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Frontier markets sovereign risk: New evidence from spatial econometric models

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ABSTRACT

This paper considers spatial linkages of bilateral trade, financial correlation, and bilateral distance to study the macroeconomic determinants of sovereign risk for frontier markets. It applies (Shi and Lee, 2017) dynamic spatial Durbin model with interactive fixed effects. Analysis confirms the existence of spillover effects stemming from the explanatory variables' movement towards the Credit default swaps (CDSs) premium of itself and neighboring countries. Bilateral distance and trade are the most significant spatial linkages. All macroeconomics except reserves impact CDS spreads directly and through feedback effects. Spatial dependence strengthens during recessions. Findings suggest policymakers should account for regional contagion channels that transmit sovereign risk.

1. Introduction

Credit default swaps (CDSs) of sovereign debt has been the subject of tremendous attention and criticism since the beginning of the credit crunch in mid-2007. Sovereign CDSs are credit derivative contracts that are designed to transfer the default risk of fixed-income government securities between banks, hedge funds, and asset managers and trades for a variety of reasons[1] or in simpler terms; as Gündüz et al. (2007) defines credit default swap is a contract that provides insurance against the risk of default of a specific commercial or sovereign entity. The level and behavior of CDS spread, also known as premiums, have been considered a major indicator of the economic health of a given country. They shed light on the default risk by signaling how much investors are willing to pay to insure themselves against the sovereign risk (Gündüz and Kaya, 2014).

European financial markets witnessed some bailouts and recovery programs between 2008 and 2011. The global financial crisis that occurred in late 2007 sparked a chain reaction in the United States (US) and its primary European Partners. The European sovereign CDS spreads rose significantly following the Lehman Brothers' collapse in September 2008 (Kışla and Önder, 2018). Sovereign CDS spreads in the frontier,[2] and emerging markets exhibited a similar pattern. Emerging markets' CDS spreads were

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[1] Among the reasons (Scheicher et al., 2010), for instance, mention (i) hedging against country risk as an insurance-type offsetting instrument, (ii) relative-value trading (having a short position in one country and a long one in another) and (iii) basis arbitrage trading (purchase/sale of government bonds vs. sale/purchase of sovereign CDSs).

[2] Frontier markets classification is based on Morgan Stanley Capital International (MSCI) 2019 index, and MSCI examines each country's economic development, size, liquidity, and market accessibility to be classified in a given investment universe. Frontier markets are countries that are considered less mature because of demographics, development, politics, and liquidity than emerging markets. As of 2019, MSCI listed 21 countries, and due to data shortage, especially on CDS, the paper only considers 14 of them that have complete data (MSCI, 2019).

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under the level of 500 basis points (bps) between 2004 and 2008. In particular, frontier markets' CDS spreads were under the level of 700 basis points (bps) between 2007 and 2010. However, after 2010, they all rose above those levels. For these markets, the literature suggests that there could be other factors that determine the CDS spreads besides their own-country fundamentals (see, e.g., Aizenman et al. (2013) and Beirne and Fratzscher (2013)).

Prior research shows international trade and financial linkages transmit sovereign risk and crisis across economies (Glick and Rose, 2002; Caramazza et al., 2004). Recent studies demonstrate time-varying financial interdependencies between emerging and developed markets (Aloui et al., 2011), negative spillovers from sovereign rating downgrades (Böninghausen and Zabel, 2015), the importance of trade linkages for sovereign CDS spreads (Kışla and Önder, 2018), two-way relationship between non-performing loans and sovereign ratings (Boumparis et al., 2019), and both one-way and feedback causality running from sovereign credit ratings to economic risk (Athari et al., 2021). However, frontier markets remain understudied regarding spatial interactions and CDS spreads. This paper extends the analysis of macroeconomic determinants and spatial linkages to the frontier market context using advanced spatiotemporal econometric models. It examines empirical evidence on how macro fundamentals and interconnectedness across frontier economies shape CDS spreads, building on prior emerging market research.

Kışla and Önder (2018) examines spatial linkages and macroeconomic determinants of sovereign risk for emerging markets, finding the trade channel is most important for sovereign CDS spreads. My study focuses on frontier markets, mainly differing in econometric methodology by applying the spatial Durbin fixed-effects model with IFE by Shi and Lee (2017) suited for large N and T data. I also employ a dynamic model variant without IFE. These methodologies test for spatial spillover effects from movements in explanatory variables to CDS spreads. My paper contributes by (1) applying (Shi and Lee, 2017) 's SDM model to examine CDS determinants in frontier markets, introducing this dynamic spatial fixed-effect model not previously used, (2) investigating frontier markets per Morgan Stanley Capital International (MSCI) 's 2019 classification, unexploited in literature, (3) determining geographical, trade and financial linkage impacts on CDS spreads as integration measures, (4) analyzing macroeconomic impacts across economic periods, and (5) measuring direct, indirect and total effects of determinants on CDS spreads through spatial spillover hypothesis testing in short and long runs.

Section 2 presents the spatial econometrics methodology, while Section 3 presents the data and the selected variables. Section 4 contains the empirical analysis, and Section 5 concludes.

2. Econometric methodology

2.1. Dynamic spatial Durbin model with interactive fixed-effects

2.1.1. The Shi and Lee model

With N individual units and T time periods, the general form of the dynamic spatial panel data model with interactive fixed-effects (from now on, IFE) (Shi and Lee, 2017) take the form,

$$\begin{aligned} Y_t = \tau Y_{t-1} + \rho W Y_t + \eta W Y_{t-1} + X_t \beta + \Gamma f_t + U_t, \\ and\ U_t = \alpha \tilde{W} U_t + \epsilon_t \end{aligned} \tag{1}$$

where Y_t is an N dimensional column vector of observed dependent variables and X_t is an $N \times (K-2)$ matrix of exogenous regressors with associated response parameters β, so that the total number of variables in Y_{t-1}, WY_{t-1} and X_t is K. The parameter τ, i.e., the response parameter of the lagged dependent variable Y_{t-1}, is also known as the autoregressive time dependence parameter and the term τY_{t-1} captures the pure dynamic effect. ρ is called the spatial autoregressive coefficient and the term $\rho W Y_t$ describes the contemporaneous spatial interactions. η might be labeled as the lagged spatial autoregressive coefficient and thus, $\eta W Y_{t-1}$ is a spatial time lag of interactions, which captures diffusion. Consequently, the variables WY_t and WY_{t-1} denote contemporaneous and lagged endogenous interaction effects among the dependent variable. The idiosyncratic error U_t with elements of ϵ_t being i.i.d. (0, σ^2) also possesses a spatial structure $\tilde{W}$, which may or may not be the same as W. If W is row-normalized, ρ and η are defined on the interval ($1/r_{min}$,1), where r_{min} equals the most negative purely real characteristic root of W (LeSage, 2008). The parameter τ is assumed to be restricted to the interval (−1,1) (Debarsy et al., 2012). The model accommodates two types of cross-sectional dependencies: local dependence and global (strong) dependence. Individual units are impacted by potentially time-varying unknown common factors f_t, which captures global (strong) dependence. The effects of the factors can be heterogeneous on the cross-sectional units, as described by the factor loading parameter matrix Γ.

The number of unobserved factors is assumed to be a fixed constant r much smaller than N and T. The matrix of $N \times r$ factor loading Γ and the $T \times r$ factors $F_T = (f_1, f_2, \dots, f_T)'$ are not observed and are treated as parameters. The fixed-effects approach is flexible and allows an unknown correlation between the common factor components and the regressors. The $N \times N$ spatial weights matrices W and $\tilde{W}$ in Eq. (1) are used to model spatial dependencies. The specification[3] in Eq. (1) is general and encompasses many models of empirical interest.

[3] This represents a dynamic spatial simultaneous autoregressive (SAC/SARAR) with IFE, and the addition of the spatially lagged independent variables into the equation without the autoregressive components of the error term leads to a dynamic spatial Durbin model (SDM) with IFE. In general, additive fixed individual and time effects are a special case of the factor structure.

This paper employs three existing methods[4] proposed in the literature of factor models to select the number of unobserved factors. The underlying theory regarding the composition of N and T varies across the methods. With a relatively small N compared to T, this paper considers all applicable existing methods for comparison and theory validation, in line with the Shi and Lee (2017) model and Belotti et al. (2017) 's `xsmle` stata command.

The rationale behind the strategy in this paper is that for a correctly specified model, the residuals should be cross-sectionally independent. Therefore, applying the factor selection tests to identify the number of factors that produce independent residuals is a convincing approach. Furthermore, many empirical studies use point estimates of one or more spatial regression models to test if spatial spillover effects exist. However, LeSage (2008) has pointed out that this may lead to erroneous conclusions and that a partial derivative interpretation of the impact from changes to the variables of different model specifications represents a more valid basis for testing this hypothesis.

To estimate the parameters of the model in Eq. (1), Shi and Lee (2017) consider quasi maximum likelihood estimation (QML) and provide conditions for identification and show that the QML estimation method works well. The estimator is shown to be consistent and asymptotically normal. Asymptotic biases of order $\frac{1}{\sqrt{nT}}$ exist due to incidental parameters, and a bias correction method is proposed, provided that the model is stable.

3. Data

Prior studies by Caramazza et al. (2004), Glick and Rose (1999) and Fernández-Avilés et al. (2012) provide evidence for using bilateral trade to model spatial spillover, calculated as in (Fernández-Avilés et al., 2012):

$$F_{ij,t}^{BT} = 2 - \left(\frac{exp_{ij,t}}{GDP_{i,t}} + \frac{exp_{ji,t}}{GDP_{j,t}}\right), \quad (2)$$

where F_{ij} measures distance between countries i and j.

Financial variables are incorporated following Caramazza et al. (2004) using return correlations. Geographic distance is a spatial weight following Fazio (2007), Orlov (2009) and Flavin et al. (2002). Defining the spatial weight matrix warrants detailed discussion[5]

3.1. Explanatory variables

In this study, 5-year sovereign CDS spreads measured in basis points (bps) is chosen as a proxy for the sovereign risk (Kışla and Önder, 2018; Oliveira et al., 2012; Augustin and Tédongap, 2016). Furthermore, the study utilizes five explanatory macroeconomic variables that prior research has linked to sovereign risk, as measured by CDS spreads. Current account balance (CAB/GDP) indicates a country's debt position, with uncertain impacts per (Afonso et al., 2011). GDP growth (GDPGR) reflects economic health and solvency, expected to reduce spreads per (Baek et al., 2005). External debt (EXDEBT/GDP) relates to repayment capacity, found to increase spreads by Ismailescu and Kazemi (2010). Inflation (INFL) signals instability that heightens risk according to Aizenman et al. (2013). Reserves (RES/GDP) proxy liquidity and ability to repay debt, associated with lower spreads per (Remolona et al., 2008). Variables are derived from the World Bank, Thomson Reuters, and Datastream. The panel dataset covers 14 frontier markets from 2000–2018, including pre-crisis, crisis, and post-crisis periods. Macroeconomic factors are selected based on empirical evidence of their relationships to sovereign credit risk in prior research.

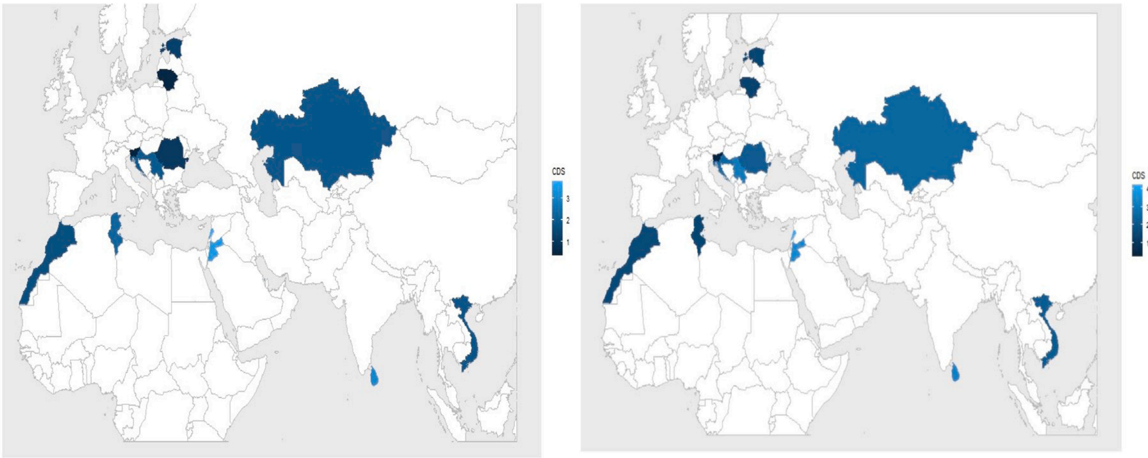
4. Empirical results

4.1. Visual assessment

This section performs both a preliminary data analysis based on visual assessments and formal statistical tests. For the visual assessment, a choropleth map displays the correlation of the CDS premium in geographical space. Fig. 1(a) is the CDS premium at one point in time (January 2017) and shows a cluster of CDS premium by their semi-darker color. Fig. 1(b) is the average CDS

[4] The first to consider is the IC criteria by Bai and Ng (2002) which resembles information criteria frequently used in time series analysis with the important difference that the penalty here depends on both N and T. The related theory is based on large N and T. Shi and Lee (2017) also use this criterion for factor selection. The second method is the joint use (simultaneously) of the Pesaran (2020) CD test and Bailey et al. (2019) 's exponent of cross-sectional dependence for residuals to test the number of factors that produce residuals that are cross-sectionally independent. For a correctly specified model, the residuals are expected to be cross-sectionally independent such that implementing the tests simultaneously to select the correct number of factors that produce residuals that are cross-sectionally independent is straightforward. The Pesaran (2020) CD test is based on the average pair-wise correlation coefficients of the OLS residuals from the individual regressions in the panel and can be used to test for cross-sectional dependence. Further, Bailey et al. (2019) propose an estimator of the exponent of cross-sectional dependence denoted by α, based on the number of non-zero pair-wise cross-correlations of these errors. An α exponent around 0.5 indicates cross-sectionally independent residuals. Furthermore, this paper, at last, considers (Onatski, 2010) which determines the number of factors from the empirical distribution of eigenvalues by exploiting the covariance structure of idiosyncratic terms.

[5] Since this study focuses on integration measures connecting CDS markets, specifying the spatial weight matrix **W** is crucial. **W** is obtained by row standardizing a contiguity matrix **C** based on distances F_{ij} as in Eq. (2), allowing asymmetric dependencies.



(a) *CDS premium for Jan 2017* (b) *mean CDS premium (2000 - 2018)*

Fig. 1. CDS premium between 2000 and 2018.

Table 1
Results for the dynamic SDM with IFE estimation (1-factor).

Variables	Trade		Fin.		Dist. Cap.		Dist. Haus.
	SDM	SDM - IFE	SDM	SDM - IFE	SDM	SDM - IFE	SDM - IFE
$\tau(y_{t-1})$	0.842***	0.946***	0.840***	0.946***	0.839***	0.943***	0.943***
$\eta(W y_{t-1})$	−0.342***	−0.195***	−0.318***	−0.258***	−0.349	−0.316***	−0.321***
$\rho(W y_t)$	0.451***	0.213***	0.419***	0.253***	0.457***	0.344***	0.348***
AIC	32 518	32.922	32 560	32.9183	32 526	32.923	32.918

Dist. Cap and Dist. Haus. stands for the distance between capital cities and the distance between the centroid of the polygon (Hausdorff distance), respectively.
***, **, *; statistical significance at the level of 1%, 5%, & 10%, respectively.

premium for the whole sample period and shows a cluster of high CDS premiums by their darker color. In general, the shades in the map distribute non-randomly, and some of the clusters behave similarly. Regarding statistical tests, the paper employs the CD test (Pesaran, 2004) on different panel models to check for local and global cross-sectional dependence.[6]

4.2. Dynamic spatial durbin model with interactive fixed-effects

While the estimation is not straightforward given the very small N compared to T, the joint use of the Pesaran (2020) and Bailey et al. (2019) models provides a convincing result regarding factor selection. For all spatial weights, their joint use suggests that one factor produces residuals that are cross-sectionally independent, with an α-exponent around 0.5, indicating no evidence of cross-sectional dependence (The results are available upon request).

Table 1 shows the results of the dynamic SDM with IFE a.k.a (Shi and Lee, 2017) model in comparison with the model without IFE.[7]

The coefficients of the lagged dependent variable Y_{t-1} are positive and significant, indicating relatively stronger time dependence (Table 1, row 1). In contrast, the coefficients of the spatially and temporally lagged dependent variable WY_{t-1} are negative and

[6] The results showed significant p-values, indicating the existence of global cross-sectional dependence. I used the local CD test on the raw data and residuals for local cross-sectional dependence. The local CD test found a statistically significant average correlation between neighboring pairs. The test on residuals showed spatial correlation remained after controlling for cross-sectional common factors. The tests demonstrated global and local spatial dependence in the data and models.

[7] Additional detailed results, including dynamic SDM without IFE, dynamic SAR, SEM and SAC/SARAR for trade, financial correlation and distance matrices, along with outcomes using one, two, three, and four factors, are available upon request. Furthermore, model diagnostic test results like multicollinearity, heteroskedasticity, stationarity, serial correlation, normality, Hausman's specification test, the Breusch and Pagan test, and decision rule specifics can also be provided if needed. Also, the estimation strategy followed a General-to-Specific approach. Note that for the dynamic SDM & SAC with IFE, the dynamic SAR & SDM (without IFE), and also for estimation and inferences of static spatial fixed-effects models, I used `xsmle` stata package by Belotti et al. (2017) and instead, for dynamic SEM and SAC/SARAR, I used Matlab.

Table 2
Spatial auto-correlation coefficient (ρ): s comparison.

SDM	Trade	Fin.	Dist.
ρ: Dynamic with IFE (1-factor)	0.213	0.253	0.344
ρ: Dynamic	0.451	0.419	0.457
ρ: Static	0.566	0.542	0.579

significant. The coefficient of WY_t, the contemporaneous interaction effect, is positive for all spatial weights, consistent with static estimation results (Results are available upon request). Bilateral distance best captures positive spatial dependence, indicating distance matters most. Financial correlation is least able to capture spatial linkage.

Unlike prior emerging market research, such as Kışla and Önder (2018), this study finds bilateral distance is more influential than trade linkages for transmitting sovereign risk between frontier economies. This is puzzling, given the lack of proximity for some market pairs. However, regional clusters create localized spillover zones, explaining the significance of physical proximity. Though frontier countries are remote overall, distance facilitates contagion between neighboring markets within geographic blocs like North Africa and Central/Southeast Europe. Further analysis of intra-regional dynamics using alternative distance metrics tailored to clusters could shed light on this unexpected result. While more research is needed, preliminary evidence suggests geographic proximity enables localized sovereign debt contagion between frontier markets despite their widespread nature. Careful examination of regional transmission channels could help reconcile why physical distance matters beyond economic ties.

In summary, regional clusters suggest physical proximity acts as information friction, capturing localized interactions, and driving sovereign risk spillovers between frontier economies within geographic spheres of influence. Though counterintuitive initially, a granular analysis of regional contagion effects could unlock why bilateral distance is the crucial spatial linkage transmitting frontier market sovereign risk (see Table 2).

4.3. Marginal analysis

As explained in the previous section, in all scenarios (with small exceptions[8]) the direct effects, and the *beta*'s coefficient sign of the dynamic with IFE (both short-term and long-term), the dynamic, and the static long-term effects are similar.[9] In accordance with the recommendation of Herrera et al. (2019), the financial correlation was selected as the spatial weight to illustrate the marginal analysis details since it yielded the minimum AIC value. The sign and magnitude of the results for the other weights were also similar (refer to Appendix). In general, the macroeconomic variables' coefficient estimates and their direct effects are consistent with the literature and strongly significant, except for international reserves.

The sign for CAB/GDP is negative, which means that a positive change in the CAB/GDP decreases the CDS spread. Unlike the uncertain effect found in some prior studies (Afonso and Gomes, 2007), this paper finds a negative impact of CAB/GDP on frontier market CDS spreads. Current account deficits may be riskier in more structurally constrained and externally dependent frontier economies compared to emerging markets. A higher current account deficit could signal an economy's tendency to over-consume, undermining long-term sustainability. Alternatively, it could reflect the rapid accumulation of fixed investment, leading to higher growth and improved sustainability over the medium term.

A unit increase in the EXDEBT/GDP increases the CDS spread as stated in Hilscher and Nosbusch (2010) since a country's ability to pay its external debt affects its sovereign risk. It means that rising external debt can lead to higher sovereign risk. While the positive effect on spreads aligns with previous research, the magnitude is larger here for frontier markets. The greater sensitivity could be explained by the lower debt tolerance and higher repayment risks faced by frontier vs. emerging economies.

Afonso et al. (2011) suggests the higher real growth indicated by GDP strengthens the government's ability to pay its outstanding obligations. Although the results of the dynamic model with IFE suggest a positive effect, based on the model without IFE, I have also encountered a similar result (−ve) that shows a decrease in the CDS spread. The negative impact on spreads is consistent with earlier studies, but again larger in magnitude. Given their structural constraints, the slower GDP growth significantly raises default risk for more volatile frontier economies.

Aizenman et al. (2013) and Ghosh et al. (2013) argue that rising inflation rates can lead to instability of the economy and higher sovereign risk. Accordingly, I have found a similar result: an increase in the inflation rate variable increases the CDS premium. However, the magnitude of the inflation effect is larger here for frontier markets compared to prior emerging market studies. On the inflation impact, the author could note frontier markets generally have weaker institutions and less monetary policy credibility than emerging markets. This results in higher and more volatile inflation, amplifying its effect on sovereign risk premiums.

[8] The sign of the dynamic long-term effects and the dynamic with IFE for β, and the marginal effects of trade and distance weights for RES/GDP and GDPGR, are both positive.

[9] The short-term and long-term coefficient signs for direct effects, indirect effects, and total effects are all similar (The results are available upon request). Given the number of spatial weights and the variables considered, I will focus on the economic interpretations of the macroeconomic variables in the following paragraphs.

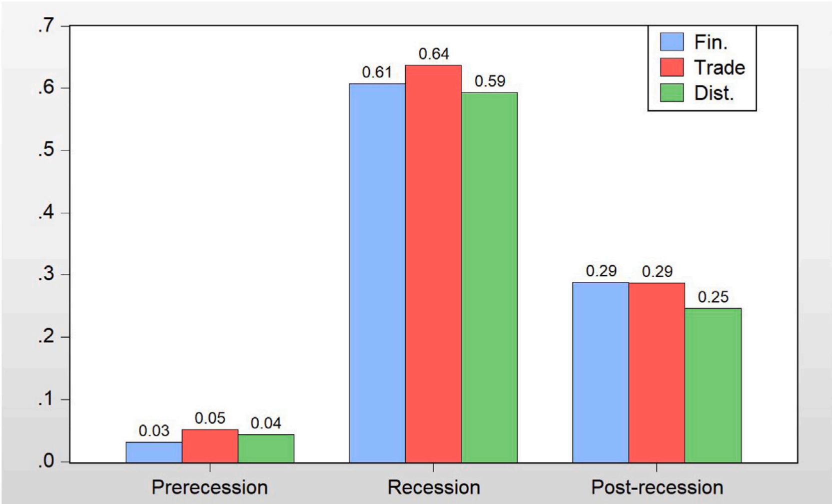


Fig. 2. Comparison of the ρ estimates for different economic periods.

The sign for the coefficients of the reserves (RES/GDP) is negative. Reserve shows the ability of a country to repay its foreign debt and is used as a good proxy for liquidity. Thus, following (see, e.g., Remolona et al., 2008; Baek et al., 2005) higher reserve levels are related to lower sovereign risk. While many studies associate reserves with reduced sovereign risk, this paper finds reserves have an insignificant effect on frontier market CDS spreads. Frontier markets hold lower average reserves and have less flexible exchange rates. This reduces the buffering capacity of reserves against external shocks compared to emerging markets.

Data limitations for frontier markets may introduce additional uncertainties when comparing results to emerging markets. However, the findings still provide valuable insights into frontier economy characteristics.

4.4. Sensitivity analysis

This section uses NBER recession classifications to examine macroeconomic determinants' impact on CDS premiums across economic periods. The sample covers pre-recession, recession, and post-recession periods[10] (see Fig. 2).

During pre-recession, macroeconomic changes decreased CDS premiums except for reserves. The opposite held in recession and post-recession, increasing premiums except for GDP growth and CAB/GDP, respectively. Magnitudes also differed, e.g., with financial linkages, a percentage of CAB/GDP change decreased spreads (0.068 bps) pre-recession but increased (12.30 bps) substantially during the recession (The results are available upon request). Overall, spatial linkage across CDS markets was greater during the recession than during pre- and post-periods, warranting further study. The results indicate spatial dependence strengthens during recessions for frontier economies, unlike evidence for emerging markets where spillovers increase after crises. Mostly, frontier markets lacked the financial safety nets and regional financing arrangements that emerging economies established after prior crises. This left them more vulnerable to contagion during the recession.

5. Summary and conclusions

This research paper utilizes spatial econometric models to assess the macroeconomic factors influencing frontier markets' sovereign risk. The study considers spatial connections via bilateral trade, financial correlations, and geographic proximity. The outcomes reveal that macroeconomic variables such as external debt, current account balance, GDP growth, inflation, and reserves significantly impact CDS spreads directly and indirectly through spatial spillover effects. Positive spatial dependence is evident among CDS markets, with bilateral distance and trade linkages being the most significant factors. The analysis of marginal effects confirms that neighboring countries exert considerable feedback effects. Furthermore, spatial dependence becomes stronger during recessions. The findings suggest that policymakers should consider the actions of neighboring countries when regulating macroeconomics. Investors should also take spillover risks into account when making investment decisions. Explicitly modeling spatial relationships provides valuable insights into sovereign risk interdependencies and transmission mechanisms. This can inform policy and investment strategies involved in global portfolios.

[10] Pre-recession: Jan 2000–Nov 2007; recession: Dec 2007–Jun 2009; post-recession: Jul 2009–Dec 2018.

Table 3
Marginal results for dynamic SDM with IFE (one factor) and without IFE.

Variables	Trade (Shi & Lee)						Trade (Dyn.)					
	Short-term (ST)			Long-term (LT)			Short-term (ST)			Long-term (LT)		
	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.
CAB/GDP	−0.382***	0.463	0.080	−6.664	15.113	8.449	−0.470***	0.066**	−0.403	−2.590	−7.371	−9.960
EXTDEBT/GDP	0.039***	0.034	0.074	0.584	−1.267	−0.682	0.066*	0.434*	0.501**	0.263*	−1.684*	−1.947**
GDPGR	0.196	0.342	0.539	3.696	6.661	10.357	−0.982***	1.621**	0.638	−9.770**	−2.82	−12.590
INFL	0.111	0.263	0.375	1.400	−4.016	−2.616	0.164**	1.011	1.175	3.57*	4.99**	8.561*
RES/GDP	0.057	−0.024	0.032	1.294	2.304	3.599	−0.082	1.503	1.420**	0.321*	1.281*	1.602*
Variables	Fin. (Shi & Lee)						Fin. (Dyn.)					
	Short-term (ST)			Long-term (LT)			Short-term (ST)			Long-term (LT)		
	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.
CAB/GDP	−0.452***	−0.326	−0.779	−14.736	−84.911	−99.647	−0.502***	−0.882	−1.384	−3.123	−4.684	−7.807*
EXTDEBT/GDP	0.043***	0.052	0.095	1.75	13.073	14.823	0.051***	0.187	0.239	0.169**	−0.942**	−0.772*
GDPGR	0.147	−0.364	−0.217	4.054	7.47	11.524	−0.982***	0.748	−0.233	−6.087*	4.966**	−1.120
INFL	0.147**	0.492	0.640**	3.359	17.174	20.534	0.180**	1.094**	1.275**	1.277**	8.184*	9.462
RES/GDP	0.045	0.421	0.466	−2.923	−40.262	−43.186	−0.216	0.806	0.589**	−1.924	−2.795*	−4.719
Variables	Dist. (Shi & Lee)						Dist. (Dyn.)					
	Short-term (ST)			Long-term (LT)			Short-term (ST)			Long-term (LT)		
	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.	dir. eff	Indir. eff	Tot. eff.
CAB/GDP	−0.416***	0.083	−0.332	−7.033	4.888	−2.145	−0.502***	−1.209	−1.712**	−2.352	−2.878	−5.230
EXTDEBT/GDP	0.037***	0.085	0.123	0.655	1.406	2.062	0.069*	0.397**	0.466*	0.037**	1.973	2.01
GDPGR	0.059	0.446	0.505	0.869	5.491	6.36	−0.940***	0.670**	−0.269	5.477**	13.674**	19.151**
INFL	0.095	0.014	0.11	1.495	−2.070	−0.574	0.158	0.843**	1.002*	2.447**	1.83**	4.278***
RES/GDP	0.053	−0.333	−0.280	1.11	−3.439	−2.325	−0.098	1.168	1.069	−0.321	6.702***	6.381**

– Dyn. refers to the model without IFE and i.f.e IFE.
*** statistical significance at the level of 1% ; ** statistical significance at the level of 5% ; * statistical significance at the level of 10%.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix. Marginal effects results for dynamic SDM with IFE model (1-factor)

See Table 3.

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