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SOVEREIGN DEFAULT RISK IN OECD COUNTRIES: DO GLOBAL FACTORS MATTER?

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ABSTRACT. We study the determinants of sovereign default risk for a group of 23 OECD countries using quarterly data spanning the period between 2000:Q1 and 2016:Q3. Applying the recently developed panel dynamic heterogeneous common correlated effects estimator of Chudik and Pesaran [2015] our study innovates in considering potential endogeneity issues and cross-sectional dependence. We control for global risk appetite and country risk ratings. The results show that common factors are the main drivers of solvency risk for our set of countries. Specially relevant, we find that macroeconomic determinants are not significant predictors of long-term sovereign spreads.

Keywords: Dynamic Heterogeneous Panel; Sovereign Default Risk; Common Correlated Effects.
JEL Classification: C33, F34, G15.

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1. INTRODUCTION

The study of sovereign risk occupies an important place in the international finance literature. Understanding the determinants of countries' default risk sheds important light both for investors and national policy managers issuing sovereign debt. It is not surprising, then, that this strand of the literature has produced a vast amount of papers focusing both in emerging and developed economies. While initially this literature focused on the former, the recent global financial crisis renewed interest in the study of the latter, as many developed economies had difficulties in making debt repayments and a group of them experienced significant credit rating downgrades.

Most empirical papers on sovereign risk use interest rate spread differentials on government bonds traded in secondary debt markets. These spreads are traditionally computed with respect to US treasuries at different maturities. The pioneering paper in this literature is Edwards [1986] who studies the main determinants of interest rate spreads using a sample of 13 low-development countries during the late 1970s. A large amount of papers deal with developing economies. The first generation focus in primary debt markets (Min [1998], Eichengreen and Mody [1998]; Kamin and von Kleist [1999], among others) while the second uses data on secondary markets (for instance, Arora and Cerisola [2000]; Gupta et al. [2008]; Hilscher and Nosbusch [2010]). Secondary markets are normally more liquid than primary debt markets, as more agents participate in them, and therefore are better suited for studying sovereign default risk.

The subprime financial crisis motivated the appearance of a new wave of papers on developed economies. Most of them consider yield spreads for a unique maturity, frequently 10-year bonds. Up to our knowledge there are only three papers studying the term-structure of sovereign default risk, using several yield maturities. One is a single-country study (Ojeda-Joya and Gómez-González [2014]) while the other two include information on European economies (Eichler and Maltritz [2013]; and, Trück and Wellmann [2016]).

We contribute to this literature by implementing two novel panel data models that allow the incorporation of common factors and country heterogeneity in a dynamic setting (Chudik and Pesaran [2015]), as well as testing for predictability (Westerlund et al. [2017]). Additionally, both produce consistent estimators even if violations of strict exogeneity occur. This is an important advantage in our context as interest rate spreads may influence some frequently included determinants such as the ratio of total debt to GDP among others (see Uribe and Yue [2006]).[1] It is worthy to mention that both methods account for cross-sectional dependence frequently encountered in cross-country studies.

We use quarterly data on a sample of 23 OECD countries, spanning the period comprised between the first quarter of 2000 and the third quarter of 2016. We focus in long maturities, including 7-, 10- and 15-year sovereign bond spreads in secondary markets. Hence, our results deal with solvency more than with liquidity aspects of sovereign risk. We include the traditional determinants

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[1] For example, interest rate spreads may affect the access to debt markets of some countries, limiting debt issuance in international markets.

of sovereign debt spreads used in the literature while controlling for unobservable common factors.

Our results suggest that unobservable common factors are the main determinants of sovereign default risk. These results go in line with those of Longstaff et al. [2011] who find that the majority of sovereign credit risk can be linked to global factors, and with Banerji et al. [2014], who find that common external factors are more important determinants of sovereign risk than country-specific covariates for a set of Asian economies. Specially relevant, variables such as the ratio of trade balance to GDP and the openness indicator do not affect government bond yield spreads. Additionally, and in a similar fashion to Eichler and Maltritz [2013], we find that the ratio of investment to GDP and the degree of government indebtedness are not important determinants of solvency.

We provide evidence that further adds to the current knowledge about the determinants of sovereign risk. First, our empirical method accounts properly for potential endogeneity problems that may exist between spreads and some of their macroeconomic determinants. Second, this study is one of the first in modeling cross-sectional dependence explicitly through the use of a common factor model.[2] Hence, we disentangle the importance of individual versus common factors in the determination of country risk spreads in a better way than the majority of related studies. Third, we show that common factors are the main determinants of solvency risk. These results are consistent with those of recent papers which have shown that global financial conditions have gained importance for the dynamics of sovereign spreads after the international financial crisis.

The rest of the paper is organized as follows. Section 2 presents the data used in our empirical analysis. Section 3 presents the methodology used for identifying the main determinants of sovereign default risk. Section 4 describes our main results and the final section concludes.

2. DATA

For our empirical application we consider data from 23 OECD countries spanning the period 2000:Q1 - 2016:Q3. The list of countries is shown in Table 5 of Appendix B. Not all the countries have data for the whole period. Thus, we deal with an unbalanced panel dataset. Our estimations follow Chudik and Pesaran [2013], who show how to deal with these type of issues in a common correlated effects framework.

Following the literature, we construct our sovereign risk indicator using the yield spread of each country's government bonds for different maturities (7, 10 and 15 years) with respect to the yield of US treasuries. We collect information from secondary bond markets. Figure 1 shows the evolution of our sovereign risk indicator for the 10-year maturity. The top-left panel presents spreads for the European countries that were most affected by the global financial crisis (Greece, Ireland, Italy, Portugal and Spain). The top-right panel shows spreads for non-European countries. The bottom panels present spreads for the set of remaining Western European countries (left) and the

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[2]Up to our knowledge, the only existing paper that uses common correlated effects estimation in a similar setting is Özmen and Yaşar [2016].

group of Eastern and Nordic European economies (right).

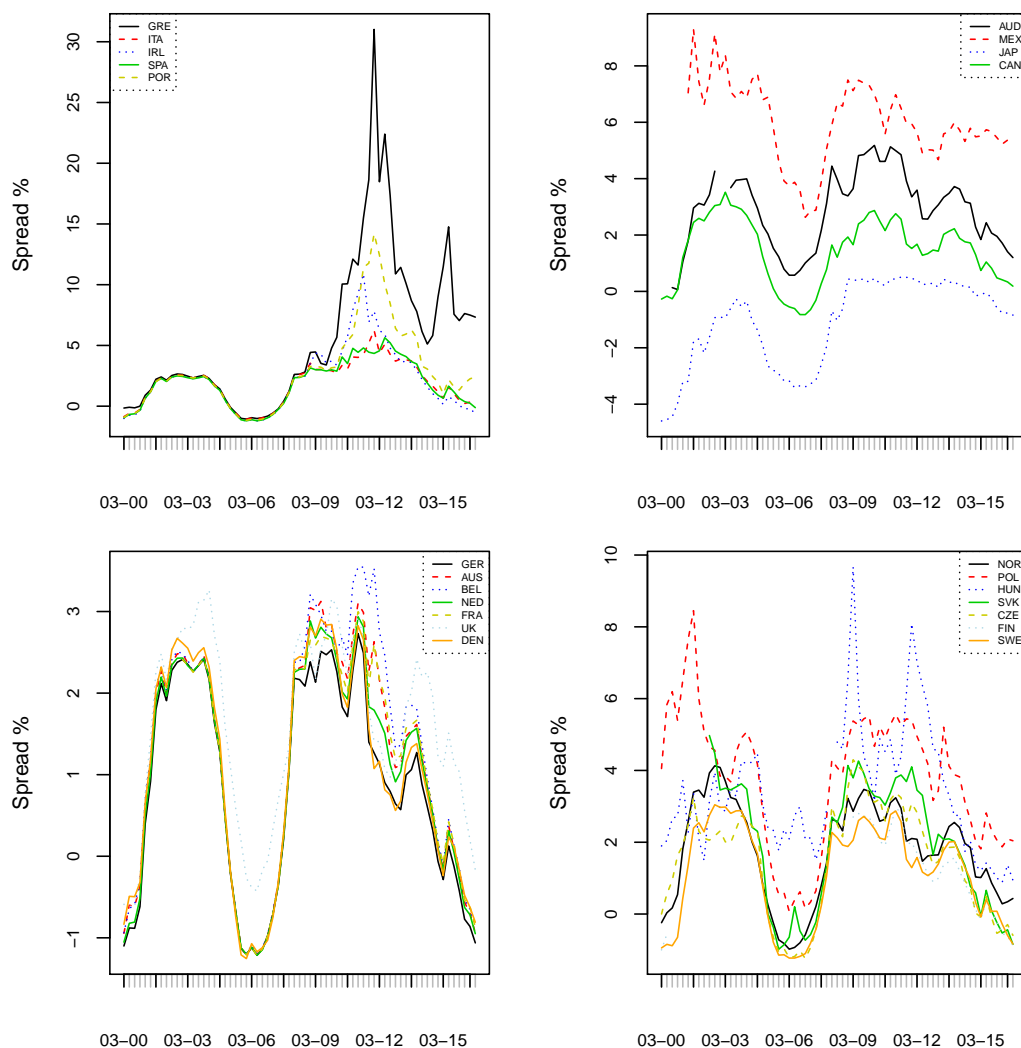FIGURE 1. 10Y government bonds yield spreads with respect to U.S treasuries.

Figure 1 shows that interest rate spreads co-move within the four sets of countries. Of special relevance, spreads exhibit more variation between groups than within them, as expected. The level of spreads for countries in the top-left panel are substantially higher than for the other three groups. For all countries, interest rate differentials present their highest levels around the US subprime crisis of 2008-9 and near the European sovereign debt crisis of 2011-12.

To evaluate the determinants of sovereign risk spreads we include several variables that have been used in the literature, reflecting both the government's debt situation, the state of the economy and external sector variables. Existing studies are emphatic in showing that the expected effect of most of these variables on yield spreads should be unambiguous (see, for instance, Eichler and Maltritz [2013]). A notable exception is the effect of the degree of openness, for which the expected sign is unclear.[3] Given our emphasis relies in long maturities, we exclude variables that have shown to be important determinants of liquidity risk only (for instance, implicit interest rates and the ratio of net lending to GDP). Table 6 in Appendix B presents the definition of the variables included in this study.

As some of our countries have different currencies, we acknowledge that the existence of exchange rate risk may affect our results. We account partially for this issue by including a proxy of currency risk measured by the pairwise foreign exchange rate volatility with respect to the US dollar. Furthermore, it is important to note that as we include only OECD countries in our sample for which exchange rate markets are highly developed and liquid, we consider that exchange rate risk is not a major issue in this case.

3. ECONOMETRIC METHODOLOGY

The analysis of cross section dependence in heterogeneous panel data models has been of great interest in the panel econometrics literature. Several authors have modelled the dependence through the use of common factor models. The idea behind them is that variations in several economic variables are related to the dynamics of a small number of reference factors. In this vein, Pesaran [2006] proposes the common correlated effects estimation method for heterogeneous panel data models with a multi-factor error structure. The main idea of this estimation method is to filter the effects of these common factors through cross section averages so that asymptotically, as the number of individuals goes to infinity, parameters of the included regressors can be consistently estimated. A useful feature of the method proposed by Chudik and Pesaran [2015] is that it allows a consistent estimation of parameters even in the presence of weakly exogenous covariates. This dynamic heterogeneous panel data model can be written as

$$y_{it} = c_{yi} + \phi_i y_{i,t-1} + \beta'_{0i} x_{it} + \beta'_{1i} x_{i,t-1} + u_{it}$$
$$u_{it} = \gamma' f_t + \varepsilon_{it}$$

$$\omega_{it} \equiv \begin{pmatrix} x_{it} \\ g_{it} \end{pmatrix} = c_{\omega i} + \alpha_i y_{i,t-1} + \Gamma'_i f_t + v_{it} \qquad (1)$$

For $i \in \{1,...,N\}, t \in \{1...,T\}$. Where x_{it} is a k_x-column vector of regressors and g_{it} is a k_g-column vector of covariates specific to unit i. While x_{it} includes variables that affect y_{it}, g_{it} encompasses

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[3]In this case, more open countries are prone to contagion effects which might increase their default risk in times of crisis. However, it can be argued that more open countries suffer more from trade punishments caused by unfulfillment of debt obligations which increases their willingness to pay.

variables that depend on the common factors but not on the dependent variable.[4] f_t is an m-column vector of unobserved common factors, ε_{it} represents the idiosyncratic errors, Γ_i is a $m \times (k_x + k_g)$ matrix of factor loadings. Furthermore, α_i is an unknown $(k_x + k_g)$-column vector of coefficients and v_{it} follows a covariance-stationary process independent of the idiosyncratic errors ε_{it}. The model proposed in equation (1) can be readily extended to the case where the data generating process includes additional lags of the dependent variable, other deterministic terms or even when the process ω_{it} depends on its own lags.

In addition, the vector of coefficients $\pi_i \equiv (\phi_i, \beta'_{0i}, \beta'_{1i})'$ as well as the factor loadings γ_i and Γ_i are assumed to follow random coefficient models

$$
\begin{aligned}
\gamma_i &= \gamma + \eta_{\gamma,i}, \quad \eta_{\gamma,i} \sim IID(0, \Omega_\gamma) \\
vec(\Gamma_i) &= vec(\Gamma) + \eta_{\Gamma,i}, \quad \eta_{\Gamma,i} \sim IID(0, \Omega_\Gamma) \\
\pi_i &= \pi + \eta_{\pi,i}, \quad \eta_{\pi,i} \sim IID(0, \Omega_\pi)
\end{aligned}
\tag{2}
$$

No further assumptions are made over $\eta_{\gamma,i}$ and $\eta_{\Gamma,i}$. However, it is assumed that $\eta_{\pi,i}$ is distributed independently of $\gamma_j, \Gamma_j, \varepsilon_{jt}, v_{jt}$ and $f_t \ \forall i, j, t$. In the case that we consider in this paper, the support of ϕ_i is assumed to lie strictly inside the unit circle.[5]

Finally, regarding idiosyncratic errors and common factors, the m-column vector f_t is assumed to follow a covariance stationary process independently of the individual specific errors $\varepsilon_{it'}$ and $v_{it'}$ $\forall i, t, t'$. The ε_{it} errors are assumed to be independently distributed of the v_{it} and cross-sectionally correlated.

Using the fact that for a large N the model in equation (1) implies that

$$
\bar{z}_t = \bar{c}_z + \Lambda(L)Cf_t + O_p\left(N^{-\frac{1}{2}}\right)
\tag{3}
$$

Where $\bar{z}_t \equiv (\bar{y}_t, \bar{x}'_t, \bar{g}'_t)$ is a $(1 + k_x + k_g)$-column vector of cross section averages. $\Lambda(L)$ is a matrix polynomial in the lag operator, $C \equiv (\gamma, \Gamma)'$ and $\bar{c}_z$ is a constant term. Chudik and Pesaran [2015] propose using lags of cross section averages to replace the unobserved common factors and suggests the following estimator of π_i

$$
\hat{\pi}_i = (\Xi'_i \bar{M}_q \Xi_i)^{-1} \Xi'_i \bar{M}_q y_i
\tag{4}
$$

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[4]In our empirical application we assume $k_g = 0$.

[5]Some conditions regarding the support of α_i have to be imposed so the model in equation (1) is stable, see Chudik and Pesaran [2015].

Where

$$
\Xi_i = \begin{pmatrix}
y_{i,P_T} & x'_{i,P_T+1} & x'_{i,P_T} \\
y_{i,P_T+1} & x'_{i,P_T+2} & x'_{i,P_T+1} \\
\vdots & \vdots & \vdots \\
y_{i,T-1} & x'_{i,T} & x'_{i,T-1}
\end{pmatrix}
$$

$$
\bar{M}_q = \mathbf{I}_{T-p_T} - \bar{Q}_\omega(\bar{Q}'_\omega\bar{Q}_\omega)^+\bar{Q}'_\omega \tag{5}
$$

$$
\bar{Q}_\omega = \begin{pmatrix}
1 & \bar{z}'_{P_T+1} & \bar{z}'_{P_T} & \cdots & \bar{z}'_1 \\
1 & \bar{z}'_{P_T+2} & \bar{z}'_{P_T+1} & \cdots & \bar{z}'_2 \\
\vdots & \vdots & \vdots & & \\
1 & \bar{z}'_T & \bar{z}'_{T-1} & \cdots & \bar{z}'_{T-P_T}
\end{pmatrix}
$$

Where P_T is a predefined lag cutoff and A^+ denotes the Moore-Penrose generalized inverse of A.

Under the assumption that the matrix C in equation (3) has full rank along with some other conditions, the estimator proposed in (4) is consistent as long as $\frac{P_T^3}{T} \to k, \quad 0 < k < \infty$. Chudik and Pesaran [2015] also establishes the consistency of the group mean estimator $\hat{\pi}_{MG} \equiv \frac{1}{N}\sum_{i=1}^N \pi_i$ even when matrix C is not of full rank. In the latter case, the full rank assumption is replaced by assuming that the common factors f_t are serially uncorrelated.

The asymptotic variance of the mean group estimator ($\bar{\pi}_{MG}$) can be estimated non parametrically by

$$
\bar{\Sigma}_{MG} = \frac{1}{N-1}\sum_{i=1}^N (\hat{\pi}_i - \hat{\pi}_{MG})(\hat{\pi}_i - \hat{\pi}_{MG})' \tag{6}
$$

As a robustness check of our main results, we follow Westerlund et al. [2017] in order to test for predictability in our panel data model. Particularly, as we are interested in identifying the potential effect of the included covariates on spread yields in the context of a dynamic panel setting, we need to test that the non-significant effect of these variables is not simply a reflection of the inclusion of dependent variable lags.

Westerlund et al. [2017] proposes an explicit test for predictability in panel data models using a Wald test that is asymptotically distributed as a chi-square random variable with degrees of freedom equal to the number of regressors included. This method assumes a single common factor structure in the error term and hence accounts for cross-sectional dependence. To estimate the unobserved common factor Westerlund et al. [2017] suggests using the cross-sectional mean of the forward recursively detrended independent variable. The estimator proposed for the coefficients is

similar to those of other panel data methods, but it uses backward and forward recursive detrended dependent and independent variables. The inclusion of the latter allows the achievement of an asymptotically pivotal statistic. The test is robust to both unit root and near unit root behaviour in the regressors and violations of strict exogeneity.

4. EMPIRICAL RESULTS

Table 4 of Appendix A presents results of the Pesaran [2007] panel unit root test for the variables used in our empirical analysis. As shown, most series are stationary. Specifically, the spreads and all but four regressors[6] are I(0). Non-stationary variables are included in first differences.

We construct two different panels. The first includes all the 23 countries mentioned in the Data section. The second excludes five European economies that were strongly affected during the recent global financial crisis (Greece, Ireland, Italy, Portugal and Spain). We do this for robustness purposes. Table 1 presents results for the CD test of Pesaran [2004] for both samples. We find strong statistical evidence of cross-sectional dependence, justifying the use of a panel data method that controls it.

TABLE 1. Pesaran [2004] CD statistic

	7 Year Spread	*10 Year Spread*	*15 Year Spread*
23 Countries	51.18***	52.41***	53.07***
18 Countries	42.75***	43.22***	42.99***

Authors' calculations. *, **, and *** indicate significance at the 10%, 5 %, and 1% levels, respectively.

In controlling for observable global factors we include the VIX index as a measure of the price of risk[7], S&P country credit ratings and time-dummy variables taking on the value of one for the periods in which quantitative easing policies were implemented. All the variables described in Table 6 of Appendix B are used as country-specific regressors. First lags of the dependent variables are considered as well as in Attinasi et al. [2009]. Their inclusion permits testing for the contemporaneous effect of the regressors on sovereign risk spreads and accounts for the fact that bond yield spreads are highly persistent.

Group-mean estimation results are presented in Table 2. It is important to mention that estimations are performed imposing the restriction $\beta_1 = 0$ in Equation (1). Note that only lagged spreads

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[6]The null hypothesis of at least one unit root could not be rejected for the ratio of debt to GDP, current account to GDP, reserves to GDP and the share index.

[7]We included variables that do not exhibit cross-country variation in the projection matrix $\bar{M}_q$ of Equation (5) following Pesaran [2007].

have explanatory power when the 23 countries are included in the sample. All other covariates are statistically equal to zero. This means that on average the regressors frequently used in the literature do not exert a significant effect on sovereign spreads. This conclusion remains valid when the sample of 18 countries is used. In that case, lagged spreads are also statistically insignificant except for 7-year maturities.

Our results suggest that common factors are the main determinants of sovereign risk at long-term maturities for our set of OECD countries. In other words, only the mean trend of each variable seems to have explanatory power on the dynamic behavior of country risk spreads.

Note that the persistence of spreads tends to decay as maturities become longer. Specifically, while the persistence coefficient has a value of 0.67 for 7-year spreads, its value is of 0.53 for 15-year spreads when the sample of 23 countries is used. A similar result is obtained when considering the reduced sample.

TABLE 2. Chudik and Pesaran [2015] Group-mean estimation results

| | 23 Countries | | | | | | 18 Countries | | | | | |
| | 7Y Spread | | 10Y Spread | | 15Y Spread | | 7Y Spread | | 10Y Spread | | 15Y Spread | |
	$\hat{\beta}$	Sd	$\hat{\beta}$	Sd	$\hat{\beta}$	Sd	$\hat{\beta}$	Sd	$\hat{\beta}$	Sd	$\hat{\beta}$	Sd
Lag	0.67***	0.25	0.62**	0.26	0.53**	0.26	0.48*	0.25	0.46	0.30	0.42	0.28
GPSD % GDP	-0.02	0.10	-0.02	0.09	-0.01	0.08	-0.01	0.12	-0.01	0.11	-0.01	0.10
GCF % GDP	13.04	24.62	11.14	21.13	10.12	21.94	10.14	20.80	9.46	20.82	7.78	22.57
CAB % GDP	-0.01	0.06	-0.01	0.06	-0.01	0.06	0.01	0.05	0.01	0.06	0.01	0.07
OI % GDP	-9.57	35.27	-4.76	38.00	5.79	39.35	2.07	32.68	5.41	43.31	8.15	48.76
RER	-0.02	0.05	-0.01	0.05	-0.01	0.05	-0.01	0.03	-0.01	0.03	-0.01	0.03
RES % GDP	-1.45	35.64	-0.68	35.50	-2.69	36.08	-5.18	27.87	-4.87	28.83	-5.86	32.07
SI	-0.04	0.10	-0.01	0.12	-0.08	0.22	-0.06	0.09	0.00	0.26	-0.10	0.16
SIV	-0.06	0.60	0.00	0.46	0.08	0.32	-0.05	0.53	0.01	0.34	0.00	0.46
FV	0.50	37.12	-15.21	130.85	12.96	82.39	-54.58	187.98	-60.31	221.51	-39.24	180.12

Authors' calculations. *, **, and *** indicate significance at the 10%, 5 %, and 1% levels, respectively. SI and SIV coefficients and standard deviations multiplied by 100 due to the small size.

Our findings contrast with those of the traditional literature and shed light on several different aspects. First, given the potential endogeneity issues that arise between spreads and some of their macroeconomic determinants (see Uribe and Yue [2006]), a method that accounts for these problems must be used in empirical applications. In this sense, most of the previous papers in this

literature may be subject to inconsistent estimates of the parameters of interest as they do not account explicitly for this problem. Second, results of studies that do not explicitly consider the role of common factors may be contaminated as these can influence country-specific macroeconomic variables. Hence, the importance of individual versus common factors cannot be disentangled appropriately in most papers (see, for instance, Banerji et al. [2014]). Third, there is evidence that global risk factors have become more dominant in explaining sovereign risk after the recent global financial crisis (Gómez-Puig et al. [2014] provide evidence for European monetary union countries while Amstad et al. [2016] for emerging markets and advanced economies). In that sense, our results use a more informative sample period than most previous papers. Fourth, papers focusing in the study of global factors frequently use principal component analysis that do not allow identifying explicitly the effect of country-specific variables on risk spreads (Longstaff et al. [2011]).

As a robustness check of our empirical results we use the panel data method proposed by Westerlund et al. [2017]. This method includes an explicit test of predictability and allows the existence of a common factor. Thus, it accounts for cross-sectional dependence. However, it does not include lags of the dependent variable as regressors.[8] Results are shown in Table 3. Note that all the included regressors are jointly statistically insignificant, except for the case of the 7-year spread when 18 countries are included in the regressions. This result further confirms those presented previously, showing that common factors are the main determinants of long-term sovereign spreads in OECD countries.

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[8]Note that the exclusion of dependent variable lags in a dynamic setting may induce serial correlation in the error term. However, if the persistence originates in the common factor, under certain conditions the test can be applied without correction.

TABLE 3. Westerlund et al. [2017] predictability test

	23 Countries			18 Countries		
	7Y Spread	**10Y Spread**	**15Y Spread**	**7Y Spread**	**10Y Spread**	**15Y Spread**
	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
GPSD % GDP	-0.04	-0.04	-0.02	0.12	0.11	0.10
GCF % GDP	184.58	247.97	-502.95	-35.88	-48.95	-62.73
CAB % GDP	-0.09	-0.12	0.23	0.05	0.05	0.05
OI % GDP	-326.42	-438.25	878.24	162.98	174.66	184.77
RER	-0.07	-0.09	0.07	-0.08	-0.08	-0.08
RES % GDP	6.95	11.68	-28.47	-3.58	-4.88	-5.57
SI	0.01	0.01	-0.02	-0.01	-0.01	-0.01
SIV	0.04	0.05	-0.07	-0.03	-0.03	-0.03
FV	-20.84	-26.47	45.44	9.36	7.67	6.41
P-value	**0.31**	**0.39**	**0.61**	**0.01**	**0.13**	**0.38**

Authors' calculations. SI and SIV coefficients and standard deviations multiplied by 100 due to the small size.

5. CONCLUDING REMARKS

This study uses a dynamic heterogeneous common correlated effects estimator to study the determinants of sovereign bond spreads for a set of 23 OECD countries. Spreads are obtained from secondary bond markets and calculated with respect to US treasuries. Our focus is in solvency risk determinants, and therefore we use 7-, 10- and 15-year spreads.

Our contributions to the literature are mainly methodological. Our method accounts for the endogeneity problems that can arise between spreads and some of their macroeconomic determinants (see Uribe and Yue [2006] and Banerji et al. [2014]). Additionally, this study is one of the first in explicitly modeling cross-sectional dependence using a common factor model. Therefore, our proposal permits disentangling the importance of individual and common factors in the determination of country risk spreads. Furthermore, we study spreads in a dynamic setting, which entails two important advantages. On the one hand, sovereign spreads exhibit high inertia as shown by Attinasi et al. [2009], and this characteristic has to be considered for an adequate modeling. On the other hand, in this setting we can assess the existence of a contemporaneous effect of the included regressors.

The findings of this study show that, after controlling for risk appetite measured by the VIX and risk sovereign ratings, common factors are the main determinants of solvency risk. These results go in line with those of recent papers that have shown that global financial conditions are gaining importance in the dynamics of sovereign spreads (Gómez-Puig et al. [2014] and Amstad et al. [2016]). While our results may seem surprising at first sight, they are not completely unexpected as our group of countries are fairly homogeneous and among the most developed in the world. Probably results for emerging market economies may differ, since there are reasons to believe that individual country fundamentals matter more for these countries (Ojeda-Joya and Gómez-González [2014]).

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APPENDIX A. UNIT ROOT TEST

TABLE 4. Pesaran [2007] truncated CADF statistic

	23 Countries	**18 Countries**
7Y Spread	-2.51***	-2.77***
10Y Spread	-2.52***	-2.69***
15Y Spread	-2.50***	-2.50***
GPSD % GDP	-1.85	-1.80
GCF % GDP	-2.77***	-3.13***
CAB % GDP	-2.05	-1.85
OI % GDP	-2.49***	-2.39**
RER	-2.26**	-2.15**
RES % GDP	-1.69	-1.68
SI	-1.64	-1.97
SIV	-3.47***	-3.51***
FV	-4.53***	-4.60***

Authors' calculations. *, **, and *** indicate significance at the 10%, 5 %, and 1% levels, respectively. Interpolated critical values based on Pesaran [2007] Table II(b). $H_0 : y_{it}$ is I(1) for all i, $H_a :$ at least one y_{it} is I(0).

APPENDIX B. DATA

TABLE 5. Countries considered

Australia	*AUD*	Germany	*GER*	Sweden	*SWE*	Czech Republic	*CZE*
Mexico	*MEX*	Austria	*AUS*	Greece	*GRE*	Japan	*JAP*
Belgium	*BEL*	Poland	*POL*	Ireland	*IRL*	Canada	*CAN*
Netherlands	*NED*	Finland	*FIN*	Hungary	*HUN*	Slovak Republic	*SVK*
Denmark	*DEN*	Portugal	*POR*	Spain	*SPA*	United Kingdom	*UK*
Norway	*NOR*	France	*FRA*	Italy	*ITA*		

TABLE 6. Description and sources of the variables

Variable	Definition	Source
GPSD % GDP	Gross Public Sector Debt, Central Gov., All maturities, All instruments, Nominal Value, % of GDP	IMF/World Bank
GCF % GDP	Gross Capital Formation as % of GDP	IMF
CAB % GDP	Current Account, Net (excluding exceptional financing) as % of GDP	IMF
OI % GDP	Sum of Goods, Value of Exports, FOB and Goods, Value of Imports, CIF, as % of GDP	IMF/WTO
RER	Real Effective Exchange Rate, based on Consumer Price Index	IMF
RES % GDP	Total reserves minus gold as % of GDP	IMF
SI	Country Stock Exchange Index	Bloomberg
SIV	Standard deviation of Country Stock Exchange Index using 24-month windows	Authors' calculations/ Bloomberg
FV	Standard deviation of official Foreign Exchange rate with respect to USD using 24-month windows	Authors' calculations/ Bloomberg