting the role of common factors may lead to the magnification of true volatility spillovers within markets. These papers recommend, then, factoring-out unobserved common factors before applying the traditional Diebold-Yilmaz framework to the data.

We follow this recommendation and we account for common factors that affect debt markets disregarding their nature, i.e., private or public, emerging or developed, etc., before estimating our spillover statistics for the globally integrated debt markets. We compare spillover results when global factors are explicitly considered and when their role is ignored. We show that results are substantially different in both scenarios. Specifically, spillovers are considerably larger when the role of global common factors is ignored, as most papers in the literature do. Additionally, spillover directions and intensities change considerably when global financial factors are factored-out before volatility spillovers are computed. The magnitude of spillovers under both scenarios differs most during periods of financial distress, indicating that global financial factors associated with financial uncertainty prevail among global common factors. We illustrate our results through network analysis for time series.

[4] See in this literature recent examples by Lee et al. (2017), Norden (2017), Oehmke and Zawadowski (2017), Siriwardane (2019) and Tang and Yan (2017).

In general, we document that most spillovers in the analyzed markets take place within groups, i.e., within countries and within global corporations. However, considerable spillovers are also registered from Latin American sovereigns to global corporations and vice versa. Like in most related studies, spillovers show considerable time-variation, being larger during times of financial or economic distress. When looking at total system spillovers over time, those corresponding to raw series are always larger than those corresponding to the series that account for the global common factors. This points out the overestimation of system spillovers that is produced when the effect of such global common factors is neglected. Indeed, the difference between the two time-series is largest in times of distress, indicating that global factors play a major role during financial crises.

This paper is comprised of six sections, this introduction being the first of them. The second is a literature review section briefly discussing the nexus between corporate and sovereign debt markets, emphasizing on the important nexus of global corporate debt with emerging market sovereign debt markets. This section shows why the assets under study are relevant. Sections three and four present the methodology and data used in this study. The fifth section presents the main results of our empirical analyses. The last section concludes.

2. Nexus between Corporate and Sovereign Debt markets: A literature review

The literature agrees that sovereign and corporate debt spreads- which move alongside credit default swaps (CDS) spreads- respond to some 'common macro factors'. Hence, we can expect to observe strong co-movements between the two types of markets, and also across different national markets, which could be even larger in times of financial and economic distress. As highlighted by Dailami (2010), due to the fact that corporate bonds are usually priced with respect to sovereign curves and, in turn, sovereign debt bears basically macroeconomic risks, there exists a structural link between sovereign and corporate bonds. This link can be reinforced by lack of liquidity in specific markets, asset classes, or during crisis episodes. The macro factors that underlie corporate and sovereign markets identified by the recent literature can be broadly summarized as: i) monetary policy interventions and reference rates; ii) global financial conditions, including policy and financial uncertainty, iv) market-wide liquidity; v) the time-varying level of risk aversion and, to a lesser extent, vi) crude oil prices and vii) real estate prices.

The first, and most commonly advocated factor underlying credit spreads, are central bank policy interventions that affect both private and public debt markets. Krishnamurthy et al.

(2018) examine the effects of Securities Markets Programme, Outright Monetary, Transactions, and the Long-Term Refinancing Operations by the European Central Bank, on euro- and dollar- denominated sovereign bonds, corporate bonds, and corporate credit default swap (CDS) rates. They documented falling yields across countries after the implementation of these measures, especially in Italy, Spain and Portugal, with a reduction in market segmentation that amounts to a half of the total estimated effect, which is consistent with the findings of Zaghini (2017) for the corporate yield spreads, which use data of the Eurozone as well. On their side, Pancotto et al. (2019) quantify the impact of the European Bank Recovery Resolution Directive on the sovereign-bank nexus. Their main results point out against the effectiveness of the measure in weakening the interconnectedness between sovereign and bank risks, since no significant effect is found in comparison with the corresponding effect on the control group of non-financial corporations. Nevertheless, their results still admit and, indeed, point out common factors leading the dynamics of all three sectors, financial and non-financial corporates, alongside sovereigns.

Another common shock that has been proposed is the global deterioration of financial conditions, and closely related, aggregate uncertainty, the level of risk aversion and market-wide liquidity in the financial markets. Zhu (2018) identifies shocks to the banking sector as the main driver of sovereign, banking and corporate CDS spreads in 11 Eurozone countries from 2008 to 2013. Hui et al. (2013) study the role of funding liquidity, risk aversion and equity market performance, and find all of them to be crucial for the determination of financial, corporate and sovereign risks in Europe. On their side, Calice et al. (2013) emphasize on the role of liquidity as a main determinant of the interplay between different debt maturities and also across countries, during the GFC, while Liu and Spencer (2013) point out to investors' confidence as a main factor underlying the cost of the debt for the corporate sector in emerging economies. Also regarding emerging markets, a remarkable study by Asis et al. (2021) provides evidence on the predictive power of US interest rates, changes in global liquidity and risk aversion, on corporate distress. Other studies, among which Wisniewski and Lambe (2015), Augustin (2018) and Wang et al. (2019), Shahzad et al. (2017), and Tang (2017) are prominent examples, also document a significant effect of numerous macro-uncertainty and liquidity proxies on the corporate and sovereign CDS premiums, across global debt markets. Finally, Hkiri et al. (2018) adds crude oil to the equation, while Benbouzid et al. (2018) includes real estate prices.

Regarding the direction of the shocks between the corporate and public sectors, most authors identify an unidirectional link from sovereign to corporate risk of default, and hence from sovereign to corporate spreads. Nevertheless, some important examples in the literature recognize complex and bidirectional interplays between the two markets, especially after considering the informational flows from financial institutions to sovereign markets, and in turn from corporations to banks.

A modern treatment of the subject in the former set of studies is due to Dailami (2010), who using a comprehensive database of emerging market corporate and sovereign entities, from 1995 to 2009, shows that investors' perception of sovereign debt turbulence results in larger costs of capital for private corporate issuers. Augustin et al. (2018) examine the transmission of sovereign to corporate credit risk using the Greek Bailout on April 11 2011 as a natural experiment. These authors estimated that a 10% increase in sovereign credit risk raises corporate credit risk about 1.1%. The risk spillover from sovereign to corporate credit suggests the presence of a financial and a fiscal channel, because the authors find larger effects associated with firms that are directly dependent on banks or the government, while they find no support for indirect risk transmission through a deterioration of macroeconomic fundamentals. Mohapatra et al. (2018), employing a sample of 47 emerging markets and developing economies, examine the distance between sovereign credit ratings and the ratings assigned to new foreign-currency bonds issued by sub-sovereign entities (i.e. public sector enterprises, financial firms, private non-financial corporations). Their results support stronger sovereign-corporate links between public sector enterprises and financial firms relative to the rest of the firms. Esteves and Jalles (2016) investigate the impact of sovereign defaults on the ability of corporations in emerging economies to fund their operations abroad. Using data from 1880 to 1913, their results confirm a large and persistent credit rationing phenomenon occurring after the event of a sovereign default. Pianeselli and Zaghini (2014) and Hui et al. (2013) point out to sovereign debt market turbulence as a main determinant of risk premium paid by non-financial corporations when issuing bonds or of CDS contracts.

Gray and Malone (2012) and Yu (2017) adopt a more comprehensive perspective by modeling the spillovers and feedback effects between sovereign and banking sector risks. In their frameworks, risk spillovers between banks and sovereign markets may arise basically for three main reasons: bank holdings of risky sovereign debt, guarantees from sovereigns to banks in case of bankruptcy, and enlarged borrowing costs for banks as a consequence of widening sovereign spreads. Regarding the link between corporate debt and sovereign risk, Wu (2020) studies the role of dollarized corporate external debt in emerging countries and documents that an increment in foreign-currency corporate debt leads to an increase in sovereign risk premium.

Even after considering the common factors that likely determine global debt markets, there exists another possible channel that complements Bernanke's (2005) view, discussed in the introduction, by which private corporations, either financial or non-financial firms, may impact sovereign spreads, or which can even explain spillovers between seemingly unrelated sovereign markets and corporate sectors of a foreign market. It corresponds to a portfolio view of the transmission and has been scarcely explored by the literature. Hipper et al. (2019) documented that, indeed, such a channel may likely exist, since there are considerable diversification opportunities of adding corporate CDS indices to a traditional financial portfolio consisting of stock and sovereign bond indices. These authors emphasize that risk-diversification benefits mainly result from institutional investors replacing sovereign bonds (as opposed to stocks) by credit default swaps.

Both, common macro factors and idiosyncratic risk spillovers motivate our study, and methodological choices.

3. Methodology

In this section we review the methods used to construct the default indices on an industry level, and the global common factors that jointly determine the dynamics of CDS markets in both emerging and advanced economies. We also present the methodology to construct spillover and connectedness statistics between the corporate and sovereign sectors and to characterize the network structure of the CDS market.

a. Factor estimation

The methodology used to construct the indices consists of two steps. In the first step we impute missing values in the original database using an iterative regularized PCA algorithm due to Josee and Husson (2013), while in the second we use the complete data set to construct the sector indices and the global factors by traditional PCA. PCA analysis is a popular technique for dimensionality reduction and representation learning in artificial intelligence, and it is the most popular method in finance and macroeconomics to estimate factors in factor analysis of large data sets. Factor analysis seeks to encapsulate the time dynamics of large panels using a few common factors. While the general underlying dynamics is assumed to be the same for the whole system, idiosyncratic factor loads provide the way each series in the panel is related to the common time-varying factors. In particular, we use the first principal component to estimate the sector indices, which corresponds to a linear combination of the original series within each industry sector, with the weights of the linear combination obtained by an optimization process that maximizes the variance encapsulated in the index series.

Nevertheless, before using PCA it is preferable to impute any missing observations, instead of simply assuming that they are all equal to zero or to a constant term. Imputation should be ideally conducted in such a way that factors' estimation and imputation itself feed into each other, preventing the factor series from experiencing "jumps" when several individual CDS series appear in the database at the same time, as it frequently occurs with CDS data. The way in which this interactive optimization is conducted is known as regularized PCA:

i. Regularized PCA

To estimate the sector factors indices, we use the method of regularized principal components, proposed by Josse & Husson (2013). In this methodology the objective is to determine a subspace that effectively reduces the distance between individual CDS and their projections. This is indeed, equivalent to finding two matrices labeled $\mathrm{F}_{T\times S}$ and $\mathrm{U}_{N\times S}$ with $S < T$ being the respective ranks, which provide the optimal approximation of the matrix constructed using the original dataset $\mathrm{X}_{T\times N}$, where *T* refers to time and *N* to cross-sectional units (either individual CDS series for corporations or for countries). For this, we need to minimize the following criterion:

$$\vartheta = \left|\left|\mathrm{X} - \mathrm{M} - \mathrm{FU}'\right|\right|^2 = \sum_{t=1}^{T}\sum_{n=1}^{N}\left(X_{tn} - m_n - \sum_{s=1}^{S} F_{ts}U_{ns}\right)^2, \tag{1}$$

M has dimensions $T{\times}K$ and each row equals $(m_1, \dots, m_N)$, i.e., the vector with the mean of each variable. A common way to deal with missing values in traditional PCA is to ignore such missing values, and then minimizing the least-squares criterion in Equation 10 overall non-missing entries. An alternative way consists on minimizing the following criterion, by introducing a weighted matrix W, where $\mathrm{W}_{tn} = 0$ if X_{tn} is missing or $\mathrm{W}_{tn} = 1$ otherwise:

$$\vartheta = \sum_{t=1}^{T}\sum_{n=1}^{N} W_{tn}\left(X_{tn} - m_n - \sum_{s=1}^{S} F_{ts}U_{ns}\right)^2. \tag{2}$$

The iterative (regularized) PCA algorithm that minimizes (2) in the following steps:

1- Initial values such as the mean of each variable are used to replace missing values.

2- Regular PCA using the complete data set. Then, you impute the missing values with the reconstruction formulas (regularized). The number of components used for the imputation of missing data is calculated by cross-validation.

3- Steps are repeated 2-a) and 2-b) until convergence is achieved.

The output of the algorithm is used to estimate the sector indices in our application. In any case the solution satisfies the following two Equations 3-4:

$$\widehat{\mathrm{U}}' = \left(\widehat{\mathrm{F}}'\widehat{\mathrm{F}}\right)^{-1}\widehat{\mathrm{F}}'\left(X - \widehat{\mathrm{M}}\right), \tag{3}$$

$$\widehat{\mathrm{F}}' = \left(X - \widehat{\mathrm{M}}\right)\widehat{\mathrm{U}}\left(\widehat{\mathrm{U}}'\widehat{\mathrm{U}}\right)^{-1}. \tag{4}$$

On a final note, the original CDS series were standardized to construct the variance-covariance matrix, before applying the PCA algorithms, as to have unit variance and zero mean and facilitate comparison across series.

b. Spillover statistics

The spillover indices were built upon the associated forecast error variance decomposition (FEVD) of a VAR representation with *N=20* variables: 11 sector indices for global corporations, 1 corporate index for large firms with main operations in Latin American and Caribbean countries, and 8 country indices for the main markets in the region. We follow the traditional literature by Diebold and Yilmaz (2009, 2012) and provide both dynamic and static spillover analyses.

Notice that before estimating the baseline VAR, we factor-out the unobserved common variation from our 20 original series (and other 40 CDS series for sovereign CDS around the globe) as suggested by the recent econometrics literature (see for instance Fan et al. (2021)). The common variation is identified using the first 5 PC series of the 60 assets, which are subsequently used as regressors of the 20 original CDS in our database.

To simplify notation we will refer to the VAR system of factorized series as:

$$X_t = \Theta(L)\varepsilon_t, \tag{5}$$

$$X_t = \sum_{t=0}^{\infty} B_i \varepsilon_{t-i}, \tag{6}$$

where X_t is a matriz $T \times N$, $\Theta(L) = (I - \phi(L))^{-1}$, ε_t is a vector of independently and identically distributed errors with mean equal to zero, and Σ covariance matrix. $B_i = \phi B_{i-1} + \phi B_{i-2} + \cdots + \phi B_{i-p}$ is the matrix of parameters, p is the number of lags included in the estimation, selected in our case according to the *Bayesian Information Criterion*, and T is the number of days. We also estimate spillover statistics using the unfiltered original series, as a way of estimating the bias induced into the spillover statistics when global factors are not taken into consideration.

To estimate the FEVD from the h-step ahead forecast, we first need to identify the structural VAR innovations. As is traditional in this literature since Diebold and Yilmaz (2012), we follow Koop et al. (1996) and Pesaran and Shin (1998), to construct generalized VAR systems, and their associated generalized FEVD. Rambachan and Shephard (2021) analyze the conditions under which predictive time series estimands, such as the aforementioned impulse response, can be interpreted as a dynamic causal effect of assignments on outcomes, and show that indeed such conditions are considerably weaker than those required by traditional orthogonality conditions. This analysis is extendable to FEVD which are based on the same assumptions and indeed, provide further support to this popular methodological option, widely used in the literature to construct spillover statistics.

Following Diebold and Yilmaz (2012) the errors in the FEVD can be divided into *own variance* shares and *cross variance* shares. The former are the portion of the errors associated with a shock to x_i on itself, while the second are the fraction of the shocks on x_i associated with the rest of the variables in the system. The h-step ahead FEVD can be expressed as follows:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i{}' B_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i{}' B_h \Sigma B_h{}' e_i)}, \tag{7}$$

where σ_{jj} is the standard deviation of the *j*-th equation, e_i is a selector vector that takes the value of one in the *i*-th element and it is zero otherwise. Naturally, Σ is the variance matrix of ε_t. To ensure that the sum of each row is 1, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$, each entry of the variance decomposition must be normalized in the following way:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)}. \tag{8}$$

where $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.

After we have computed the normalized variance decomposition, a total spillover indicator can be estimated as:

$$C(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100. \tag{9}$$

The indicator in the equation above measures the percentage variance that can be attributed to cross-spillovers. We can also construct a *directional spillover* index, according to which the effect of a shock from all other variables j on the variable x_i will be described by:

$$C_{i \leftarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100, \tag{10}$$

analogously , the effect of a shock from x_i on all other CDS markets j will be given by:

$$C_{i \rightarrow j}(H) = \frac{\sum_{j=1, i \neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100, \tag{11}$$

Net spillover indicators can be constructed as follows:

$$C_i(H) = C_{i \rightarrow j}(H) - C_{i \leftarrow j}(H). \tag{12}$$

The type of indicators in the above equation measure the effect associated with a shock to variable x_i on the rest of the system variables.

c. Time series networks

We use the proposal by Baragozzi and Brownless (2019) to estimate the network representation of our system of CDS. This methodology allows us to construct two different representations: 1) the first one consists of an adjacency matrix that defines the links between the CDS markets in our sample, by the means of a conditional long-run correlation between any pair of series, and it is an undirected network. 2) The second representation uses a Granger-causality approach, thus it establishes the edges (i.e. links) between the nodes in the (directed) network according to the existence of directional predictability between any pairs of series in the sample.

Formally, we can consider the autoregressive representation of the system described in equations 5 and 6, which is given by:

$$X_t = \sum_{k=1}^{p} A_k X_{t-k} + \boldsymbol{e}_t, \tag{13}$$

where $\boldsymbol{e}_t \sim iid(0, \mathbf{C}^{-1})$, A_k and $\mathbf{C}$ are $n \times n$ matrices. Baragozzi and Brownless (2019) focus on the cases of sparse VAR systems, in which both A_k and the concentration matrix $\mathbf{C}$ are assumed to be sparse, with typical entrances a_{jij} and c_{ij}. Indeed, this is the right assumption because we are inducing sparsity via the factorization of common forces before estimating the CDS network.

Networks are useful to represent the interdependence structure of the time series in X_t. We can define a network by the graph $\mathcal{N} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ represents a set of vertices or nodes and $\mathcal{E}$ is the set of edges or links. Baragozzi and Brownless (2019) propose two ways to measure interdependence in the network, in a traditional Granger causality sense and via estimation of long-run variance-covariance matrices for the system. In the former case, we have that x_{jt} Granger causes x_{it} if adding x_{jt} as predictor improves the mean square forecast error of x_{it+k} for any $k > 0$. We say that if $a_{jij} = 0$ for all *k*, then x_{jt} does not Granger cause x_{it}. Thus, a Granger network is defined as a directed network $\mathcal{N}_G = (\mathcal{V}, \mathcal{E}_G)$, where the presence of an edge from *i* to *j* means that *i* Granger causes *j*, i.e., $\mathcal{E}_G = \left\{(i,j) \in \mathcal{V}\times\mathcal{V}: a_{kij} \neq 0, \text{ for at least one } k \in \{1, \dots, p\}\right\}$. On its side, the contemporaneous network is defined as an undirected network $\mathcal{N}_C = (\mathcal{V}, \mathcal{E}_C)$, where a link between *i* and *j* denotes that both are partially correlated $\mathcal{E}_C = \left\{(i,j) \in \mathcal{V}\times\mathcal{V}: \rho_L^{ij} \neq 0\right\}$, where ρ_L^{ij} is the coefficient of partial correlation, estimated based upon the long-run covariance matrix of the series. The long run covariance is defined as follows:

$$K_L = \Sigma_L^{-1} = \left(I - \sum_{k=1}^{p} A'_k\right) C \left(I - \sum_{k=1}^{p} A_k\right), \tag{14}$$

where $\rho_L^{ij} = -\frac{k_{Lij}}{\sqrt{k_{Lii}k_{Ljj}}}$.

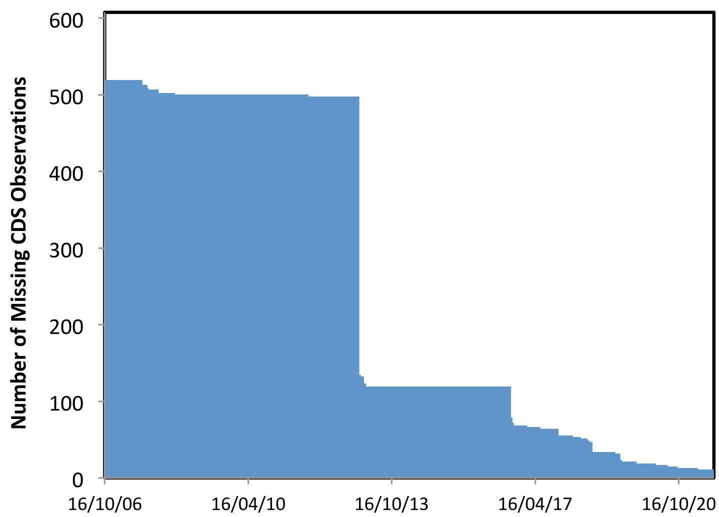
4. Data

We collect daily data on CDS from October 14 2006 to August 23 2021. Our database includes 608 corporate CDS and 48 sovereign CDS from emerging, frontier, and advanced economies. All information was retrieved from Bloomberg data services.

Corporate CDS are from large firms belonging to eleven economic sectors according to general Standard and Poors classification: Consumer discretionary- DISC (e.g., Amazon and McDonald's); consumer staples- STAP (e.g., Coca-cola, Pepsi, Kellogs); communications- COMM (e.g., AT&T, Warner); energy - ENG (e.g., Chevron, Exxon); financials -FIN (e.g., Bank of America, Citigroup); healthcare- HEAL (e.g., Baxter, J&J, Pfizer); industrials- IND (e.g., 3M, Boeing, General Electric); materials- MAT (e.g., Air Products, Cemex); real estate - REST (e.g., American Tower, Equity commonwealth); technology - TECH (e.g., Apple, Cisco, Intel, Xerox); and, utilities- UTI (e.g., CMS Energy, Dominion Energy, PSEG Power).

Corporate CDS data is characterized by many missing values. Figure 2 graphically depicts them, splitting the sample into three subsamples: Oct 2006-Dec 2012, Dec 2012-Aug 2016, and Sep 2016-Aug 2021. As expected, missing values are more frequent at the beginning of the sample and significantly decrease at the end of it.

Figure 2: Missing values in corporate CDS data



Note: Number of missing values in the sample of corporate CDS

The presence of the numerous missing values motivated us to focus only on the most liquid CDS series for global corporates to construct representative indices of industry categories. We balanced both the number of non-missing values from the beginning to the end of the sample, and the observed time variation of the CDS, which speaks about a CDS contract liquidity, to select our sub-sample of analysis. We ended up using 109 corporate and 48 sovereign CDS to estimate the corporate indices and to construct the global common factors of debt. Moreover, we conduct our network analysis using only six Latin American markets as representative of emerging markets economies, due again to data availability considerations and a perceived greater variation of these CDS contracts from the beginning to the end of the sample, compared to other emerging market economies. From an economical point of view Latin American is one of the most indebted regions in the world and it has been particularly impacted by the Covid19 crisis (IMF, 2021; Franz, 2020). Also it presents strong commercial and financial ties with North America, where most of the 109 corporations used in our empirical analysis operate. This still high number of series keeps us from showing summary statistics of the original data. But the evolution of the constructed index and the global common factors in debt markets are presented in the results section. A list of the corporations included in our estimations is provided in the Appendix.

5. Results

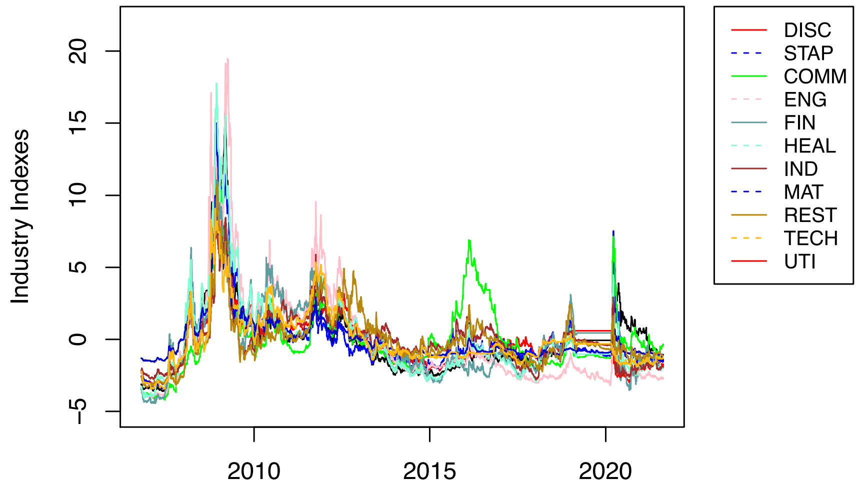
This paper studies the nexus between corporate and sovereign debt markets from Latin American countries following the volatility spillover approach. To show the importance of seriously considering the role of global common factors, we compute spillovers for two distinct scenarios. Under the first, we factor-out common global factors before performing spillover and network analyses. Under the second scenario, we compute spillovers and perform network analyses to the raw data, following the most traditional approach in this strand of the literature. We compare results under these two scenarios to show the important role that global common factors play, especially during times of financial turmoil.

a. Corporate indices and global CDS factors

As mentioned before, the large number of corporate CDS series combined with the also large number of missing values led us to work with corporate sector indices, shown in Figure 3. Sector indices were constructed for the eleven sectors shown in the data section. These indices were constructed using only 109 firms for which CDS information contained only a few numbers of missing observations. We also constructed an index for LATAM corporate sector consisting of information for very large corporations in this region: Televisa, Telmex, Univision, Petrobras, Pemex, Cemex, Codelco. This index is presented in Figure 4. The reason for studying such index if that we aim to consider in our estimations of spillovers the direct effect of companies operating in the region of study, and to observe whether the documented spillover between the price of global companies' debt and sovereign debt of emerging markets in LA survive after controlling for this direct linkage.

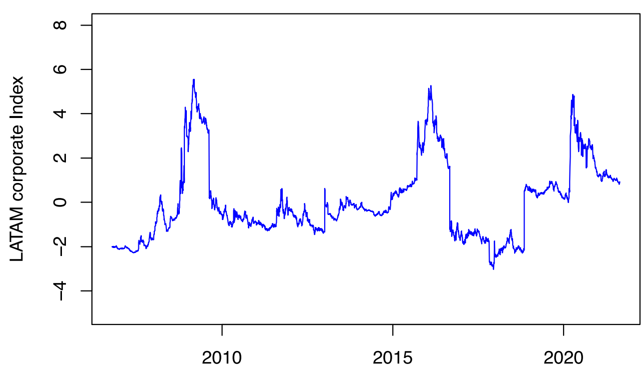
To construct the indices, in the two cases, we used an interactive procedure based on the Expectation Maximization algorithm combined with Principal Components Analysis, due to Josse and Husson (2013) and implemented by Josse and Husson (2016) in the statistical software R, to impute the missing NAs before we carried out our factor estimation. This reduces the possibility of inducing spurious correlations in the variance-covariance matrix, when several series appear simultaneously in the database.

Figure 3: Time series behavior of corporate sector indices, three subsamples



Note: CDS indices according to 11 industry categories in Standard and Poor's 500

Figure 4: Time series behavior of the Corporate LATAM index



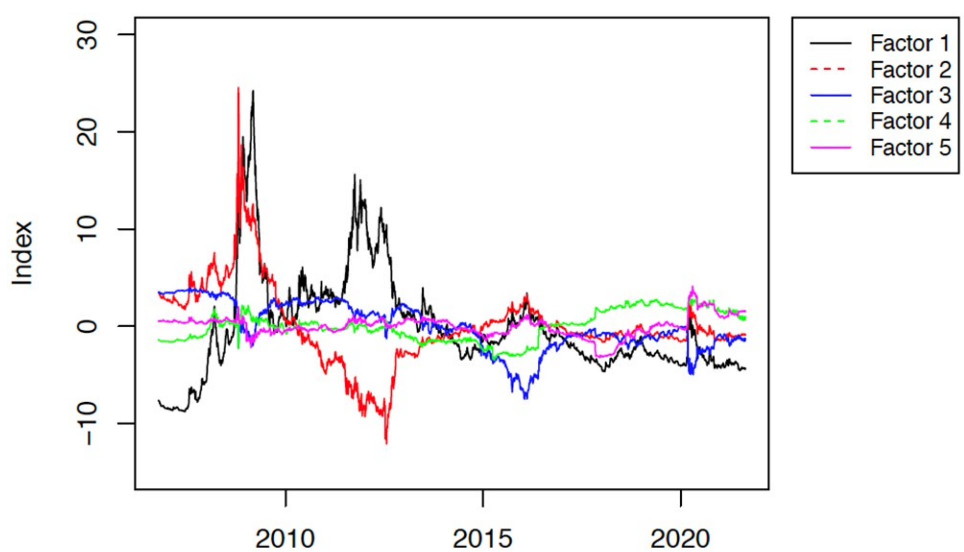
Note: CDS index for six Latin America Corporations.

Note that CDS indices (eleven sectors and LATAM) show similar time-series patterns. For instance, peaks are observed around the Global Financial Crisis of 2008-2010, the European Debt Crisis of 2013-2015, and the Covid-19 Crisis (2020). However, interestingly, while for the eleven sectors the highest peaks occurred around the Global Financial Crisis, the LATAM index shows similar peaks in the three episodes of distress.

This reflects the fact that Latin America was one of the most affected regions by the Covid-19 pandemic.

A well-known fact is that a relatively small number of international factors are important drivers of the behavior of financial markets worldwide. Dynamic Factor Models, Global VAR Models, Panel-VAR Models, and others are all constructed to reflect this observation. To properly identify market spillovers using our data and avoid confounding them with global unobservable factor movements, we estimate a few global factors explaining a large percentage of common variation in our selected time series. We factor-out these common variations from our data and use residual information for estimating dynamic spillovers between the selected time series. While various ways for estimating global factors exist, we use PCAs on our complete database for their estimation. We chose the first five factors, explaining together over 90% of total variance. Figure 5 depicts these five factors.

Figure 5: Global Factors

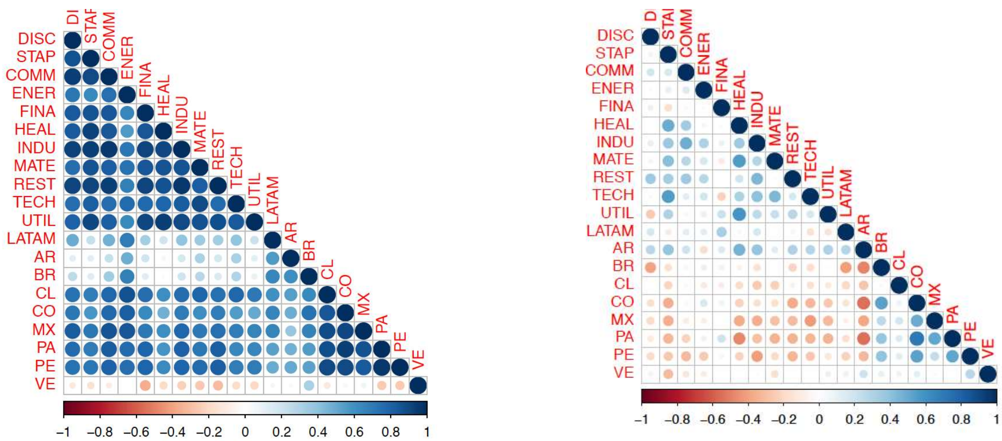


Note: Global CDS factors estimated using the five first principal components of the sample conformed by the 12 corporate CDS series and 48 Sovereign CDS.

b. Networks and connectedness considering global factors and without considering them

Figure 6 shows that correlations between the sample time series are substantially different when the original series are used as when the residual series are used. Hence, studies using series that do not account for these common factors may have misleading results. In other words, correlations between the original series are likely driven by common omitted causes that should be taken into account when constructing the network. Such common causes may be even transversal to all financial markets, instead of being specific to debt markets.

Figure 6: Estimated correlations when original (left) and residual (right) series are used



Note: Correlation matrix between original series (left) and filtered series (right) using the five macro factors presented in figure 5 in individual regressions.

System spillovers are presented in Table 1. Panel A presents spillovers computed following the method proposed by Diebold and Yilmaz (2009, 2012), applied to the residual series computed after factoring out the five main common factors.

Table 1 Panel A: Total spillovers residual series

	DISC	*STAP*	*COMM*	*ENER*	*FINA*	*HEAL*	*INDU*	*MATE*	*REST*	*TECH*	*UTIL*	*LATAM*	*AR*	*BR*	*CL*	*CO*	*MX*	*PA*	*PE*	*VE*	*C. from others*
DISC	23.0	4.1	5.4	7.4	1.2	1.0	7.1	3.3	8.3	3.0	1.4	1.1	3.7	3.3	0.2	4.8	6.5	5.8	7.1	2.1	**77.0**
STAP	9.3	41.3	3.6	2.0	1.3	5.9	4.3	5.0	5.2	2.9	2.7	0.4	4.1	0.9	0.1	1.9	2.4	2.3	2.5	2.0	**58.7**
COMM	5.8	2.9	28.5	6.1	1.9	2.3	9.3	6.2	7.4	7.6	0.8	0.6	1.9	1.1	0.1	1.7	3.8	5.0	5.4	1.7	**71.5**
ENER	5.8	0.8	5.2	23.2	2.0	0.5	5.2	3.7	7.6	3.6	3.1	1.8	1.0	3.5	0.1	5.7	8.4	7.9	8.3	2.4	**76.8**
FINA	0.5	0.6	1.2	0.9	76.7	0.6	2.0	2.7	5.1	1.6	5.9	0.0	0.9	0.1	0.0	0.0	0.3	0.2	0.1	0.6	**23.3**
HEAL	2.4	7.4	5.4	1.6	1.8	48.3	9.8	7.4	1.5	4.3	3.2	0.2	2.5	0.0	0.1	0.1	0.7	1.2	0.8	1.5	**51.7**
INDU	5.8	2.2	9.3	4.7	4.3	3.9	24.1	8.1	8.3	6.0	2.5	0.4	2.4	1.1	0.2	2.5	4.4	3.7	4.3	1.8	**75.9**
MATE	3.2	4.3	6.7	2.6	4.4	4.1	9.6	39.9	5.8	8.2	2.6	0.1	0.5	0.1	0.0	0.6	2.2	2.0	1.6	1.5	**60.1**
REST	7.6	2.8	7.0	6.3	4.4	0.6	6.8	4.2	24.1	3.9	3.6	1.2	2.4	3.0	0.0	4.8	6.3	4.0	5.0	2.1	**75.9**
TECH	4.2	2.6	8.7	2.9	1.9	2.1	7.5	8.3	4.8	39.3	1.7	0.1	0.8	0.9	0.1	2.5	4.2	3.1	2.8	1.7	**60.7**
UTIL	1.3	2.7	1.2	4.1	14.8	2.1	3.2	3.3	5.1	2.4	46.9	0.5	2.4	0.8	0.2	3.1	2.7	1.2	1.0	1.0	**53.1**
LATAM	3.6	0.2	5.3	5.8	0.4	0.0	3.2	1.1	3.9	0.9	0.7	47.2	0.3	4.0	0.4	6.9	5.7	4.5	5.6	0.5	**52.8**
AR	7.8	4.6	4.8	2.9	2.7	2.9	5.7	1.7	6.6	2.3	3.6	0.2	28.9	5.3	1.0	5.2	4.2	4.5	4.9	0.2	**71.1**
BR	4.3	0.3	2.1	3.3	0.0	0.0	2.5	0.3	4.1	1.3	0.5	3.3	4.0	36.4	0.5	10.8	8.5	8.0	9.0	0.8	**63.6**
CL	1.9	0.9	1.1	1.2	0.2	0.1	1.3	0.7	1.2	0.8	0.3	0.5	2.6	3.8	63.4	6.3	6.8	3.8	3.3	0.0	**36.6**
CO	3.8	0.5	2.0	5.4	0.1	0.0	2.4	0.7	4.2	1.8	1.4	2.4	2.2	8.8	0.7	25.0	12.2	12.5	13.2	0.6	**75.0**
MX	5.0	0.9	4.6	6.6	1.1	0.3	4.4	2.6	6.1	3.2	1.7	1.5	1.5	6.2	0.8	11.1	21.0	9.9	10.5	0.9	**79.0**
PA	3.3	0.3	2.8	4.6	0.0	0.3	2.8	1.6	2.5	1.9	0.4	0.8	1.6	6.9	0.4	13.2	8.5	28.0	19.8	0.5	**72.0**
PE	3.9	0.3	3.2	5.4	0.0	0.1	3.2	1.4	3.5	1.7	0.4	1.3	1.5	6.5	0.5	13.0	8.9	18.5	25.8	0.8	**74.2**
VE	4.3	2.1	4.1	7.5	2.0	1.0	3.9	4.4	7.0	3.8	2.5	0.4	0.2	1.2	0.1	2.6	4.2	2.8	3.6	42.4	**57.6**
C. to others	**83.7**	**40.5**	**83.7**	**81.3**	**44.8**	**27.8**	**94.2**	**66.7**	**97.8**	**61.1**	**39.1**	**16.7**	**36.5**	**57.6**	**5.5**	**96.8**	**100.7**	**100.8**	**108.8**	**22.8**	

Spillovers are particularly large between global corporate sectors. Specifically, 48.5% of total system spillovers are registered between global corporate CDS, including LATAM corporate, which have access to international debt markets (box on the left-top of Table 1, Panel A). Sovereign debt spillovers in Latin America countries go in second place, accounting for 28.5% of total spillovers (box on the right-top of Table 1, Panel A). Interestingly, spillovers of sovereigns in Latin America to global corporates and spillovers from corporates to sovereigns are of an almost identical magnitude, rounded to 11.5% of total spillovers each. This result indicates the importance of global portfolio rebalancing when risk aversion rises. Finally, spillovers from global corporate LATAM to sovereigns are almost negligible, ranging from 0.2% in the case of Argentina to a maximum of 3.3% in the case of Brazil, which represents a modest 0.5% of total spillovers.

Table 1, Panel B, shows spillovers computed to the raw data, i.e., without factoring-out common global factors. Results differ from those shown in Table 1, Panel A. Specifically, while spillovers within sectors are lower (44.2%, compared to 48.5%), spillovers within Latin American countries' sovereign CDS increase importantly (34.3%, compared to 28.5%). Total spillovers from countries to sectors are larger (15.8% vs. 11.5%), while spillovers from the corporate sector to sovereigns decrease importantly (5.7% vs. 11.5%). These results highlight the importance of considering global factors explicitly. When their role is ignored, the composition of total spillovers changes considerably. For instance, in our study using the raw data will lead to overstating spillovers within countries and from countries to the corporate sector, while will also lead to underestimating total spillovers from the corporate sector to Latin American countries.

Table 1, Panel B: Total spillovers raw data

	DISC	*STAP*	*COMM*	*ENER*	*FINA*	*HEAL*	*INDU*	*MATE*	*REST*	*TECH*	*UTIL*	*LATAM*	*AR*	*BR*	*CL*	*CO*	*MX*	*PA*	*PE*	*VE*	*C. from others*
DISC	14.9	8.1	6.9	5.1	4.3	5.9	7.5	6.3	7.0	5.0	3.3	0.7	0.1	3.9	3.1	5.0	4.3	4.5	4.0	0.1	**85.1**
STAP	10.9	15.5	5.5	3.1	4.4	7.1	6.2	6.7	7.1	5.3	4.3	0.6	0.1	3.6	2.6	4.4	4.1	4.4	4.0	0.0	**84.5**
COMM	8.8	5.5	14.2	6.1	3.6	5.6	7.5	6.4	6.2	7.2	2.4	1.3	0.1	4.4	3.6	5.3	4.5	3.8	3.4	0.1	**85.8**
ENER	7.7	4.4	7.2	23.3	3.7	4.8	5.5	5.0	6.5	5.0	3.7	1.2	0.1	3.6	3.7	4.9	3.6	3.1	2.8	0.2	**76.7**
FINA	5.4	4.1	4.0	2.8	17.5	3.5	4.5	4.4	6.0	3.5	3.8	1.2	0.1	5.3	4.4	6.8	6.6	8.3	7.7	0.1	**82.5**
HEAL	8.6	7.8	7.4	4.7	4.6	14.1	8.4	7.0	6.1	5.9	4.4	0.6	0.1	3.5	2.4	4.1	3.5	3.5	3.2	0.1	**85.9**
INDU	8.7	5.9	7.9	4.1	5.4	6.5	12.6	7.1	7.5	5.9	3.7	0.8	0.1	3.8	2.9	4.6	4.2	4.4	3.9	0.1	**87.4**
MATE	8.5	6.7	7.2	3.7	5.4	5.8	7.8	13.2	7.6	6.1	3.5	1.0	0.0	3.7	3.1	4.5	4.1	4.3	3.9	0.1	**86.8**
REST	8.7	6.5	6.6	3.8	5.7	4.7	6.7	6.3	15.2	5.2	4.6	0.7	0.1	3.5	3.2	4.5	4.2	5.1	4.6	0.0	**84.8**
TECH	8.3	6.5	9.2	3.6	4.4	5.5	7.5	6.7	6.9	16.8	3.2	0.8	0.1	3.2	2.9	3.9	3.5	3.7	3.4	0.1	**83.2**
UTIL	6.7	7.0	5.0	3.9	10.0	5.8	6.0	5.7	8.7	4.8	17.2	0.5	0.1	2.4	2.2	3.0	3.1	4.0	3.7	0.0	**82.8**
LATAM	1.2	0.4	3.8	2.6	0.9	0.6	1.3	1.1	0.2	1.0	0.0	38.3	0.2	9.0	5.6	8.9	8.5	8.1	8.0	0.3	**61.7**
AR	0.5	0.4	0.2	0.3	0.8	0.4	0.3	0.1	0.5	0.4	0.2	0.4	84.2	1.5	1.4	1.8	1.7	2.6	2.5	0.0	**15.8**
BR	2.0	1.4	2.0	2.1	2.1	1.5	1.2	1.1	0.9	1.1	0.2	2.5	0.2	18.6	7.8	14.5	13.0	13.9	13.5	0.4	**81.4**
CL	2.2	1.4	2.0	1.8	2.8	1.4	1.4	1.4	1.3	1.3	0.4	2.4	0.2	11.9	16.7	13.1	12.5	12.9	12.3	0.3	**83.3**
CO	2.3	1.5	2.0	1.7	2.2	1.5	1.5	1.4	1.0	1.1	0.2	2.5	0.2	13.4	7.6	16.8	13.6	14.8	14.5	0.3	**83.2**
MX	2.0	1.5	1.7	1.5	2.2	1.3	1.3	1.3	1.0	1.0	0.3	2.6	0.2	13.3	8.0	14.9	16.2	15.0	14.6	0.2	**83.8**
PA	1.9	1.4	1.2	1.0	2.6	1.2	1.1	1.1	1.0	0.9	0.4	2.4	0.3	12.8	7.4	14.8	13.2	18.3	17.0	0.2	**81.7**
PE	1.9	1.5	1.2	0.9	2.6	1.1	1.0	1.0	1.0	0.9	0.4	2.4	0.3	12.5	7.4	14.8	13.0	17.2	18.7	0.2	**81.3**
VE	0.3	0.2	0.4	0.3	0.3	0.3	0.2	0.2	0.0	0.4	0.1	0.4	0.1	2.4	1.8	2.3	1.4	1.7	1.8	85.5	**14.5**
C. to others	**96.6**	**72.1**	**81.4**	**53.0**	**68.0**	**64.3**	**77.1**	**70.4**	**76.7**	**62.1**	**38.9**	**25.3**	**2.4**	**117.7**	**81.1**	**136.2**	**122.4**	**135.2**	**128.9**	**2.7**	

Results are also sensible to the definition of the sample period. To illustrate this point, we estimated total spillover indices for two sub-periods, one corresponding to the Global

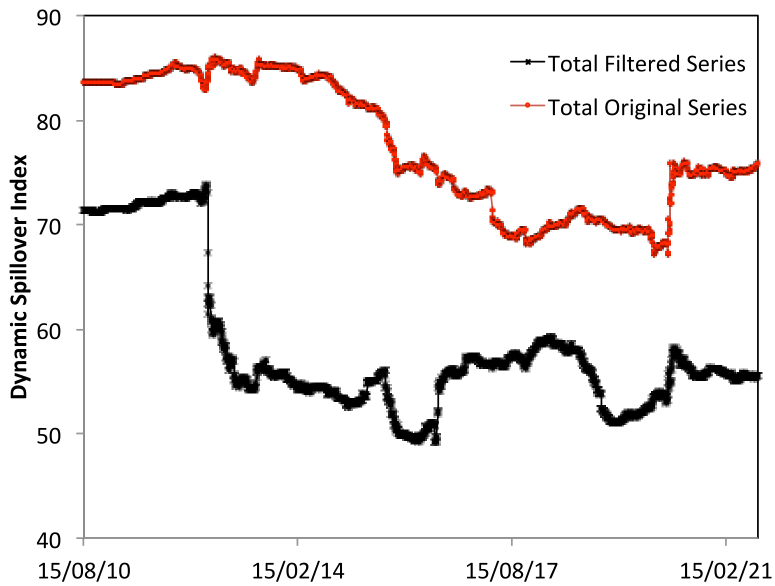
Financial Crisis and other corresponding to the Covid19 Crisis. Table 2 presents a comparison of results for the total sample and the two subsamples when the residual series is used. Note that spillovers within sectors represent a higher share of total spillovers for the full sample than during the two periods of financial and economic distress. This result indicates that spillovers within sectors are more important during normal times than during periods of distress. Similarly, spillovers within countries are greater during normal times. Conversely, spillovers from countries to the corporate sector and from the corporate sector to countries represent a larger share of total spillovers during times of financial and economic distress. This result shows that risk diversification opportunities between emerging market countries' assets and global corporate assets are significantly reduced when time goes bad. This may occur due to the balance rebalancing of global investor portfolios, which move from unsafe assets to safer assets during moments of financial turbulence.

Table 2: Total spillovers for total sample and two subsamples for residual series

	Full Sample	*GFC*	*COVID*
Within Sectors	48.5	46.8	42.4
From Countries to sectors	11.5	13.2	17.6
From Sectors to countries	11.5	18.0	12.5
Within Countries	28.5	22.0	27.5
Total	100.0	100.0	100.0

We go one step further and show that total system dynamic spillovers are considerably higher when the unfiltered (raw data) series is used than when filtered (residual) data is used (see Figure 7). Note that while the total spillover unfiltered series is above the total spillover filtered series for the whole sample period, differences between the two series are specially pronounced during periods of distress. For instance, the difference between these two series of dynamic spillovers increases importantly during the Global Financial Crisis and during the Covid19 crisis. This important result shows that global common factors are likely to be related to financial uncertainty and financial risk issues.

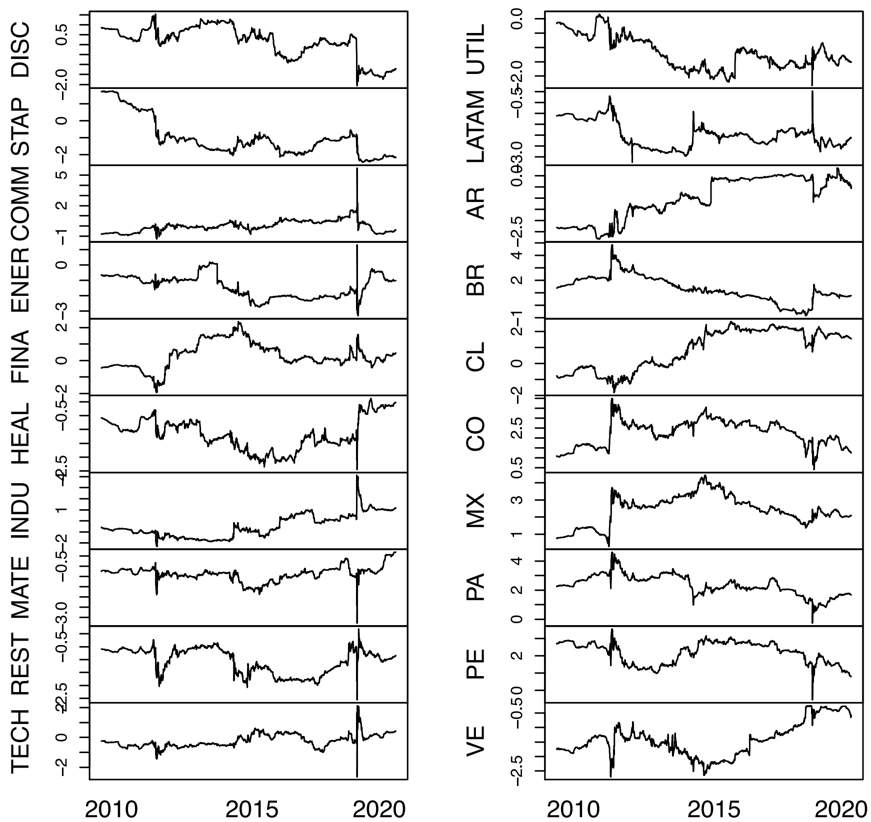
Figure 7: Comparing dynamic spillovers



Note: dynamic spillover index using a window length of 1000 days, which roughly corresponds to four years of transactions. The black line corresponds to the system based upon the filtered CDS series, while the red line corresponds to the original system that ignores common factors.

Figure 8 uses information on the residual series and shows that spillovers vary considerably over time and are especially high during times of financial distress. Similar results have been encountered in past related studies. Interestingly, we can notice that during the Covid-19 crisis, corporate tended to be net-receivers, while sovereign net-givers of volatility.

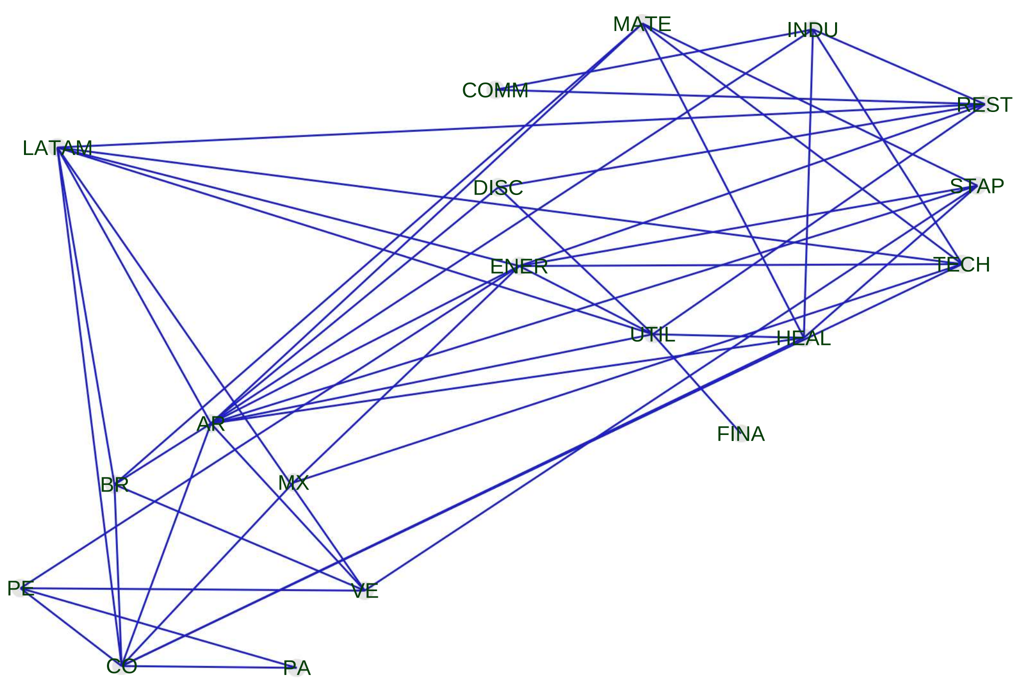
Figure 8: Dynamic spillovers residual series



Note: dynamic net spillover index by industry sector and sovereign market, using a window length of 1000 days. A positive value means that the market is a net volatility transmitter in a given day.

Figure 9 shows networks estimated following the methodology by Brownlees and Barigozzi (2019). The followed methodology allows estimating two types of adjacency matrices, to construct the market network. The first one is a "contemporaneous network" and the second one is a "predictive network". The former estimates partial correlation between any pair of series in the dataset, while the second uses the VAR representation of the system to figure out the predictive power of any pair of series on each other, after factoring out the intermediate linkages in the network. In this sense, network structure presented in Figure 9, does not only consider the five global factors that we estimated in the first step of our procedure, but also, they consider any intermediate correlation that still remains in the system after the first factorization, before plotting the representation. In this way, we can ensure the statistical and economical significance of the remaining interconnectedness. As can be observed in the figure, Network analysis based on the long run correlations of the system, shows that included markets are well integrated, in particular the LATAM Corporate sector seems very connected to both sovereign debt markets in Latin America, and global corporate debt market, in general. We can notice as well that Argentinian CDS market seems to be associated with global corporates, which emphasizes the portfolio view of global debt markets. All in all global portfolio rebalancing seems to be at the core of spillovers in global and emerging sovereign debt markets.

Figure 9: Network analysis



Note: Network graph for the contemporaneous estimation of a sparse VAR system of 12 corporate CDS and 6 Latin American Sovereign CDS.

Further information can be obtained from analyzing the adjacency matrix of the network presented in figure 9 for the original series and for the filtered series, which consider common global macro-factors. These two matrices are shown in Table 3, Panel A and B, for the filtered and raw data, respectively. Once again, we observe that using the unfiltered series, overestimate the number of significant connections within the global debt markets.

This can be quantified by counting the number of connections described by Table 3 within sectors, within countries, and between countries and sectors (the adjacency matrix of the contemporaneous network is symmetrical because it describes an undirected graph). In this case, we have that the density of the network within sectors increases from 33% to 86%, from 36% to 79% within countries, and from 19% to 67% between countries and corporates, comparing the network adjusted by common macro-factors with the network that ignores them. The differences are notorious and corroborate the analysis based on the forecast error variance of the unrestricted VAR system.

Table 3: Adjacency Matrix for the contemporaneous network

Panel A

	DISC	*STAP*	*COMM*	*ENER*	*FINA*	*HEAL*	*INDU*	*MATE*	*REST*	*TECH*	*UTIL*	*LATAM*	*AR*	*BR*	*CL*	*CO*	*MX*	*PA*	*PE*	*VE*
DISC	0	0	0	0	0	0	0	0	1	0	1	0	1	0	0	0	0	0	0	0
STAP	0	0	0	1	0	1	0	1	0	0	0	0	1	0	0	0	0	0	0	1
COMM	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0
ENER	0	1	0	0	0	0	0	0	1	1	1	1	1	0	0	0	1	0	1	0
FINA	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
HEAL	0	1	0	0	0	0	1	1	0	0	1	0	1	0	0	1	0	0	0	0
INDU	0	0	1	0	0	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0
MATE	0	1	0	0	0	1	0	0	0	1	0	0	1	1	0	0	0	0	0	0
REST	1	0	1	1	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0	0
TECH	0	0	0	1	0	0	1	1	0	0	0	1	0	0	0	1	1	0	0	0
UTIL	1	0	0	1	1	1	0	0	1	0	0	1	1	0	0	0	0	0	0	0
LATAM	0	0	0	1	0	0	0	0	1	1	1	0	1	1	0	1	0	0	0	1
AR	1	1	0	1	0	1	1	1	0	0	1	1	0	1	0	1	0	0	0	1
BR	0	0	0	0	0	0	0	1	0	0	0	1	1	0	0	1	0	0	0	1
CL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CO	0	0	0	0	0	1	0	0	0	1	0	1	1	1	0	0	1	1	1	0
MX	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0
PA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0
PE	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	1
VE	0	1	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	1	0

Panel B

	DISC	*STAP*	*COMM*	*ENER*	*FINA*	*HEAL*	*INDU*	*MATE*	*REST*	*TECH*	*UTIL*	*LATAM*	*AR*	*BR*	*CL*	*CO*	*MX*	*PA*	*PE*	*VE*
DISC	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
STAP	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
COMM	1	1	0	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1
ENER	1	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1
FINA	1	1	1	0	0	1	1	1	1	1	1	0	0	1	1	0	1	1	1	0
HEAL	1	1	1	1	1	0	1	1	1	1	1	0	0	1	0	1	0	1	1	0
INDU	1	1	1	0	1	1	0	1	1	1	0	0	1	0	1	1	0	0	0	0
MATE	1	1	1	1	1	1	1	0	1	1	1	0	0	0	0	1	1	0	1	0
REST	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	1	1	1	1	1
TECH	1	1	1	1	1	1	1	1	1	0	1	0	0	0	1	1	1	0	1	1
UTIL	1	1	0	1	1	1	0	1	1	1	0	1	0	1	1	1	0	1	1	1
LATAM	1	1	1	1	0	0	0	0	1	0	1	0	0	1	0	0	1	0	0	1
AR	0	1	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0
BR	1	1	1	1	1	1	0	0	1	0	1	1	0	0	1	1	1	1	1	1
CL	1	1	1	1	1	0	1	0	0	1	1	0	1	1	0	1	1	1	1	1
CO	1	1	1	1	0	1	1	1	1	1	1	0	0	1	1	0	1	1	1	1
MX	1	1	1	0	1	0	0	1	1	1	0	1	0	1	1	1	0	1	1	1
PA	1	1	1	1	1	1	0	0	1	0	1	0	0	1	1	1	1	0	1	1
PE	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	0	0
VE	1	1	1	1	0	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0

Finally, we also estimate Granger-causality networks. No predictive causality is detected between any pair of time series. This is a very interesting result, indicating that while high spillovers are found between the included series, none of these high spillovers imply a predictive causality effect.

6. Conclusions

We study the relationship between the corporate sector and Latin American country CDS markets, focusing on volatility spillovers. We use daily data on CDS from October 14 2006 to August 23 2021. Our database includes 608 corporate CDS and 48 sovereign CDS. We focus our main analysis on six Latin American sovereign debt contracts, and 109 corporates. We further summarize the corporate information in 12 corporate debt indices according to the 11 Standard and Poor's industry categories, and one additional index for large corporations operating in Latin America.

Spillovers are computed both for the raw data and for filtered series which factor out the effect of global common factors on the various CDS used in this study. Various interesting results are found. First, most spillovers correspond to within group spillovers, i.e., within countries and within global corporations. However, important spillovers are also registered from emerging market sovereigns to corporations and vice versa. Interesting differences are encountered between filtered and unfiltered data. Specifically, spillovers from countries to corporations are overestimated and spillovers from corporations to sovereigns are underestimated when unfiltered data is used. This result calls for a revision of results obtained from studies that do not consider the role of global common factors on system spillovers.

Like in most related studies, spillovers show considerable time-variation, being larger during times of financial or economic distress. When looking at total system spillovers over time, those corresponding to unfiltered series are always larger than those corresponding to filtered series. This points out once more the overestimation of system spillovers that is produced when the effect of global common factors is not excluded from the data. The difference between the two time-series is largest in times of distress, indicating that global factors play a major role in times of crises.

All in all, we emphasize the role of a portfolio view of corporate and sovereign debts, as a likely explanation for the significant spillovers that we estimate even after controlling for global macro macro-factors in the market, and both, from a traditional perspective using the forecast error variance decomposition of a traditional VAR system, and a more recent perspective using sparse VAR systems for estimating the network.

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Appendix: Corporate CDS used for the calculation of indices.

	Name	Sector
1	AutoZone Inc	Consumer Discretionary
2	Avis Budget Group Inc	Consumer Discretionary
3	Ford Motor Credit Co LLC	Consumer Discretionary
4	Gap Inc/The	Consumer Discretionary
5	Home Depot Inc/The	Consumer Discretionary
6	Kohl's Corp	Consumer Discretionary
7	Lowe's Cos Inc	Consumer Discretionary
8	Macy's Inc	Consumer Discretionary
9	Marriott International Inc/MD	Consumer Discretionary
10	McDonald's Corp	Consumer Discretionary
11	Newell Brands Inc	Consumer Discretionary
12	Nordstrom Inc	Consumer Discretionary
13	Royal Caribbean Cruises Ltd	Consumer Discretionary
14	Stellantis NV (EUR)	Consumer Discretionary
15	Whirlpool Corp	Consumer Discretionary
16	Campbell Soup Co	Consumer Staples
17	General Mills Inc	Consumer Staples
18	Kraft Heinz Foods Co	Consumer Staples
19	Kroger Co/The	Consumer Staples
20	PepsiCo Inc	Consumer Staples
21	Procter & Gamble Co/The	Consumer Staples
22	Target Corp	Consumer Staples
23	Tyson Foods Inc	Consumer Staples
24	Walmart Inc	Consumer Staples
25	AT&T Inc	Communications
26	Comcast Corp	Communications
27	Cox Communications Inc	Communications
28	Expedia Group Inc	Communications
29	Omnicom Group Inc	Communications
30	TWDC Enterprises 18 Corp	Communications
31	Telefonos de Mexico SAB de CV	Communications
32	Verizon Communications Inc	Communications
33	ViacomCBS Inc	Communications
34	Canadian Natural Resources Ltd	Energy
35	Enbridge Inc	Energy
36	Energy Transfer Operating LP	Energy
37	Halliburton Co	Energy
38	Hess Corp	Energy
39	Kinder Morgan Energy Partners LP	Energy
40	Petroleos Mexicanos	Energy
41	TransCanada PipeLines Ltd	Energy
42	Valero Energy Corp	Energy
43	Allstate Corp/The	Financials
44	American Express Co	Financials
45	American International Group Inc	Financials
46	Assured Guaranty Municipal Corp	Financials
47	Bank of America Corp	Financials
48	Capital One Financial Corp	Financials
49	Chubb Ltd	Financials
50	Citigroup Inc	Financials
51	Goldman Sachs Group Inc/The	Financials
52	Hartford Financial Services Group In	Financials
53	JPMorgan Chase & Co	Financials
54	Lincoln National Corp	Financials
55	Loews Corp	Financials
56	Marsh & McLennan Cos Inc	Financials
57	MetLife Inc	Financials
58	Morgan Stanley	Financials
59	Prudential Financial Inc	Financials
60	Wells Fargo & Co	Financials
61	Amgen Inc	Health Care
62	Baxter International Inc	Health Care
63	Boston Scientific Corp	Health Care
64	Bristol-Myers Squibb Co	Health Care
65	CVS Health Corp	Health Care
66	Cardinal Health Inc	Health Care
67	Danaher Corp	Health Care
68	HCA Inc	Health Care
69	Johnson & Johnson	Health Care
70	McKesson Corp	Health Care
71	Quest Diagnostics Inc	Health Care
72	UnitedHealth Group Inc	Health Care
73	Universal Health Services Inc	Health Care
74	Block Financial LLC	Industrials
75	Boeing Co/The	Industrials
76	CSX Corp	Industrials
77	Caterpillar Inc	Industrials
78	Deere & Co	Industrials
79	General Electric Co	Industrials
80	Honeywell International Inc	Industrials
81	Johnson Controls International plc	Industrials
82	Lockheed Martin Corp	Industrials
83	Norfolk Southern Corp	Industrials
84	Ryder System Inc	Industrials
85	Southwest Airlines Co	Industrials
86	Union Pacific Corp	Industrials
87	United Parcel Service Inc	Industrials
88	Ardagh Packaging Finance PLC	Materials
89	EI du Pont de Nemours and Co	Materials
90	Eastman Chemical Co	Materials
91	Packaging Corp of America	Materials
92	Sherwin-Williams Co/The	Materials
93	Vale SA	Materials
94	ERP Operating LP	Real Estate
95	Simon Property Group LP	Real Estate
96	Weyerhaeuser Co	Real Estate
97	Arrow Electronics Inc	Technology
98	Avnet Inc	Technology
99	DXC Technology Co	Technology
100	HP Inc	Technology
101	International Business Machines Corp	Technology
102	Motorola Solutions Inc	Technology
103	Pitney Bowes Inc	Technology
104	Xerox Corp	Technology
105	American Electric Power Co Inc	Utilities
106	Dominion Energy Inc	Utilities
107	National Rural Utilities Cooperative Finance	Utilities
108	NextEra Energy Capital Holdings Inc	Utilities
109	Southern Co/The	Utilities

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