ESSAYS IN GLOBAL COMOVEMENTS

by

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ABSTRACT

This dissertation looks into comovements in the global macroeconomic aggregates across countries by applying Bayesian econometric models. The first essay provides new results on the significance and relative importance of global and regional comovements in sovereign credit risk. I employ a dynamic factor model with time-varying stochastic volatility to examine the time-varying effects of global comovements. I find that the effects of the global comovements on individual countries are smaller than commonly perceived, especially after the end of the Eurozone debt crisis. Moreover, contrary to previous findings, I find that the net effects of the global and regional factors are greater than those of global macroeconomic variables.

The second essay provides evidence of significant international co-movements of public debt in the form of the common global and regional factors. International events such as the global financial crisis and Eurozone sovereign debt crisis suggest the existence of global and regional factors that can generate synchronizations of public debt across countries. In contrast with previous studies that are focused mostly on domestic economic fundamentals in explaining public debt, I find distinct global factors in the public debt-to-GDP ratio, from both principal components analysis and the Bayesian dynamic factor model. I show that the global factor accounts for a significant fraction of the variation of public debt often more substantial than those explained by domestic variables in many countries.

In the third and final essay, I develop a new panel cointegration model based on the well-known autoregressive distributed lag (ADL) models. I adopt the generalized method of moments procedure of Arellano and Bond, noticing that the ADL cointegration model is a special case of dynamic panel data models. The suggested procedure can overcome the difficulties found in the studies based on the panel vector autoregressive models, which can be biased in the presence of cointegration.

DEDICATION

This dissertation is dedicated to my beloved parents, my wife Zoda, and my daughter Maryam for always inspiring me during my time of writing this work.

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I would like to express my appreciation to those who helped me in making this dissertation possible. First and foremost, I would like to acknowledge the continued mentorship provided by Dr. Junsoo Lee throughout my time of conducting this research. His constant encouragement and guidance played a big role in my ability to complete my doctoral studies. I would also like to thank the committee members of my dissertation for their time and effort: Dr. Robert Reed, Dr. Xiaochun Liu, Dr. Shawn Mobbs, and Dr. Vladimir Arčabić. In addition, I would like to recognize all the support provided by the Department of Economics, Finance and Legal Studies during my stay at the University of Alabama.

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COMOVEMENTS IN SOVEREIGN CREDIT DEFAULT SWAPS

Introduction

The recent global financial crisis followed by the European sovereign debt crisis has induced a great interest in the dynamics of sovereign credit risk from both researchers and the policymakers. Among a plethora of credit derivatives, sovereign credit default swaps (CDS) are increasingly accepted as a reliable measure of sovereign credit risk due to the unprecedented increase in their market value and liquidity leading up to the financial crisis and onward. In particular, the popularity of sovereign CDS, as well as their ability to describe the overall health of the economy, triggered sizeable attention from researchers trying to disentangle their main drivers[*].

This chapter examines the significance of global and regional comovements in sovereign CDS. Instead of focusing on local macroeconomic determinants, we recognize the global factor as a significant determinant of sovereign CDS spreads, but we also consider regional factors as potential sources of commonalities. The chapter further examines the effects of the global and regional factors on the variation in sovereign CDS. In particular, we are interested in the role of the global and regional comovements in sovereign CDS in comparison to the domestic fundamentals and global macro variables, such as US stock prices, S&P500 volatility index (VIX) and oil prices. In addition, we compare the importance of global and regional factors with regards to other determinants. The analysis is based on quarterly sovereign CDS data for 35 countries for the period between 2006 Q4 and 2018 Q4.

There is extensive research looking at the factors determining sovereign CDS. In their influential work, Aizenman et al.[4] note that macroeconomic conditions can drive sovereign CDS spreads. They examine the pricing of sovereign credit risk based on

[*]Even though some governments point to sovereign CDS as one of the causes of debt crises due to their speculative nature, the literature is still yet to deliver conclusive evidence to back that claim. Such claims led Germany to ban short sales of European sovereign debt in May 2010, which was later adopted by European Union in November 2012.

de facto fiscal space using the debt/tax and the deficits/tax ratios. They also consider other economic fundamentals, such as external debt, nominal depreciation, inflation, economic growth, trade openness, and the foreign interest rate. Instead of using sovereign CDS, Von Hagen et al.[68] employ data on government bond yields denominated in DM/euros and US dollars relative to the benchmark of German and US federal government treasuries. They maintain the hypothesis that the yield spread depends on the government's probability of default on its debt, where the ratio of the central government debt to GDP and the ratio of the central government budget surplus to GDP are major factors for the default probability. Clearly, all these factors are important determinants for the overall health of the economy, sovereign credit risk, and thus sovereign CDS spreads.

However, an important question has been raised in the literature. The pioneering work of Pan & Singleton[59], followed by Longstaff et al.[53], suggests that sovereign credit risk is driven more by global market factors than by country-specific fundamentals. Pan & Singleton[59] initially observe high levels of comovements among countries after studying sovereign CDS of Turkey, Korea, and Mexico. They adopt the principal components (PC) analysis and find that the first PC explains over 96 percent of the variation in sovereign CDS. Using monthly CDS data for 26 countries between 2004 and 2010, Longstaff et al.[53] also find that the effect of commonality in sovereign credit spreads on sovereign credit risk is much larger than that of country-specific factors. They indicate that the first PC explains 64 percent of the variation in sovereign CDS spreads during the 2000-2010 period, and 75 percent during the 2007-2010 crisis period. Overall, they note that the first three PCs can explain about 80 percent of the variation of sovereign CDS over the whole sample period. Thus, they argue that major global drivers explain a big portion of the variability in sovereign CDS spreads among countries, and sovereign credit risk is much more related to global factors than country-specific factors or domestic economic fundamentals. Besides, they show that those global comovements can be largely explained by the U.S. stock market returns measured by VIX, which is an evidence of the existence of a common global factor. That is, they find that the effects of the global financial markets are more pronounced in the sovereign credit risk of a country. Along these lines, Augustin & Tédongap[15] argue that the U.S. expected growth and consumption volatility are major sources of global comovements in CDS spreads.

This chapter adopts a dynamic factor model with time-varying stochastic volatility (DFM-TV) of Del Negro & Otrok[37] to estimate the global and regional factors driving sovereign CDS spreads. There are several important advantages of using the DFM-TV approach for analyzing comovements in sovereign CDS. First, the DFM-TV is flexible, and it allows us to simultaneously decompose sovereign CDS spreads into global, regional, and idiosyncratic factors. Doing so makes it possible to pin down the common drivers of sovereign CDS, which is often unfeasible using principal component analysis. Second, the time-varying nature of DFM-TV allows us to examine the changing effects of the common factors on sovereign CDS spreads over time. This feature of DFM-TV is crucial in analyzing sovereign risk since the effects of global factors can be different at different periods, especially during crisis periods (Ang & Bekaert[9])[*] . Finally, the stochastic volatility introduced in the model can help us capture shifts in the dynamics of common factors, which would be inevitable given the turbulence that the countries in our sample have been through within the past few years.

Our results can be summarized as follows. First, we present clear evidence that global and regional factors are significant. Although previous studies using principal component analysis show that the worldwide factor accounts for 80 - 96 percent of the variation of the CDS, we find that their effects are much smaller than generally perceived, especially after the sovereign debt crisis in Eurozone.

Second, we observe a significant effect of the regional factors, which has not been examined in the literature. We find that regional factors have started playing an in-

[*]Although to a limited extent, the literature has shown that there is a significant time variation in the effect of global factors on individual countries. Fontana & Scheicher[42], for instance, examine the variations in the spread between bonds and sovereign CDS and find that traditional financial and macroeconomic variables affect CDS spreads differently during the crisis than they do during tranquil times. Similarly, Fender et al.[41] use a GARCH model to investigate volatilities in sovereign CDS spreads of emerging market economies. Their results show that the effect of macroeconomic variables on CDS spreads is different before than after the financial crisis.

creasingly more significant role in explaining the variance in CDS, especially in a group of EMU countries. The regional factor's effect has been more important during the financial crisis period and onward compared to the period before the financial crisis. The effect is more significant than that of the global factor in the EMU and Latin American countries during and after the financial crisis period. On the other hand, as expected, the regional factor's effect is negligible in non-EMU countries.

Third, we adopt a structural VAR model and partial correlation analysis to assess further the importance of the estimated global and regional factors. We find that they are more dominant determinants of sovereign CDS spreads than domestic economic fundamentals (such as public debt, fiscal deficit, and exchange rate volatility). We find that the effects of country-specific shocks and local economic fundamentals are much less significant than expected, compared to the global or regional factors. Moreover, contrary to previous findings, the net effects of the global and regional factors far exceed the effects of the global macro variables such as VIX, oil prices, and uncertainty, which were considered previously as essential components for the sovereign CDS.

The next section discusses the CDS data used in our estimations and presents brief results on preliminary principal component analysis.

Data and Preliminary Analyses

Data

The literature defines CDS as insurance obtained by debt-holders against the credit event, such as the borrower's default, from a protection seller. Aside from other minor contractual technicalities, the most significant difference between CDS and traditional insurance contracts is that the protection buyer does not have to own the insured asset (e.g., a bond). This feature renders CDS a handy tool for transferring credit risk between entities with a minimum amount of frictions. Hence, even though government bonds are perceived to be a safer investment during financial distress, sovereign CDS tend to be more prevalent during tranquil times due to their liquidity. Thus, CDS can contain relatively accurate information about the underlying sovereign credit risk (Pan

& Singleton[59]). CDS are one of the several highly traded swap contracts in the over-the-counter (OTC) derivatives market, along with interest rate and currency swaps. CDS represent a contract between a debt-holder, who acts as a protection buyer, and an insurer, who agrees to receive a certain amount of premium on a semi-annual basis in exchange for ensuring the debt-holder against a credit event*. The premiums are usually expressed as basis points (bp), where each basis point represents one-hundredth of a percentage point†. CDS are traded in 1, 2, 3, 5, and 10-year maturities.

In our analysis, we use daily 5-year maturity sovereign CDS data for 35 countries. The series cover the period between November 2006 and December 2018. The data source is the Thomson Reuters CDS database, which collects intra-day CDS quotes from multiple investment banks and provides aggregated data. In order to match the frequency of other variables in our dataset, we have converted the daily CDS data into quarterly observations by taking quarterly averages. We present the summary statistics in Table 1‡.

Figure 1 plots the mean CDS spreads for four regions described above, which illustrates regional commonalities and differences in the dynamics of CDS spreads across time. We have assigned 35 countries into four different geographical regions: Eurozone (EMU), non-Eurozone European Union (non-EMU), Latin America, and Asia. We include Latvia and Lithuania to non-EMU countries since they entered the EMU in 2014 and 2015, respectively, which is closer to the end of our sample. Moreover, from what follows, they seem to have more commonalities with the non-EMU region than with EMU countries. Estonia and Slovakia were classified as EMU countries since they entered the EMU towards the beginning of the sample.

To provide further insight into the data, we plot the CDS spreads by regions in Fig-

*See Pan & Singleton[59] for the detailed layout of sovereign CDS market structure.

†For instance, 100 bp would require the debt-holder to pay 1 percent of the total debt amount each year to insure its debt against a credit event.

‡Sweden has the lowest mean spread of 26.4 bps, while the highest mean spread of 276.03 bps is in Portugal. Both the standard deviations and minimum and maximum values indicate that there is a considerable variation in the data across time. For instance, CDS spreads of Latvia went from as low as 7 bps in November 2006 to 1004 bps in March of 2009. Maximum values differ starkly across regions. Maximum values for EMU countries range from 103.49 bps (Germany) to 1594.67 bps (Cyprus), while for Latin American countries, the range is only from 260.18 bps (Chile) to 486.13 bps (Brazil).

Table 1 Summary statistics for sovereign CDS spreads

Region	Country	Mean	SD	Min	Median	Max
EMU	Austria	49.74	48.73	2.08	29.84	181.25
	Belgium	69.12	71.57	2.25	42.92	310.70
	Cyprus	368.22	384.87	6.71	215.02	1371.60
	Estonia	108.83	114.61	8.23	64.56	628.40
	France	53.38	48.12	1.88	40.28	202.80
	Germany	27.81	23.33	3.34	19.46	97.14
	Ireland	175.88	225.41	4.88	60.35	902.98
	Italy	153.14	117.15	6.36	127.02	495.89
	Netherlands	35.14	28.99	1.88	26.53	119.84
	Portugal	274.19	293.77	4.31	175.38	1198.01
	Slovakia	76.86	61.82	5.56	50.12	267.46
	Spain	138.76	129.24	2.82	90.53	531.85
non-EMU	Bulgaria	176.25	113.28	14.83	145.02	562.50
	Croatia	234.14	124.95	16.80	254.91	510.30
	Czech Rep.	65.13	46.14	2.69	49.69	252.77
	Hungary	219.00	143.66	18.70	166.31	568.87
	Latvia	199.10	204.28	8.52	118.02	914.71
	Lithuania	161.03	142.32	11.76	116.22	704.29
	Poland	100.72	66.71	8.56	78.24	315.73
	Romania	199.25	134.59	18.38	153.63	648.39
	Sweden	26.23	23.32	1.70	17.03	116.57
Asia	China	83.21	37.47	10.51	76.66	209.69
	Hong Kong	46.38	20.52	4.38	45.28	97.35
	Indonesia	191.10	112.29	87.72	162.85	723.89
	Japan	48.46	30.78	2.57	43.46	125.21
	Malaysia	105.20	49.24	14.56	95.02	258.00
	Philippines	141.27	74.18	63.48	119.06	442.02
	South Korea	87.58	68.45	15.49	66.51	363.56
	Thailand	105.43	49.65	30.38	99.38	270.13
Latin America	Brazil	186.64	89.22	69.67	148.86	453.62
	Chile	82.34	41.81	13.33	77.81	240.90
	Colombia	150.30	62.91	82.07	129.97	399.45
	Mexico	128.01	61.74	33.07	118.12	380.39
	Panama	130.80	64.32	62.54	115.53	398.71
	Peru	131.71	59.41	68.50	115.59	384.11

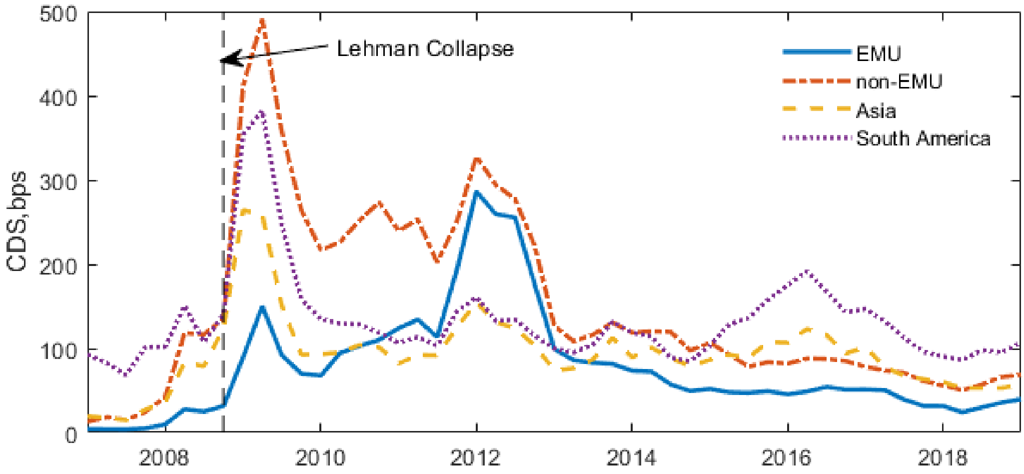

Figure 1: Mean regional CDS spreads

ure 2. At first glance, it is easy to notice the presence of comovements both within and across regions. It is not surprising that the cross-regional comovements are particularly pronounced during the global financial crisis and the European sovereign debt crisis, which are highlighted with light and dark grey areas, respectively. Nevertheless, there is a substantial difference in volatility around major economic events. While Asian, Latin American, and non-EMU countries have higher volatilities around the global financial crisis, the EMU countries have considerably higher volatility during the Eurozone sovereign debt crisis. This phenomenon is not unexpected, given the origins of both crises. A special case is non-EMU countries.

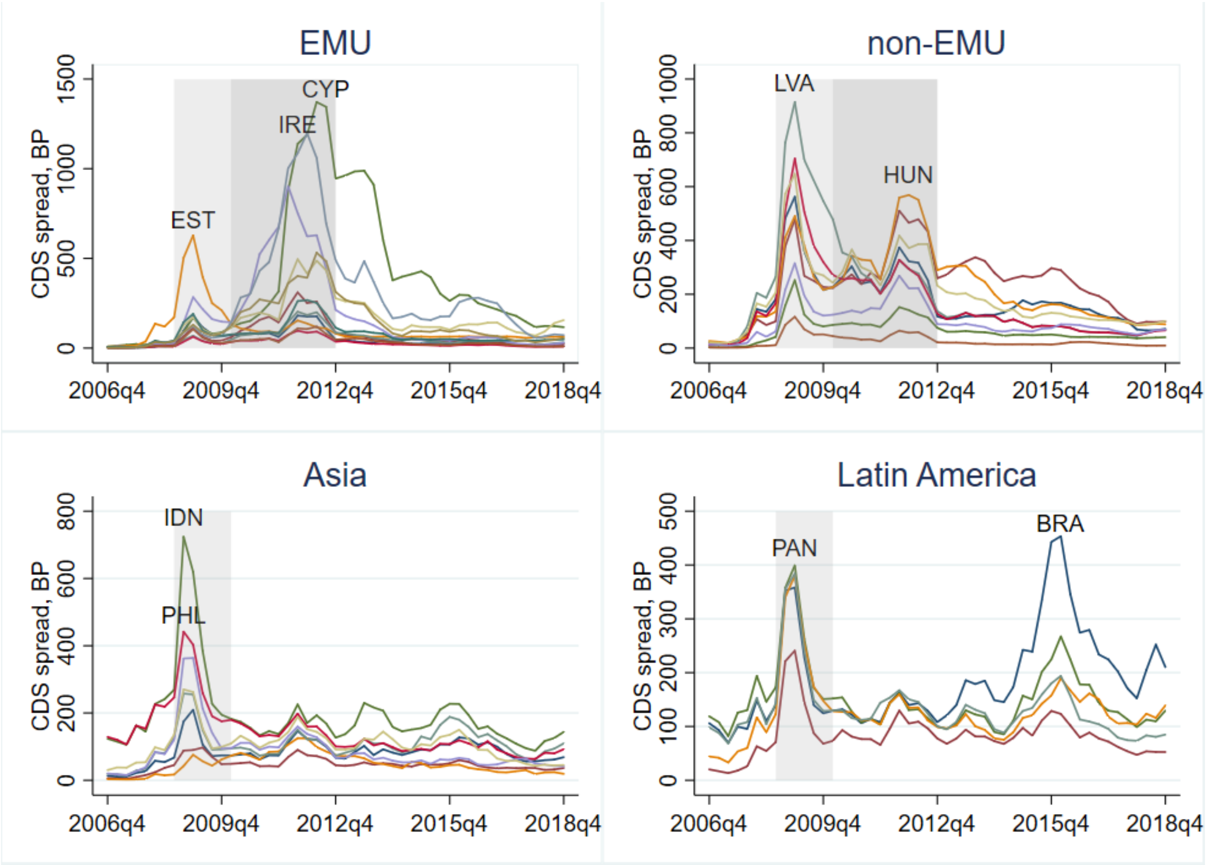

Figure 2: Plots of CDS spreads by region

PC analysis

As a preliminary analysis, we employ principal component analysis to estimate the common factors of sovereign CDS spreads. This preliminary analysis extends and confirms the results of Pan & Singleton [59] and Longstaff et al. [53] by using a more recent and broad dataset. Based on the results from information criteria, the optimal number of factors (k) is estimated as 5*. In Table 2, we report the average of the explained variances by the first principal component in each region†. They reflect the relative contribution of the first principal component to the variation of sovereign CDS. The detailed results of each country are given in Appendix A. To see whether effects change over time, we have divided the sample into three different periods: pre-crisis, crisis,

*The procedures for principal component analysis including the information criterion that we use are formulated in Appendix B.

†Here, after PCs are estimated, we evaluate the percentage of variances explained by each PC for each country based on equation (5) in Appendix B. Table 2 gives the summary of this measure by region and by three different time periods. This result can be compared to the corresponding result from the dynamic factor model in the next section.

Table 2 Contribution of the first PC: Regional averages

	Full Sample	**Pre-Crisis**	**During Crisis**	**Post-Crisis**
World	0.639	0.933	0.616	0.693
	(0.217)	(0.081)	(0.378)	(0.340)
EMU	0.554	0.923	0.218	0.903
	(0.197)	(0.095)	(0.294)	(0.056)
non-EMU	0.846	0.971	0.793	0.903
	(0.107)	(0.037)	(0.165)	(0.056)
Asia	0.650	0.953	0.777	0.564
	(0.154)	(0.031)	(0.320)	(0.343)
Latin America	0.487	0.867	0.930	0.130
	(0.245)	(0.112)	(0.024)	(0.134)

Note: The numbers in the parentheses are standard deviations of the associated means.

and post-crisis periods. We did so to see whether comovements were affected by the volatilities caused by the financial crisis. The pre-crisis sample includes dates before the third quarter of 2008, the crisis period consists of the time between the fourth quarter of 2008 and the first quarter of 2011, and the post-crisis period encompasses dates after the first quarter of 2011.

Table 2 shows that, on average, 64 percent of the variance in sovereign CDS spreads is explained by the first principal component. This result is in line with the findings of Longstaff et al.[53]. Considering the sub-samples, the period before the financial crisis has strikingly high percentages explained by a common factor (i.e., the first principal component), reaching as high as 97 percent for non-EMU countries. It is interesting to note that the relative contribution of the first principal component is generally lower during the financial crisis, except for the countries in Latin America. The share of the variance explained by the first principal component is much lower in the EMU countries than non-EMU countries and the rest of the countries. On the other hand, this common factor's relative contribution is higher after the financial crisis in both EMU and non-EMU countries than in the rest of the nations. In addition, it is also worth mentioning that the standard deviation of the relative contribution is higher during the financial crisis period and onward.

Although principal component analysis is a convenient tool to estimate commonalities among time-series, one of its major shortcomings is that it assumes the relative contribution of principal components to be constant over time. This feature is rather restrictive. Therefore, we consider a more general dynamic factor model in the next section.

Bayesian Dynamic Factor Analysis

The model

Following the influential work of Del Negro & Otrok [37], we consider the following dynamic latent factor model with the world and regional factors:

$$y_{i,t} = \alpha_i + \beta_{i,t} f_t^w + \gamma_{i,t} f_t^r + \varepsilon_{i,t} \tag{1}$$

where, $y_{i,t}$ is a change in sovereign CDS spreads of country i at time t, and f_t^w and f_t^r represent the world and regional factors respectively. $\beta_{i,t}^w$ and $\beta_{i,t}^r$ are time-varying factor loadings, which measure changing sensitivities of country i to world and regional factors and both follow a random walk process:

$$\delta_{i,t} = \delta_{i,t-1} + \eta_{i,t} \tag{2}$$

where, $\delta = [\beta \quad \gamma]'$ and $\eta_{i,t} \sim N(0, \sigma_{\eta_i}^2)$. The innovations to the model parameters $\eta_{i,t}$ are assumed to be independent across countries. This assumption is necessary for the co-movements to stem solely from the world and regional factors. The idiosyncratic component in this setup, given by $\varepsilon_{i,t}$, is believed to capture variances in CDS spreads which are country-specific, as well as measurement errors in the data. Following the standard technique in the dynamic factor literature, we further allow the factors and idiosyncratic term to follow AR(q) and AR(p_i) processes respectively:

$$f_t = \phi_{0,1} f_{t-1} + \cdots + \phi_{0,q} f_{t-q} + exp\{h_{0,t}\} u_{0,t} \tag{3}$$

$$\varepsilon_{i,t} = \phi_{i,1}\varepsilon_{i,t-1} + \cdots + \phi_{i,q}\varepsilon_{i,t-p_i} + exp\{h_{i,t}\}u_{i,t} \tag{4}$$

where, $u_{i,t} \sim i.i.d.N(0, \sigma_i^2)$, for $i = 0, 1, 2, ..., n$. For estimation purposes, we select $q = p_i = 2$. The stochastic volatility is introduced to the model through the term $exp\{h_{i,t}\}$, where $h_{i,t}$ follows a random walk process:

$$h_{i,t} = h_{i,t-1} + \sigma_i^h \nu_{i,t} \tag{5}$$

where, $\nu_{i,t} \sim i.i.d.N(0, 1)$, for $i = 0, 1, 2, ..., n$ and σ_i^h represents the standard deviation of $h_{i,t}$ measuring the degree of time-variation in factors. The key assumption in the above-stated model is that $u_{i,t}$'s are independently and identically distributed across countries and across time which removes the possibility of cross-sectional dependencies in idiosyncratic terms.

In order for the model given by conditions (1)-(5) to be fully identified, one has to introduce few more identification restrictions. Namely, neither signs nor scales of factors and factor loadings are separately identified*. We tackle the first issue by restricting the loadings of global factor for Austria to be positive. For regional factors, we restrict regional loadings for Belgium, Bulgaria, China and Brazil to be positive. To bypass the second issue, as it is standard in the literature†, we simply set all factor shock variances given by σ_i^2 $(i = 0, 1, 2, ..., n)$ equal to a constant.

To construct our parameters and factors given in equation (1), we use Bayesian Markov Chain Monte Carlo (MCMC) estimation technique which is designed to perform successive draws from the joint posterior distribution of factors and parameters. In our estimations, we set the number of iterations to 11,000 including the 1,000 initial burn outs. Following the works of Chib & Greenberg[30], Kim et al.[48], Otrok & Whiteman[58], we use "Gibbs sampler" procedure to sample from the full set of conditional distributions

*For instance, one could multiple all factors and factor loading by -1 and arrive with exactly the same model. Similarly, one can multiply some constant ρ to the factor loadings given by $\beta_{i,t}$ to get $\tilde{\beta_{i,t}} = \rho\beta_{i,t}$ and use $\tilde{f_t} = f_t/\rho$ to acquire similar model.

†See Sargent et al.[65] and Stock & Watson[66] for the details of such normalization for identification purposes.

*.

Finally, we conduct variance decomposition analyses using the equation (1) to see how the importance of various factors in explaining the variation in sovereign CDS spreads has changed over time. We use the following equation to derive our estimates for variance contributions:

$$var(y_{i,t}) = \beta_{i,t}^2 var(f_t^w) + \gamma_{i,t}^2 var(f_t^r) + var(\varepsilon_{i,t}) \tag{6}$$

Then, variance contributions of global and regional factors can be calculated through the following pair of ratios:

$$\theta_{i,t}^w = \frac{\beta_{i,t}^2 var(f_t^w)}{var(y_{i,t})}, \quad \theta_{i,t}^r = \frac{\gamma_{i,t}^2 var(f_t^r)}{var(y_{i,t})} \tag{7}$$

The significance of estimated factors

We plot the estimated global and regional factors from equation (1) in Figures 3 and 4, respectively. The dotted lines around the estimated global factor indicate 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles from our simulations and they show how precisely the successive draws have been generated. The plot of the estimated global factor shows a high peak around 2008, which seems to capture the uncertainty associated with the global financial crisis. It also shows a mild increase between 2011 and 2012, which coincides with the European debt crisis. It seems clear that the global financial crisis caused more uncertainty both in terms of magnitude and volatility, compared to the European sovereign debt crisis. The presence of volatility in the global factor around the European sovereign debt crisis period indicates that spillovers from Europe to other regions of the world were sizeable. However, the estimated global factor has decreased significantly from 2014 and has converged to almost zero over time. This observation clearly shows that the global factor's significance has been changing. It undermines the previous results of the extremely high level of the common factors from the principal component analysis.

*Interested readers can consult with Appendix section of Bhatt et al.[25] to get a better insight into this procedure. We are grateful to the authors of this paper for sharing the Matlab codes for the key procedures of the MCMC estimation.

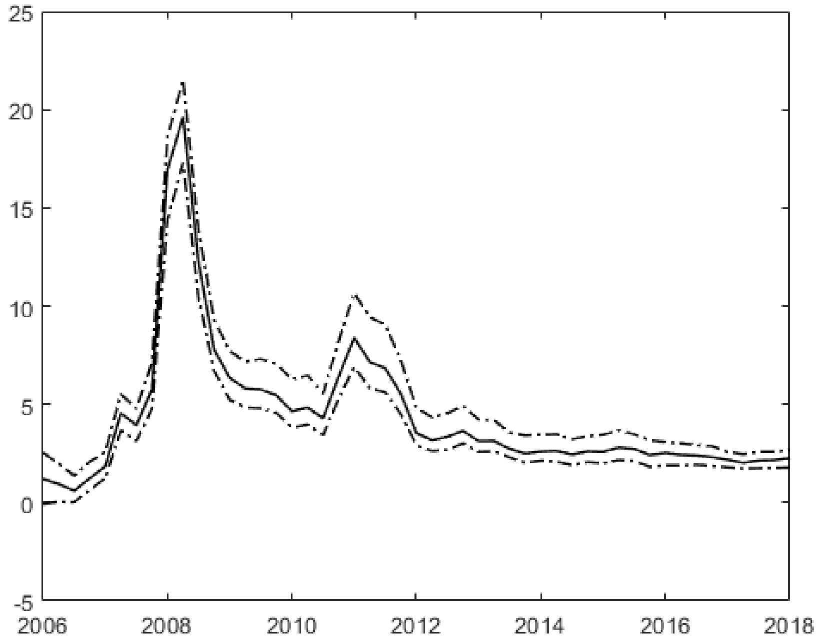

Figure 3: Estimated Global Factor

We observe that the end of the European sovereign debt crisis has led to a breakdown in the comovements on the global level. Global comovements are present only in times of economic distress, while in tranquil times, CDS spreads tend to be country-specific. These results show a big contrast compared to the results from principal components analysis, suggesting that the effects of global comovements are time-varying.

Turning to the estimated regional factors in Figure 4, it can be observed that regional factors are a lot more volatile than the global factor. A visual examination of the estimated regional factors of EMU and non-EMU reveals that they both have a distinct upsurge starting from the beginning of 2008, when the financial crisis started unfolding, until the start of 2012 when some troubled EMU governments agreed on an array of austerity measures.*. This observation shows how the onset of the subprime mortgage crisis, which originated in the U.S., spurred an increase in regional uncertainty, which eventually led to the European debt crisis. The degree of resemblance between the two regional factors points to the fact that the regional spillover from EMU to the non-EMU region of Europe was indeed sizeable. Further scrutiny of the EMU

*In particular, the government of Greece was under pressure to get austerity measures approved to qualify for the second round of bailouts from Eurozone (https://www.bbc.co.uk).

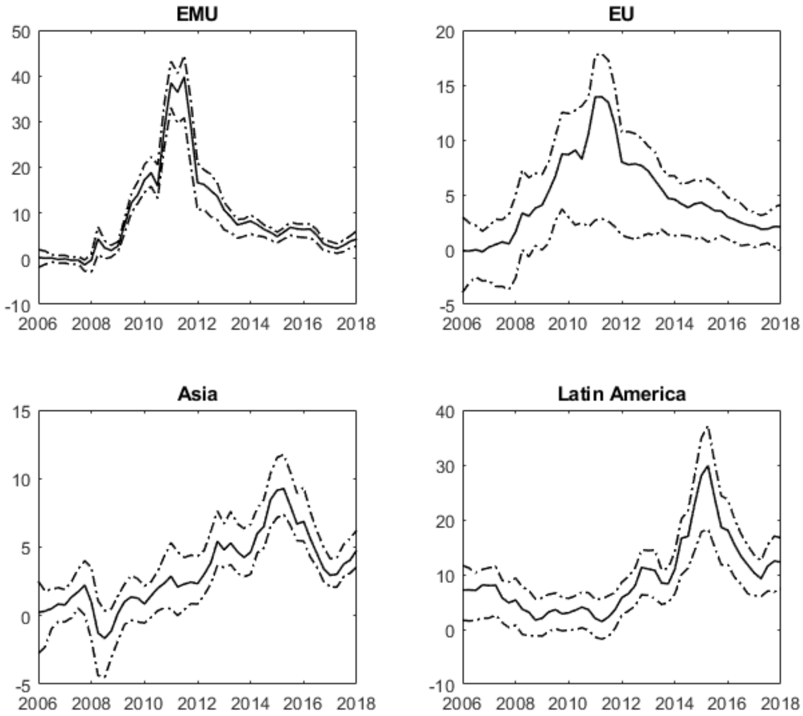

Figure 4: Estimated Regional Factors

factor shows a slight increase in the regional uncertainty at the beginning of 2016. This period coincides with the start of Brexit speculations, which led the British government to hold a referendum in June of 2016, eventually electing to opt-out from the European Union. Interestingly, even though the United Kingdom was a member of the E.U., it seems that the impact of Brexit speculations was isolated to the EMU region only.

Looking at the lower panels of Figure 4, we can see that there are a lot of similarities between the estimated regional factors of Asian and Latin American countries. Both Asian and Latin American regional factors demonstrate a relatively steady pattern up to the end of 2012, before up-ticking. The Asian regional factor seems to have undergone a swift decline right before the financial crisis, increasing steadily until 2016. A similar trend is noticeable in the Latin American regional factor, which ironically saw a relatively steady level during the financial crisis and the European debt crisis, before starting to trend upwards around 2012 and peaking at the start of 2016. It is hard to pinpoint a possible cause of such a sudden gain across both regions. Another remarkable climb across graphs starts around the middle of 2014 and peaks around the beginning of 2016, which is a lot more pronounced in the Latin American region. This pattern is most likely the result of uncertainty caused by the decline in oil prices, which started in June 2014 and lasted until February of 2016 before reverting. One of the causes of the price drop in the crude oil market was the slowdown in the Chinese economy, which, in turn, might have served to increase the skepticism among investors regarding the Asian economy.

Contributions of the Factors

The results discussed in the previous subsection demonstrate the presence of both global and regional factors in the CDS spreads. We use equation (7) to decompose the variance of CDS spreads to examine the shares of the global, regional, and country-specific factors. They reflect the time-varying nature of each factor's relative contribution to the variation of the CDS spreads in each country.

In Figures 5 - 8, we report the plots of each country by region. We can see that the global factor has contributed significantly to the variation of sovereign CDS spreads across many countries. However, the degree of involvement of the global factor varies markedly across countries and regions.

First, looking at the patterns in Figure 5, we find that the regional factor contributes more than the global factor, especially in the EMU countries. The regional factor's significance is more pronounced in Belgium, France, Germany, Italy, Netherlands, and Spain. In a few countries, such as Ireland, Portugal, and Cyprus, there is little to no contribution from the global factor. All these countries, along with Greece, were in the center of the Eurozone debt crisis. Therefore, it is not surprising to see that their CDS spreads are mainly explained by their country-specific factors during the crisis. In Estonia, which entered the Eurozone in 2011, the regional factor's effect is almost negligible, but the global factor's influence is highly significant. Slovakia showed a sudden increase in the regional factor's influence from right around when it entered the Eurozone in 2009.

Contrary to the results found in the EMU countries, the world factor explains higher shares of the variation of CDS in non-EMU countries; see Figure 6. Furthermore, there

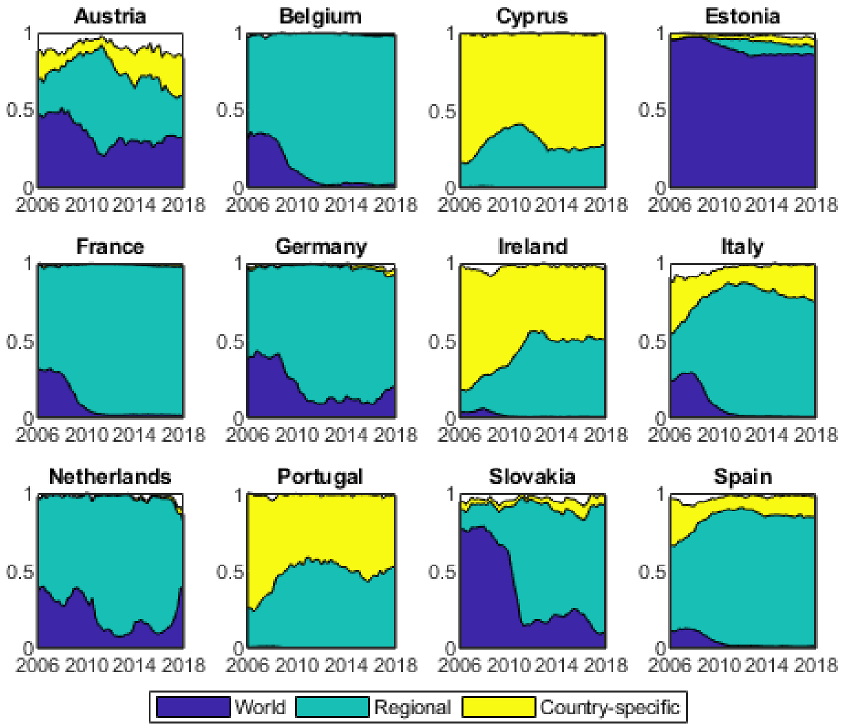

Figure 5: Variance Contributions for EMU countries

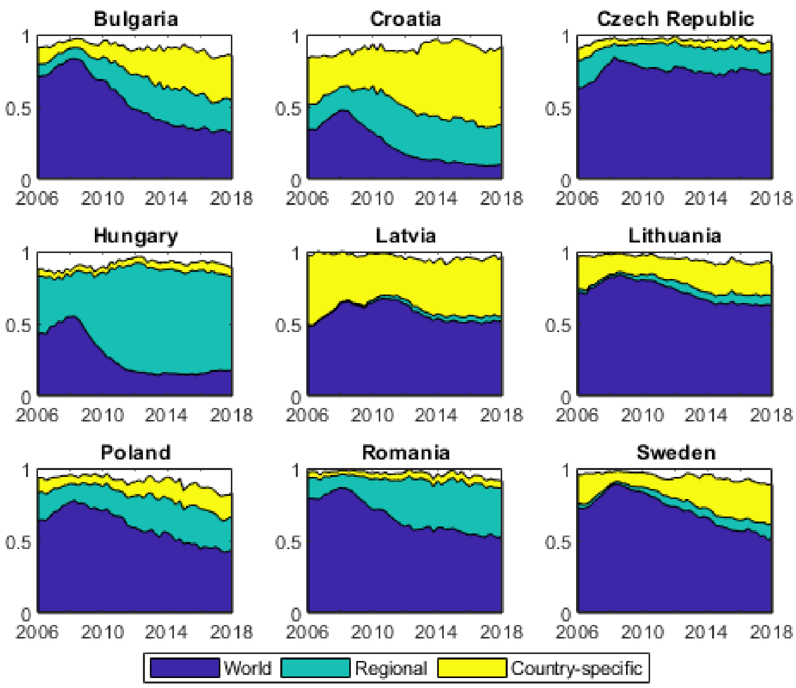

Figure 6: Variance Contributions for EU countries

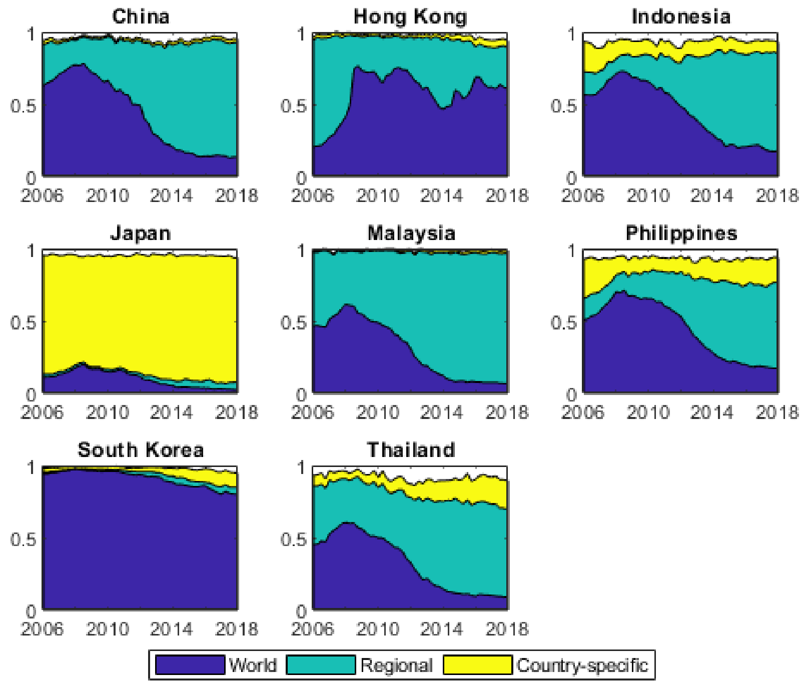

Figure 7: Variance Contributions for Asian countries

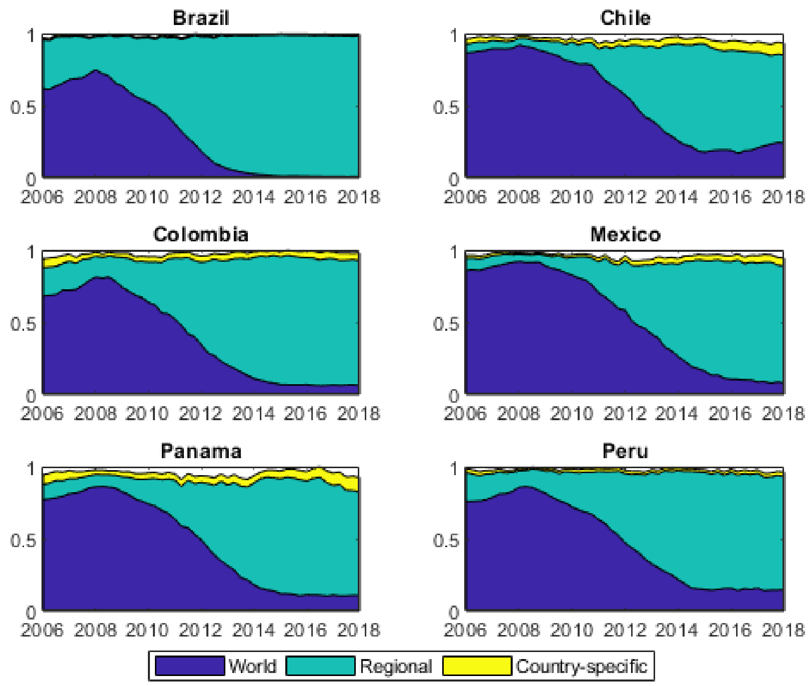

Figure 8: Variance Contributions for Latin-American countries

are many more similarities across countries regarding the effect of the global factor, an indication of higher dependence on the global economy. The general trend indicates that the regional factor's influence on the CDS spreads is gradually fading away. Interestingly, both Latvia and Lithuania have a lot less regional shares present in their variance decomposition, while these two countries joined the Eurozone in 2014 and 2015, respectively. At the same time, countries like Bulgaria, Croatia, Poland, and Sweden seem to have increasingly less global and regional importance in their sovereign CDS spreads.

In contrast to their European counterparts, Asian (Figure 7) and Latin American (Figure 8) countries show higher regional homogeneity. We observe that the relative importance of the global factor has been significant in most countries in both regions. However, its effect has decreased gradually in recent years, as shown in the EMU and non-EMU regions. In Asia, the two countries show distinctive patterns. Korea shows a highly significant share of the global factor. On the other hand, Japan shows very little global and regional influence.

To give an additional perspective, Table 3 provides the average of the explained variances for the full sample and three sub-samples: pre-crisis, crisis, and post-crisis. The world average of the global factor's relative contributions to the variation of sovereign CDS spreads is 44 percent. This value is lower than the corresponding value of 64 percent from the principal components analysis or other higher values reported in previous studies. We observe that the average value of the explained variances for the global factor stands at just 27 percent in the EMU region. In contrast, for non-EMU, Asia, and Latin America, the global factor explains, on average, 64 percent, 45 percent, and 49 percent, respectively. Considering the sub-samples, in three out of four regions, we observe a decline in the explained variance by the global factor from the pre-crisis period into the crisis and onward. We observe significant regional effects in the EMU region during the financial crisis (57 percent) and in the post-crisis period (65 percent). The effect of the global factor is small (19 percent) in EMU. On the other hand, the regional effect is negligible (7 percent) in the non-EMU region in the same period, and the effect of the global factor is rather large (57 percent). The effects of the country-specific factor are only notable in the non-EMU region.

For the last part of our discussion on the importance of global and regional factors, we have computed the correlation coefficients between each country's CDS spreads in our sample and each of the estimated global and regional factors. Our results mimic the variance decomposition outcomes derived using principal components. The results are presented in Table 4. In general, correlations of country CDS spreads with the global factor are sizeable, which confirms the robustness of our results.

Overall, there is undoubted evidence of the global factor present in the dynamics of CDS spreads across countries, in line with the current literature. We find that regional factors manifest themselves and gain more significance since the end of the global economy's tumultuous period. It seems that this point might have been mainly overlooked in the literature. Lastly, the equally important finding suggests that global factor has been receding after the financial crisis, making way for the regional and country-specific factors in many countries.

Relative Importance of the Factors

In this section, we analyze the determinants of CDS spreads. The goal is to evaluate the relative importance of the global and regional factors compared to global and country-specific macro variables. Previous studies recognize the importance of global macro variables as essential determinants of CDS spreads. Our analysis challenges this view. The question is, which variables are more important determinants of sovereign CDS spreads? We investigate the net effects of these variables in the presence of global and regional factors. We consider two sets of variables. The first one includes country-specific macro fundamentals, for which we consider the debt-to-GDP ratio, exchange rate volatility, and fiscal balance. The second set contains global macro variables, including oil prices, VIX, and the index of economic policy uncertainty (EPU).

We proceed with two different approaches. First, we estimate a dynamic structural VAR model with block-exogeneity restrictions and analyze the variance decomposition, which can give information on the relative importance of all variables in the system.

Table 3 Variance Contributions of Factors: Averages

Country	Full Sample		Pre-Crisis		Crisis		Post-Crisis	
	Global	Regional	Global	Regional	Global	Regional	Global	Regional
World	**0.44**	**0.36**	**0.61**	**0.21**	**0.55**	**0.29**	**0.32**	**0.46**
EMU	**0.27**	**0.57**	**0.46**	**0.34**	**0.29**	**0.57**	**0.19**	**0.65**
Austria	0.46	0.32	0.71	0.11	0.51	0.35	0.33	0.35
Belgium	0.27	0.72	0.50	0.49	0.12	0.87	0.25	0.73
Cyprus	0.01	0.37	0.02	0.27	0.01	0.47	0.02	0.36
Estonia	0.88	0.07	0.96	0.01	0.91	0.06	0.83	0.11
France	0.13	0.86	0.37	0.62	0.13	0.87	0.04	0.94
Germany	0.26	0.71	0.51	0.46	0.30	0.69	0.14	0.82
Ireland	0.03	0.44	0.06	0.17	0.03	0.39	0.01	0.57
Italy	0.15	0.84	0.5	0.48	0.17	0.81	0.00	0.99
Netherlands	0.44	0.54	0.67	0.32	0.58	0.41	0.29	0.68
Portugal	0.01	0.72	0.02	0.56	0.01	0.79	0.00	0.75
Slovakia	0.51	0.38	0.87	0.06	0.63	0.31	0.32	0.54
Spain	0.09	0.84	0.28	0.59	0.06	0.89	0.03	0.91
non-EMU	**0.64**	**0.06**	**0.72**	**0.04**	**0.73**	**0.04**	**0.57**	**0.07**
Bulgaria	0.63	0.06	0.81	0.03	0.77	0.04	0.49	0.07
Croatia	0.31	0.05	0.5	0.04	0.43	0.05	0.18	0.06
Czech Rep	0.85	0.07	0.81	0.08	0.91	0.05	0.84	0.07
Hungary	0.35	0.11	0.51	0.08	0.43	0.08	0.25	0.13
Latvia	0.63	0.01	0.54	0.04	0.66	0.01	0.65	0.01
Lithuania	0.79	0.02	0.83	0.01	0.86	0.01	0.74	0.02
Poland	0.73	0.11	0.79	0.07	0.79	0.06	0.61	0.12
Romania	0.76	0.11	0.88	0.05	0.84	0.07	0.68	0.16
Sweden	0.78	0.02	0.81	0.02	0.89	0.01	0.71	0.03
Asia	**0.45**	**0.33**	**0.61**	**0.21**	**0.58**	**0.19**	**0.31**	**0.44**
China	0.42	0.51	0.63	0.31	0.68	0.26	0.21	0.71
Hong Kong	0.64	0.30	0.57	0.29	0.77	0.17	0.53	0.37
Indonesia	0.46	0.36	0.6	0.13	0.65	0.17	0.31	0.54
Japan	0.15	0.04	0.18	0.03	0.15	0.02	0.05	0.04
Malaysia	0.32	0.65	0.57	0.41	0.52	0.45	0.12	0.84
Philippines	0.45	0.31	0.57	0.14	0.65	0.17	0.30	0.45
South Korea	0.88	0.03	0.93	0.01	0.95	0.01	0.82	0.05
Thailand	0.35	0.42	0.55	0.28	0.53	0.29	0.18	0.54
Latin America	**0.49**	**0.44**	**0.8**	**0.14**	**0.72**	**0.22**	**0.25**	**0.67**
Brazil	0.34	0.64	0.67	0.31	0.54	0.44	0.11	0.86
Chile	0.58	0.33	0.89	0.05	0.83	0.11	0.33	0.55
Colombia	0.42	0.52	0.75	0.17	0.67	0.27	0.17	0.75
Mexico	0.57	0.37	0.89	0.08	0.83	0.14	0.31	0.63
Panama	0.51	0.37	0.81	0.12	0.74	0.17	0.28	0.57
Peru	0.52	0.44	0.82	0.14	0.74	0.22	0.29	0.66
Peru	0.48	0.48	0.8	0.16	0.72	0.24	0.23	0.72

Table 4 Correlation of Sovereign CDS with Global and Regional factors

Country	Full Sample		Pre-Crisis		Crisis		Post-Crisis	
	Global	Regional	Global	Regional	Global	Regional	Global	Regional
World	**0.72**	**0.40**	**0.98**	**0.23**	**0.59**	**0.32**	**0.66**	**0.79**
EMU	**0.53**	**0.80**	**0.98**	**0.26**	**0.26**	**0.80**	**0.88**	**0.92**
Austria	0.81	0.70	0.96	0.35	0.58	0.77	0.89	0.84
Belgium	0.51	0.93	0.97	0.31	0.11	0.97	0.92	0.95
Cyprus	0.15	0.85	0.96	0.36	0.20	0.91	0.94	0.95
Estonia	0.95	-0.09	1.00	0.10	0.82	-0.53	0.57	0.60
France	0.44	0.97	0.99	0.25	0.17	0.98	0.92	0.98
Germany	0.64	0.88	0.96	0.35	0.27	0.96	0.90	0.95
Ireland	0.47	0.86	0.95	0.38	-0.06	0.84	0.92	0.99
Italy	0.37	0.95	1.00	0.17	0.19	0.96	0.85	0.96
Netherlands	0.72	0.79	0.96	0.36	0.43	0.87	0.92	0.94
Portugal	0.28	0.97	0.99	0.15	0.07	0.97	0.92	0.90
Slovakia	0.69	0.82	1.00	0.17	0.39	0.88	0.90	0.94
Spain	0.36	0.96	0.99	0.17	-0.05	0.96	0.92	0.98
non-EMU	**0.89**	**0.47**	**0.99**	**0.96**	**0.66**	**0.11**	**0.80**	**0.78**
Bulgaria	0.95	0.41	1.00	0.97	0.84	0.17	0.28	0.36
Croatia	0.65	0.75	1.00	0.96	0.36	0.66	0.83	0.88
Czech Republic	0.93	0.50	0.98	0.94	0.72	0.40	0.95	0.94
Hungary	0.77	0.74	1.00	0.97	0.48	0.60	0.97	0.95
Latvia	0.94	0.12	1.00	0.97	0.58	-0.88	0.92	0.95
Lithuania	0.97	0.27	1.00	0.97	0.86	-0.63	0.90	0.95
Poland	0.89	0.58	0.99	0.95	0.64	0.53	0.78	0.62
Romania	0.95	0.47	1.00	0.97	0.58	0.37	0.96	0.94
Sweden	0.96	0.35	0.98	0.93	0.92	-0.19	0.59	0.47
Asia	**0.79**	**-0.07**	**0.98**	**0.07**	**0.75**	**0.07**	**0.58**	**0.55**
China	0.74	0.26	1.00	-0.01	0.65	0.51	0.26	0.90
Hong Kong	0.82	-0.04	0.97	0.16	0.95	-0.04	0.64	0.60
Indonesia	0.85	-0.15	0.97	0.09	0.91	-0.54	0.57	0.74
Japan	0.54	-0.17	0.97	-0.16	0.09	0.84	0.92	-0.08
Malaysia	0.67	0.38	0.98	0.14	0.89	0.16	0.12	0.98
Philippines	0.87	-0.46	0.97	0.19	0.89	-0.50	0.71	0.61
South Korea	0.98	-0.37	0.99	0.02	0.97	-0.32	0.75	-0.03
Thailand	0.85	-0.01	0.98	0.13	0.65	0.47	0.65	0.64
Latin America	**0.72**	**0.15**	**0.99**	**-0.71**	**0.92**	**0.00**	**0.12**	**0.88**
Brazil	0.20	0.75	0.99	-0.68	0.96	-0.01	-0.20	0.98
Chile	0.85	0.01	1.00	-0.75	0.92	-0.30	0.41	0.78
Colombia	0.71	0.22	0.99	-0.70	0.86	0.16	-0.04	0.98
Mexico	0.85	0.01	1.00	-0.74	0.92	0.04	-0.17	0.87
Panama	0.85	-0.02	0.99	-0.72	0.92	0.08	0.32	0.84
Peru	0.87	-0.05	0.99	-0.68	0.91	0.03	0.39	0.80
Peru	0.48	0.48	0.8	0.16	0.72	0.24	0.23	0.72

Second, we conduct a static partial correlation analysis. We wish to analyze the net correlation coefficients of determinant variables. We restrict our analysis to the sub-sample of EMU and non-EMU countries due to data availability.

Structural VAR Analysis

We consider the following VAR model for each country in our sample::

$$A(L)X_t = e_t \tag{8}$$

where each $A(L)$ is a matrix of coefficients, e_t is a vector of error terms with $E(e_t) = 0$ and $E(e_t e_t') = \Sigma_e$, and X_t is a vector containing six variables. We separate variables into exogenous (or global) and endogenous (or domestic) block, e.g. $X_t = X_{1t} + X_{2t}$. Block-exogeneity restrictions imply that any variable in an exogenous block is not under the influence of the variables in an endogenous block in any period, where the endogenous block contains national variables, and the exogenous block contains the global variables and factors. The exogenous or global block X_{1t} contains global CDS factor. We define it as:

$$X_{1t} = [f_t^w]$$

The endogenous block X_{2t} contains regional CDS factor and domestic variables together with the CDS of a particular country, or more formally:

$$X_{2t} = [f_t^r \quad balance_t \quad exv_t \quad debt_t \quad CDS_t]$$

where f_t^r is the regional CDS factor, $balance_t$ is a fiscal balance, exv_t is exchange rate volatility, $debt_t$ is debt to GDP ratio, and the last variable is CDS of the corresponding country.

We impose block-exogeneity restrictions by setting $A_{12}(L) = 0$ implying that variables in the exogenous block are not affected by the variables in endogenous block in any period, thus estimating the following SVAR model:

$$\begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \tag{9}$$

This restriction is often used for an SVAR model in a small open economy; see, for example, Cushman & Zha[34], Givens & Reed[44] or Dallari & Ribba[36]. A small open economy is exposed to global shocks while global shocks are independent, affecting all countries uniformly.

We also consider an alternative SVAR model with a set of global macro variables and global and regional CDS factors. In this model, the exogenous block X_{1t} is defined as:

$$X_{1t} = [oil_t \quad VIX_t \quad EPU_t \quad f_t^w]$$

where oil_t is oil prices measured by West Texas Intermediate (WTI) crude oil price as a proxy for the global oil price, VIX_t is S&P500 volatility index (VIX), and EPU_t is the economic policy uncertainty index developed by Baker et al.[22]. A domestic block is then defined as:

$$X_{2t} = [f_t^r \quad CDS_t] \tag{10}$$

and it consists of the regional CDS factor and CDS of particular country assuming that neither regional factor nor CDS can affect global macro variables or global CDS factor in any period. Therefore, we apply restriction from equation (9).

To identify structural shocks from the model outlined in (9), we first rewrite the model in the form of moving average where $X_t = Q(L)e_t$ and then impose recursive restrictions in the form of lower triangular matrix between the variables, or:

$$X_t = B(L)\omega_t \tag{11}$$

where $B(L) = Q(L)C$ and structural shocks are $\omega_t = C_t^{-1}e_t$, with C being a Cholesky factor. We impose the following ordering of variables: the regional factor, fiscal balance, exchange rate volatility, debt to GDP ratio, and CDS of a particular country. In that case, the CDS of a particular country cannot affect the debt to GDP ratio, exchange rate volatility, fiscal balance, and the regional factor within the period. The global factor is not affected by domestic variables in any period due to block-exogeneity restrictions. In the case of the model with global variables, CDS of a particular country again cannot affect the regional factor of CDS within the period. Recursive restrictions in a global block suggest that oil prices will not respond to any other shock within the period as they often approximate supply shocks. VIX and EPU are uncertainty indicators, and they will respond only to changes in oil prices. VIX is often used as a global uncertainty measure, and it can also represent the global financial cycle (Rey[63]). Thus, we order it before the economic policy uncertainty index. Finally, we assume that the global factor of CDS will respond to shocks in global variables.

The analysis aims to identify the major determinants and driving sources of sovereign CDS spreads of each country. We are primarily interested in the variance decomposition to see how much the variables in the model can explain the variation in CDS. The model with four lags is estimated for each country by Seemingly Unrelated Regressions (SUR), and the variance decomposition is obtained from the Gibbs sampling procedure, as done in Doan[38] and Dallari & Ribba[36]. For this, we evaluate median values from the Bayesian estimation. For a robustness check, we also estimate a simpler VAR model with recursive short-run restrictions on the parameters rather than block-exogeneity restrictions and compare the variance decomposition results. Using four lags is common for quarterly data; see, for example, Givens & Reed[44].

The results on the variance decomposition at 1, 4, and 8 steps horizons are presented in Figure 9. They clearly show the importance and complete dominance of global and regional factors in explaining CDS variation in the short- and medium-run (at 1 and 8 steps horizon). The global and regional factors combined are much more important than domestic variables and explain over 60 percent of the variation of CDS. In many countries, their impact is over 80 percent. While global shocks to CDS are dominant in most countries, regional shocks seem to be especially important in some of the Eurozone countries (Belgium, Cyprus, Germany, France, Italy, Portugal, and Spain), which may suggest a high degree of integration among these countries.

We are primarily interested in the variance decomposition and how much variation in CDS can be explained by the variables in the model. The goal of the analysis is to identify major determinants and driving sources of sovereign CDS spreads of each country.

The model with four lags is also estimated for each country by SUR, and variance decomposition is obtained as a median from Gibbs sampling procedure, as suggested by Doan[38] and done in Dallari & Ribba[36]. For the robustness check we also estimate a simpler VAR model with recursive short-run restrictions on parameters, but without imposing block-exogeneity restrictions, and compare the variance decomposition between two models.

Variance decomposition results at 1, 4, and 8 steps horizons presented in Figure 9 clearly shows the importance and complete dominance of global and regional factors in explaining CDS variation both in the short- and medium-run (at 1 and 8 steps horizon). The global and regional factors combined are much more important than domestic variables and explain over 60 percent of CDS variation, but in many countries it is over 80 percent. While global shocks to CDS are dominant in most countries, regional shocks seem to be especially important in some of the Eurozone countries: Belgium, Cyprus, Germany, France, Italy, Portugal, and Spain, which suggests high degree of integration among these countries.

Regarding domestic variables, fiscal balance and debt to GDP have a somewhat important role, but it is not even close to the importance of global and regional shocks. Thus, this result makes a sharp contrast with many previous studies that have attempted to find the determinants of CDS spreads by using local economic fundamental variables but ignoring the global variables. Our finding sheds light on the importance of both global and regional factors in determining CDS spreads.

Figure 10 presents the results of the variance decomposition from the model with

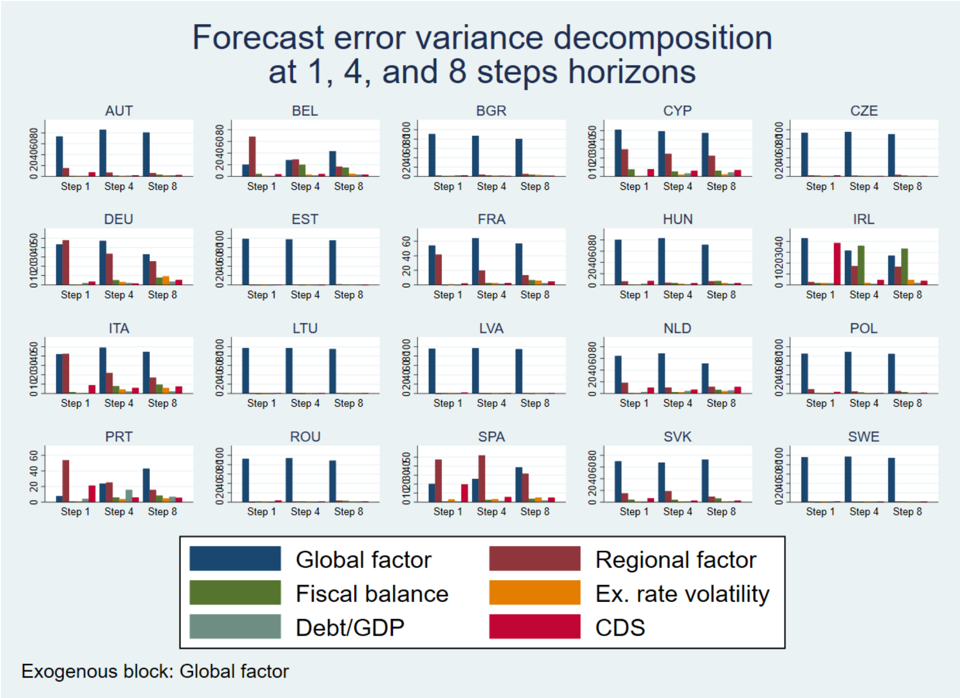

Figure 9: Forecast Error Var. Decomp.: Domestic Variables

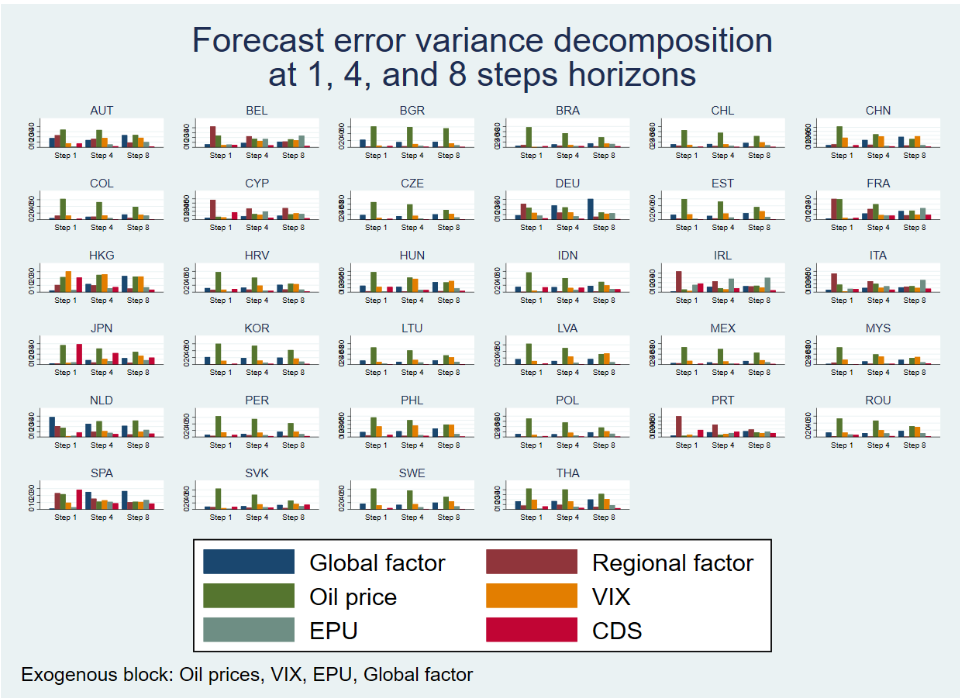

Figure 10: Forecast Error Var. Decomp.: Global Variables

global macro variables, which includes oil prices, VIX, economic policy uncertainty, and the global and regional factors of CDS. The results are very interesting. They indicate that in half of the countries of our sample, the global and regional CDS factors combined are as important or even more important in explaining the variation in CDS. The single most important variable is oil prices, and it dominates in many countries. However, the sum of the global and regional factors of CDS dominates and explains over 40 percent of the variation in many countries, including Austria, Belgium, Cyprus, Germany, France, Ireland, Italy, Netherlands, Portugal, and Spain. These results again present a strong case that the global and regional factors are very important determinants of the CDS, at least as important as global macro variables.

Overall, the results of both the model with domestic and global variables are qualitatively similar and robust when the model is estimated with the VAR model with the recursive short-run restrictions without the block-exogeneity assumption.

Partial correlation analysis

For the last part of our analysis, we check for the partial correlation of sovereign CDS with global and regional factors, given various global and local variables. Hence, we consider the following time-series regression model for each country i:

$$y_t^* = \beta_i' \mathbf{F}_t^* + \gamma_i' \mathbf{X}_t^* + \varepsilon_t \tag{12}$$

where y_t stands for the sovereign CDS of country i, F_t is a vector containing estimated global and regional factor and X_t contains control variables. We use two different model specifications: for the first model, we control for global variables:

$$(\mathbf{X}_t = [VIX_t \quad EPU_t \quad oil_t]'),$$

for the second specification, we control for local fundamentals instead:

$$(\mathbf{X}_t = [balance_t \quad exv_t \quad debt_t]')$$

The stars above the variables indicate standardized variables so that parameter estimates for β_i and γ_i stand for partial correlation coefficients.

Results of the partial correlation analysis are presented in Table 5, and they confirm major conclusions from the SVAR model. The partial correlation coefficients are obtained from the regression where all variables are standardized. The average partial correlation of the global factor for the countries in our sample stands at 0.61, and it is 0.52 for the regional factor. None of the local fundamentals seems to be highly correlated with CDS spreads in the presence of the global and local factors; the highest coefficient belongs to Cyprus for the debt-to-GDP ratio (0.26). Thus, this result makes a sharp contrast with many of the previous studies which have attempted to find the determinants of CDS spreads by using local economic fundamental variables but ignoring the global and local variables. Our finding sheds light on the importance of both global and regional factors in determining CDS spreads. The CDS spreads are more closely related to these factors than domestic macro variables.

A similar story follows when examining the effects of the global macro variables, the VIX index, the EPU index, and oil prices. The results suggest that the global and regional factors are even more pronounced than those suggested by the SVAR model. It seems that the results using the local macro variables are even stronger. On average, the partial correlation coefficients between CDS and global and regional factors are around 0.60 to 0.66. The partial correlation coefficients of the global macro variables, including the notable VIX index, are much smaller and even negligible in many countries. Although previous studies emphasize VIX as an essential determinant of CDS, our results are in sharp contrast. In the presence of global and regional factors, the net effect of VIX is not significant. This finding is a surprising result.

The partial correlation coefficient of the regional factor with CDS is 0.71, on average, in the EMU countries. It is greater than that of the global factor (0.39). The case with non-EMU countries is the opposite. The partial correlation coefficient of the global and regional factors is 0.87 and 0.22, on average, respectively. Again, the global and regional factors' net effects are highly significant, and the effects are greater than those of global variables.

Table 5 Partial correlation results

Country	Model 1 Global	Regional	Debt	Ex.Rate	Balance	Model 2 Global	Regional	VIX	EPU	Oil
World	**0.61**	**0.52**	**0.02**	**0.01**	**-0.01**	**0.66**	**0.48**	**-0.06**	**-0.02**	**-0.02**
EMU	**0.39**	**0.71**	**0.03**	**0.00**	**-0.01**	**0.43**	**0.70**	**-0.04**	**-0.03**	**-0.01**
Austria	0.66	0.53	-0.03	0.05	-0.09	0.89	0.56	-0.09	-0.15	-0.05
Belgium	0.28	0.86	-0.10	0.02	0.01	0.19	0.91	0.18	-0.04	-0.02
Cyprus	0.04	0.87	0.26	0.11	-0.07	0.23	0.77	-0.25	-0.09	0.08
Estonia	1.02	-0.35	0.01	0.02	0.00	1.11	-0.38	-0.11	0.01	-0.02
France	0.24	0.91	0.02	0.03	0.02	0.25	0.93	0.02	-0.06	-0.02
Germany	0.47	0.78	-0.02	0.00	-0.03	0.53	0.77	-0.03	-0.03	-0.01
Ireland	0.26	0.91	-0.18	-0.12	-0.17	0.09	0.79	0.17	0.13	0.05
Italy	0.27	0.85	0.19	0.01	0.08	0.19	0.89	-0.07	0.04	-0.08
Netherlands	0.61	0.61	0.11	-0.01	0.04	0.85	0.61	-0.23	-0.08	-0.01
Portugal	0.14	0.94	0.07	-0.09	0.04	0.03	0.98	0.07	-0.05	-0.02
Slovakia	0.61	0.72	0.06	-0.06	0.13	0.65	0.71	-0.03	-0.14	-0.01
Spain	0.07	0.91	-0.08	0.07	-0.07	0.16	0.84	-0.09	0.13	0.04
non-EMU	**0.87**	**0.22**	**0.02**	**0.03**	**-0.01**	**0.97**	**0.19**	**-0.09**	**-0.02**	**-0.03**
Bulgaria	0.95	0.17	0.12	0.09	0.02	0.85	0.26	0.11	-0.1	-0.13
Czech Republic	0.89	0.22	0.06	0.08	0.04	1.08	0.23	-0.25	0.02	-0.11
Hungary	0.65	0.69	-0.16	0.09	0.05	0.85	0.51	-0.22	-0.03	0.09
Latvia	0.89	-0.17	0.04	-0.02	-0.17	0.97	-0.16	-0.01	-0.04	0.05
Lithuania	0.78	0.09	-0.11	0.02	-0.19	1.07	0.01	-0.07	-0.05	0.03
Poland	0.88	0.35	0.10	0.03	0.09	0.90	0.39	-0.09	-0.01	-0.11
Romania	0.85	0.27	-0.07	0.04	0.02	0.86	0.18	-0.04	0.11	0.05
Sweden	1.08	0.11	0.17	-0.05	0.04	1.11	0.12	-0.17	-0.02	-0.15

Concluding Remarks

The recent global financial crisis followed by the European sovereign debt crisis has increased the interest of researchers and policymakers to discover a reliable measure of sovereign risk associated with countries. Given the direct implications of sovereign credit risk towards borrowing costs of a country, understanding the components and drivers of the sovereign credit risk is pivotal from the standpoint of long-term economic growth. Among the few other measures of sovereign risk, sovereign credit default swaps (CDS) are increasingly accepted in the financial world as a reliable gauge of such risk. They are being used by researchers and policymakers to understand the dynamics of sovereign credit risk.

In this chapter, we have examined international comovements and the dynamics of sovereign CDS. Following the recent advances in Bayesian econometrics, we employed a dynamic factor model with time-varying parameters, which was initially developed by Del Negro & Otrok[37]. We find clear evidence of the presence of the global and regional factors that drive sizable comovements in sovereign CDS spreads across the world. We find that the global factor explains, on average, 44 percent of the variation of sovereign CDS spreads, while the regional factor accounts for 36 percent. The effects of the regional factor are larger than that of the global factor in the EMU and Latin American countries during and after the financial crisis period, while its effect is negligible in non-EMU countries.

We showed that although the global factor indeed exists, its effect is diminishing in terms of its importance and increasingly playing less role in affecting sovereign CDS spreads. The significance of the global factor has diminished after the financial crisis. In contrast, our findings suggest that regional factors are, in turn, getting more and more important. Their effects have been more significant during the financial crisis period and onward in comparison to the period of the financial crisis.

We also presented clear evidence that the global and regional factors are much more important and dominant determinants for sovereign CDS spread in many countries than domestic economic fundamentals, such as public debt, budget deficit, and exchange rate volatility. Moreover, our results from the structural VAR models and partial correlation analysis show that the net effects of the global and regional factors far exceed the net effects of the global macro variables, such as VIX, oil prices, and uncertainty. Our results make a sharp contrast with previous studies that recognize global variables as essential components for the sovereign CDS.

INTERNATIONAL COMOVEMENTS AND

DETERMINANTS OF PUBLIC DEBT

Introduction

Traditional views on public debt suggest that public debt critically depends on a given country's politico-economic stance. An individual country accumulates public debt due to its economic conditions, mainly through government deficits. Imposing this viewpoint, one could argue that public debt is primarily determined by the economic fundamentals, such as primary surplus, GDP growth, inflation rate, and political and institutional background. Indeed, they are proven to be important determinants of public debt for an individual country (Barro[23]; Roubini & Sachs[64])[*].

There can be, however, other exogenous or non-domestic factors that significantly affect public debt. For example, the events around the recent sovereign debt crisis in the Eurozone that followed the global financial crisis have signaled that public debt is not purely determined within a country's borders. Besides, the global pandemic caused by COVID-19 at the start of 2020 is well on track to magnifying public debt levels across countries in a simultaneous fashion. Many governments activated fiscal stimulus packages of unprecedented levels. These and other examples signify that countries are not immune to global shocks to public debt levels that often bear a contagious nature. Spillover effects occur in our inherently fluid society, as turbulence inside one country tends to spread to others through the flow of people, goods, and information. Thus, one may expect a synchronization or commonalities in major economic variables.

Indeed, the literature has established evidence of common factors that affect major economic variables in many countries simultaneously. Earlier work presents empirical results of the so-called global business cycle. For example, Kose et al.[49] have

[*]There is a large body of literature that examines the effects of public debt on economic growth. Reinhart & Rogoff[62] argue that public debt higher than 90 percent could undermine GDP growth. This line of argument has been recently challenged by Chudik et al.[32]. Arčabić et al.[10] also finds that there might be no unique threshold debt ratio that hurts economic growth. They note that the intertemporal effect of public debt on economic growth is weak. Instead, the effect of economic growth on public debt is strong.

investigated the dynamic properties of GDP growth rates in the global economy and found evidence of a significant global factor capturing comovements of economic activity throughout the world economy. (see also Crucini et al.[33]; Del Negro & Otrok[37]). Commonalities across countries have also been demonstrated for other macroeconomic variables, such as sovereign credit risk (Longstaff et al.[53]), inflation rates (Neely & Rapach[57]), long-term sovereign bond yields among OECD countries (Bhatt et al.[25]), and public spending (Albanese & Modica[5]).

In this chapter, we present evidence that global and regional comovements also exist in public debt. They can be affected by exogenous factors and economic shocks within the global economy. The chapter aims to examine how significant such commonality effects are present in public debt and their impacts on individual countries' public debt. We find that the global factor accounts for a significant fraction of public debt variation more substantially than domestic variables in many countries. There are a few reasons why global and regional comovements in public debt exist, and they are significant in the global economy.

First, global and regional business cycles can affect many countries' economic activities, causing synchronization, which has been stronger in the last three decades due to globalization (Kose et al.[50]). Global value chains and intensive international trade interconnect countries through cross-border production lines. The global financial cycle affects the financial intermediation of those countries (Rey[63]), thereby strengthening the world business cycle. Additionally, global and regional shocks can cause common movement because of interconnected trade and debt markets. As noted in the above, recent events, including the sovereign debt crisis in the Eurozone, the global financial crisis, and the pandemic situation, could explain this possibility. They have caused a chain reaction to decrease economic growth and increase public debt across Europe and the rest of the world. The international business cycles can then result in comovements in government revenues, expenditures, and public debt.

Second, international policy coordination could generate comovements of public debt. For example, the European Union (EU) requires its members to limit their fiscal deficit within 3 percent of GDP each year and keep the debt-to-GDP ratio of less than 60 percent. The EU has implemented a series of measures to mitigate public debt and has imposed penalties in case of violations. Other multilateral decisions and confederations, not necessarily related to public debt, could also affect a country's balance sheet. Examples, including the United Nation's Paris Agreement commitments on climate change, are extremely abundant and could jointly affect public debt for countries worldwide.

Third, countries' institutional and structural resemblances could lead to conducting a similar fiscal policy as a whole. For instance, the literature shows that countries with a parliamentary government tend to perform "poorly" at mitigating fiscal imbalances (cf. Alesina & Tabellini[7]; Alesina & Perotti[6]; Persson & Tabellini[61]). Structural changes in the global economy, financial globalization, and rising income inequality can affect public debt by pushing governments, without explicit coordination, to choose a higher level of debt to facilitate better consumption smoothing (Azzimonti et al.[16]). As shown in Bhatt et al.[25], international comovements in interest rates can also create public debt synchronization. Indeed, Blanchard[26] asserts that interest rates lower than GDP growth rates can make a case for fiscal expansion and, thus, higher public debt in many advanced countries.

This chapter presents empirical evidence of significant international comovements of public debt in common global and regional factors. We apply a time-varying dynamic factor model with stochastic volatility *á la* Del Negro & Otrok[37] to the public debt of 115 countries over 35 years (1980-2015). We set nine regions across the globe and estimate global and regional factors of public debt. Our focus yields several implicit econometric questions to address. First, the significance of modeled global and regional factors capturing comovements can be assessed. Then, we examine the extent to which global and regional factors explain public debt variation over time. Next, we investigate these factors' role in explaining public debt and show empirical evidence that they reflect on the evolution of public debt better than its domestic determinants.

We find a significant role of global and regional factors in affecting public debt across different countries. The estimated global factor accounts for 30 percent of the total variation in public debt across the world. The relative importance of global and regional factors differs in different regions. Interestingly, we find that the regional factor plays an important role in European countries. The estimated global factor is determined by global factors of business cycles, interest rates, and government fiscal activities, all of which are considered important factors determining individual countries' public debt in the existing literature.

Our findings have significant policy implications and a unique contribution to the literature. Since economic activity in a set of countries is affected by shared global or regional economic trends, institutional structures and internal policies, the common dynamics should be accounted for in the policy implementation. For the most part, previous studies do not account for such factors but rely largely on domestic determinants of public debt. However, this chapter documents the importance of external factors in the evolution of individual countries' public debt.

The rest of the chapter is organized as follows. Section 2 discusses data and methodology, and Section 3 gives the estimation results and interpretations. In Section 4, we investigate the determinants of the public debt factors deploying various additional analyses. Finally, in Section 5, concluding remarks are given.

Data and Methodology

Data

Our main variable is the annual debt-to-GDP ratio from the Historical Public Debt Database published by the IMF and presented in Abbas et al.[1]. To obtain a balanced panel, we selected 115 countries from 1980 to 2015 with ample data availability and international comparability. To maximize the number of observations, we interpolated data using consecutive year averages in cases with up to two observations missing.

We also amass various domestic variables about fiscal and monetary policy. We draw data from the World Development Indicators (WDI) database published by the World Bank, the FRED database, and the IMF's International Financial Statistics. Fiscal variables include government spending, government revenue, primary balance, tax revenue, and a measure of government effectiveness. The primary surplus is calculated as the difference between government revenues and expenditures plus interest payments, as the percentage of GDP. The government effectiveness indicator was obtained from the World Governance Indicators of the World Bank. On the monetary side, we use money supply, inflation, real interest rate, government bond rates, foreign reserves, real effective exchange rate, and interest rate differentials to German bonds. The GDP growth rate, productivity, and oil prices are included as real sector indicators affecting debt. The GDP growth rate is based on local currency data from the WDI database. Productivity is calculated as the ratio of real GDP and employment, and the real oil price is the global price of Brent crude oil deflated by the national CPI. Table 18 in the **??** lays out the complete set of variables and their sources.

We consider nine geographical regions in our analysis: (1) Asia, (2) Australia & Oceania, (3) Caribbean, (4) European Monetary Union (EMU), (5) non-EMU European countries (non-EMU), (6) Latin America, (7) Middle East and North Africa (MENA), (8) Sub-Saharan Africa, and (9) U.S. & Canada. The assignment of groups is done primarily based on the geographical proximity of countries. As a few nuanced exceptions, we separate EMU from non-EMU European countries because the former is a more homogeneous group with a single currency. We single out the U.S. and Canada due to their heavier economic weight compared to other countries in the region.

Figure 11 presents the plots of the debt-to-GDP ratio for 115 countries divided into nine different regions, where a thick black line plots a median value of debt ratio. Based on the plots, it is hard to distinguish any obvious pattern of comovements across the regions. The median values for Asia and MENA regions are relatively constant over time, lingering around 50 percent of GDP. On the other hand, there is a clear upward trend in the regions of the Caribbean, EMU, and U.S. & Canada, especially around the financial crisis. Noticeable volatility is present in both non-EMU and Latin America regions marked by ups and downs. Although there are no evident commonalities across the regions, we observe many similarities within regions. Understandably, EMU countries have the most prominent degree of comovements among all nine regions. At the same time, countries in other regions also seem to be similar in terms of the trend in debt-to-GDP ratios, which is particularly evident towards the end of the sample.

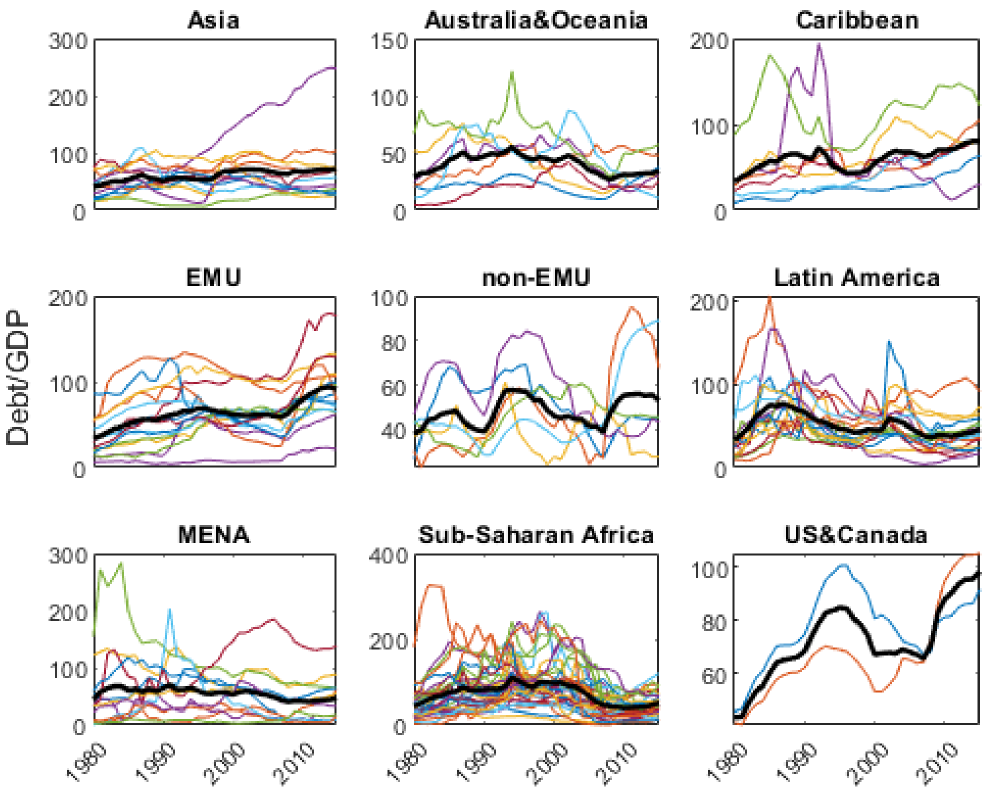

Figure 11: Plots of Debt/GDP Ratios by Region

Principal components analysis

As a preliminary analysis, we begin by estimating the comovements in public debt of 115 countries using principal components analysis (PCA), which is one of the popular methods to investigate comovements in panel data.

Suppose a panel data model of public debt ($y_{i,t}$) with the following factor structure:

$$y_{it} = \lambda_i' F_t + e_{i,t}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{13}$$

where F_t is $k \times 1$ vector of latent factors, Λ is $N \times k$ matrix of associated factor loadings and $e_{i,t}$ is the error term. Equation (13) can be expressed in the following stacked form:

$$Y_t = \Lambda F_t + \mathbf{e}_t \tag{14}$$

where $Y_t = [y_{1,t}, y_{2,t}, \ldots, y_{N,t}]'$, $\Lambda = [\lambda_1, \lambda_2, \ldots, \lambda_N]'$ and $\mathbf{e}_t = [e_{1,t}, e_{2,t}, \ldots, e_{N,t}]'$. The principal component estimator then minimizes the following sum of squared residuals:

$$V(k) = \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_t - \Lambda F_t)^2 \tag{15}$$

where k is the number of unknown common factors. We use the following information criterion of Bai & Ng[21] to determine the optimal number of latent factors in our model:

$$IC(k) = ln(V(k)) + k\Big(\frac{N+T}{NT}\Big) ln(C_{NT}^2) \tag{16}$$

where, $V(k) = 1/NT \sum_{i=1}^{N} \sum_{t=1}^{T} (y_{i,t} - \lambda_i^{k\prime} F_t^k)^2$ and $C_{NT} = min\{N^{1/2}, T^{1/2}\}$. It can be shown that the estimate for the factor term, $\hat{F}_t$, is given by the first k leading eigenvectors of YY' multiplied by $T^{1/2}$ and $\hat{\Lambda} = Y'\hat{F}_t/T$ (Bai[17]).

Despite the popularity and convenience, we wish to point out a few caveats of principal component analysis, especially with regards to the dynamic factor model below. First, it is challenging to associate the estimated factors with observable measures, and such a task can easily turn into a guess-and-check exercise. For example, in cases where there are group-level (e.g., regional) factors in addition to the common (e.g., global) factors, PCA would not be able to distinguish between them. Second, PCA assumes that each estimated factor's contribution to the variation of data is constant over time. However, it is likely the significance of each of the factors changes over time. For example, the contribution of the estimated global factor can be higher during the financial crisis. Finally, it is assumed in the PCA that the factor loadings are constant throughout the sample period, implying that individuals' sensitivity to a common factor does not change. This assumption is rather restrictive. Therefore, we use PCA only as a preliminary analysis.

Dynamic factor model

To examine common factors of public debt, we use a dynamic factor model (DFM). We estimate the unobserved global and regional factors of the debt-to-GDP ratio. We follow Del Negro & Otrok[37] and consider the following dynamic factor model, which allows for time-varying factor loading parameters and stochastic volatility, as employed in Bhatt et al.[25], among others:

$$y_{i,t} = c_i + \lambda_{i,t} G_t + \gamma_{i,t} R_{j,t} + e_{i,t} \tag{17}$$

where $y_{i,t}$ is the debt-to-GDP ratio of the country i at time t. Here, c_i denotes the deterministic term, for which we include a constant. In this model, we decompose the common component into two different factors. First, G_t denotes the global factor that affects all countries contemporaneously at time t. $\lambda_{i,t}$ is the time-varying factor loading of the global factor. It denotes the heterogeneous response of each country to the global factor. Second, $R_{j,t}$ includes regional factors at time t, and it is given as a vector considering nine geographical regions. The jth element of the vector $R_{j,t}$ denotes the regional factor of the jth region. At the same time, $\gamma_{i,t}$ denotes the time-varying factor loading parameters of regional factors; it is a row vector whose elements are non-zero if they correspond to the region of country i, and are zero otherwise. Thus, we can evaluate different regional factors that are orthogonal to the global factor and other regional factors. e_{it} is the error term that captures country-specific dynamics as well as measurement errors in the data.

We let $\beta = [\lambda_{i,t}, \gamma_{i,t}]'$ and assume that it follows a random walk process:

$$\beta_{i,t} = \beta_{i,t-1} + \sigma_{\eta_i}\eta_{it} \tag{18}$$

where, $\eta_{i,t} \sim N(0, \sigma_\beta)$ and is independent across i. We assume that both factors and country-specific components follow autoregressive processes of order q and p_i respectively:

$$G_t = \phi_1^g G_{t-1} + \phi_2^g G_{t-2} \dots \phi_q^g G_{t-q} + exp\{h_i^g\}\nu_t^g \tag{19a}$$

$$R_{jt} = \phi_1^r R_{j,t-1} + \phi_2^r R_{j,t-2} \dots \phi_q^r R_{j,t-q} + exp\{h_i^r\}\nu_{j,t}^r \tag{19b}$$

$$e_{it} = \phi_1 e_{t-1} + \phi_2 e_{t-2} \dots \phi^p e_{t-q} + exp\{h_i\}\nu_t \tag{19c}$$

where, $\nu_t^g \sim N(0, \sigma_{\nu^g}^2)$, $\nu_t^{j,r} \sim N(0, \sigma_{\nu^r}^2)$ and $\nu_t \sim N(0, \sigma_\nu^2)$. We estimate the model assuming a stationary $AR(2)$ process with $q = 2$ and $p_i = 2$ for the global and regional factors, and for country-specific component. For the purpose of identification, we let $\sigma_{\nu^g}^2 = \sigma_{\nu^{j,r}}^2 = 1$, for $j = 1, \dots, m$. We also assume that each of the time-varying stochastic volatility of the factors and the country-specific components follow a random walk:

$$h_t^g = h_{t-1}^g + \sigma_h^g \omega_t^g \tag{20a}$$

$$h_{j,t}^r = h_{j,t-1}^r + \sigma_{h_j}^r \omega_{j,t}^r \tag{20b}$$

$$h_{i,t} = h_{i,t-1} + \sigma_h \omega_{i,t} \tag{20c}$$

where, $\omega_t^g \sim N(0,1)$, $\omega_{j,t}^r \sim N(0,1)$ and $\omega_{i,t} \sim N(0,1)$. We assume that volatility shocks in the above setup are orthogonal to each other, and $h_0 = h_{j,0} = h_{i,0} = 0$ for the initial values of the stochastic volatility terms.

The DFM permits us to measure the relative contribution of global, regional, and country-specific factors to the variations in each country's public debt, as described in Crucini et al.[33]. The variance of the observable debt-to-GDP ratio can be decomposed into global, regional, and country-specific component as follows:

$$Var(y_{i,t}) = \lambda_{i,t}^2 Var(G_t) + \gamma_{i,t}^2 Var(R_t) + Var(e_{i,t}) \tag{21}$$

Then, variance decomposition can be given as a ratio of each of the right-hand side terms in (21) with respect to $Var(y_{i,t})$. For instance, the variance contribution of the global factor can be measured as $\lambda_{i,t}^2 Var(G_t)/Var(y_{i,t})$.

Estimation Results

Results from principal component analysis

In our PC estimations, we chose the number of factors as five in all cases, following the information criteria given in equation 16 . We provide the plot of the estimated first PC in Figure 12. With our specifications, the first PC shows an upward pattern beginning from the 1980s until around 2000. In Table 6, we report the relative contribution of each estimated PC on the variation of public debt. To measure the time variance in the contribution of principal components, we provide these results using the full sample and two sub-samples, 1980-2000 and 2001-2015, respectively. Accordingly, the first PC explains 83.9 percent of the variation in public debt in the full sample, and it explains 91.8 and 91.6 percent of the variation in 1980-2000 and 2001-2015 sub-samples, respectively. Thus, principal component analysis reveals a very high degree of comovements in public debt.

Although the results from PCA look very convincing, as we will show later, they look rather over-estimated compared to the results from DFM. However, it is worth mentioning that similar commonality effects are observed in other studies employing PCA to analyze global factors of various key economic variables* .

*For example, Pan & Singleton[59] and Longstaff et al.[53] examine commonality in sovereign credit spreads using PCA and find that the first principal component explains over 96 percent of the vari-

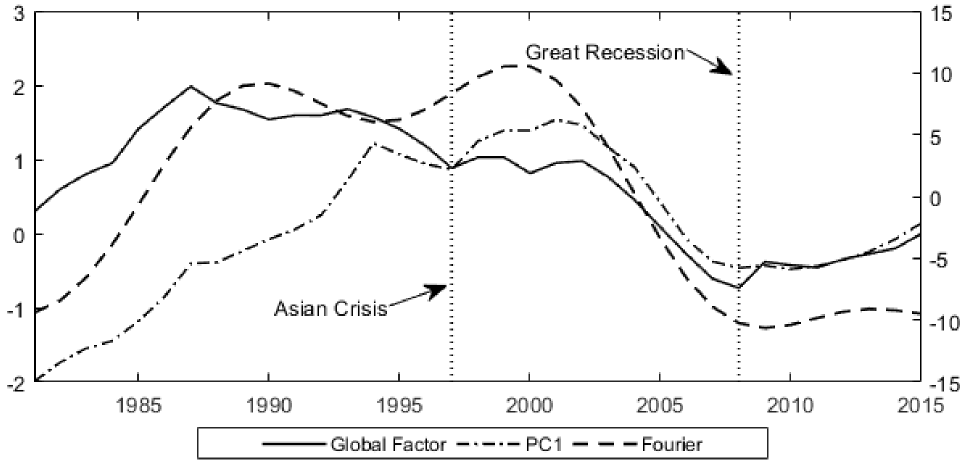

Figure 12: Estimated Global Factor, First PC and Fourier Approximation

We use variance decomposition based on PCA to evaluate the relative contribution of the common factor to the variation of public debt in each country. We let $y^*_{i,t}$ denote the standardized variable of $y_{i,t}$ and e_{i,t^*} is the corresponding error term. Since $y^*_{i,t} = \lambda'_i F_t + e^*_{i,t})/\sigma_i$, the variance of the standardized public debt $(y^*_{i,t})$ of each country can be decomposed into

$$V(y^*_{i,t}) = \frac{\lambda_i^2 V(F_t)}{\sigma_i^2} + \frac{e^*_{i,t}}{\sigma_i^2} = 1 \tag{22}$$

where, $\lambda_i^V(F_t)/\sigma_i^2$ denotes the variance explained by the common factor and $V(e_{i,t})/\sigma_i^2$ is the variance of the corresponding idiosyncratic component. As the variance of the factor term is standardized to unity for an identification purpose, we can simply calculate the explained variance of the common factor as λ_i^2/σ_i^2 *. Since the first PC explains a large portion of the variation in public debt, we use the first PC for the factor $\hat{F}_t$ and examine the relative contribution of the factor to the variation of public debt in each country. The results are presented in Table 7, where we report the summary results of different regions using the full sample, 1980-2000, and 2001-2015 sub-samples. Overall, the average of the first PC's relative contribution for all the countries (world average) is 38.2 percent in the full sample and 45.0 or 57.2 percent in two sub-samples,

ation in sovereign CDS. They note that sovereign credit risk is more closely related to the principal component factor than domestic economic fundamentals.

*Instead of calculating the explained variance this way, one can also run the regression of public debt against the estimated factor. Note that the explained variance result can be replicated with the R^2 value from this regression; see Sul[67]

Table 6 PCA Variance Decomposition - Total

Principal Components	Full Sample % Explained	Full Sample Sum	1980-2000 % Explained	1980-2000 Sum	2001-2015 % Explained	2001-2015 Sum
PC 1	**0.839**	**0.839**	**0.918**	**0.918**	**0.916**	**0.916**
PC 2	0.1	0.939	0.05	0.968	0.063	0.98
PC 3	0.03	0.969	0.015	0.983	0.011	0.991
PC 4	0.011	0.98	0.006	0.989	0.004	0.995
PC 5	0.006	0.986	0.003	0.992	0.002	0.997

respectively. These results are somewhat lower than those from the overall PCA. They can be compared to the corresponding results from the DFM below.

Table 7 PCA Variance Decomposition -Regional Averages

Region	Full Sample PC	Full Sample Country	1980-2000 PC	1980-2000 Country	2001-2015 PC	2001-2015 Country
Asia	0.314	0.686	0.507	0.493	0.661	0.339
Australia & Oceania	0.341	0.662	0.444	0.556	0.506	0.494
Caribbean	0.536	0.464	0.322	0.678	0.588	0.412
EMU	0.486	0.514	0.629	0.371	0.546	0.454
non-EMU	0.331	0.669	0.317	0.683	0.646	0.354
Latin America	0.373	0.627	0.229	0.771	0.556	0.444
MENA	0.453	0.547	0.215	0.785	0.524	0.476
Sub-Saharan Africa	0.327	0.673	0.575	0.425	0.589	0.411
U.S. & Canada	0.280	0.720	0.810	0.190	0.53	0.470
World Average	**0.382**	**0.618**	**0.45**	**0.55**	**0.572**	**0.428**

Note: The first principal component has been used to examine the contribution of the factor to the variation of each county's public debt. The figures represent average values in each region.

Results from the Bayesian DFM

The dynamic factor model characterized in Eq. (17) with time-varying parameters and stochastic volatilities is estimated using Bayesian MCMC procedure for which we apply the usual Gibbs-sampling algorithms. The prior for each of the factor loading parameters is $N(0,1)$. We follow Del Negro & Otrok[37] for the usual assumptions regarding the parameters' distributions in the above models. Technical details of the estimation procedures, including the prior distributions of the parameters and the Gibbs sampler, are provided in the Appendix of Del Negro & Otrok[37]. We have estimated the DFM using the first differences of the debt ratio and obtained the estimated factors using the cumulative sum*.

*To decide on whether to use the first difference or level of the debt ratio, we have applied vari-

In Figures 13 and 14, we present the plots of the estimated global and regional factors, along with their medians and the 5th and 95th percentiles.

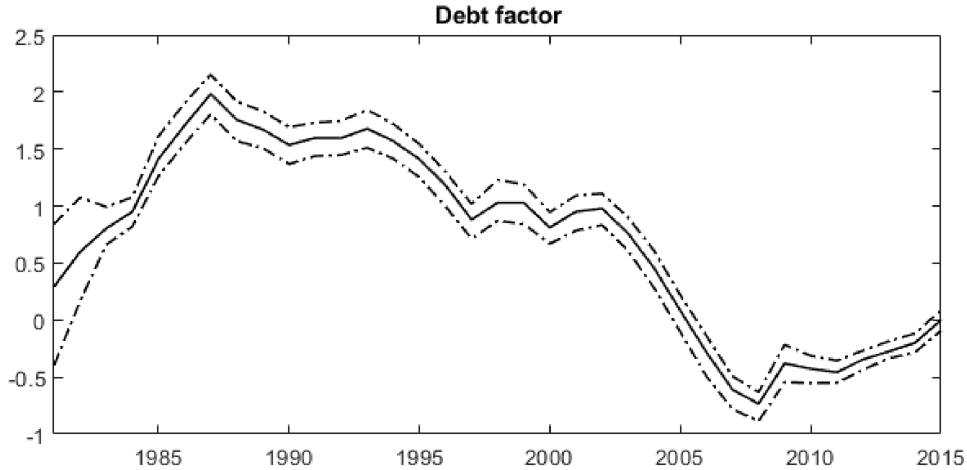

Figure 13: Estimated Global Factor

Tight confidence intervals of the global factor in Figure 13 point towards precise estimation. Visually, it is interesting to observe that the global factor is closely related to the first PC discussed above and a common nonlinear trend based on the Fourier function*.The combined plots of these estimates are provided in Figure 12. From Figure 14, we observe that the confidence intervals for the regional factors of Asia, EMU and Africa are also tight. However, broad confidence intervals occurring at various times for the regional factors of the Caribbean, non-EMU, MENA, and U.S. & Canada reveal their estimates are comparatively lacking in precision.

The plots of the global factor shown in Figure 12 and separately in Figure 13 highlight the periods associated with the past few decades' debt crises. There is a distinct increase in the global factor that started in the early 80s, which briefly plateaued go-

ous unit root tests. The results are mixed, depending on the panel unit root tests. However, when we allow for a factor structure in the panel unit root tests, we have the results favoring non-stationarity. The null of a unit root is rejected for the cases of 37, 26 and 8 countries, out of 115 countries, from the PANIC panel unit root tests of Bai & Ng [21], Bai [18] and Nazlioglu et al. (2020), respectively; these results are omitted to save space, but they are readily available upon request.

*For a robustness check, we have estimated the global factor using a common nonlinear break, based on a Fourier function with cumulative frequencies following Enders & Lee [40]. For this, we have estimated a common nonlinear deterministic function that can possibly exist for all cross-sectional units with $y_{i,t} = c + \sum_{k=1}^{m}[a_k sin(2\pi kt/T) + b_k cos(2\pi kt/T)] + e_{i,t}$, where $y_{i,t}$ is the debt ratio of each country and m is the number of cumulative frequencies. Using the information criteria for a maximum value of m less than 5, we chose $m = 3$. We present the plot of the estimated Fourier function in Figure 12. We find that the overall trend and shape of the estimated common Fourier function looks similar to those of the estimated global factor from the DFM and the first PC.

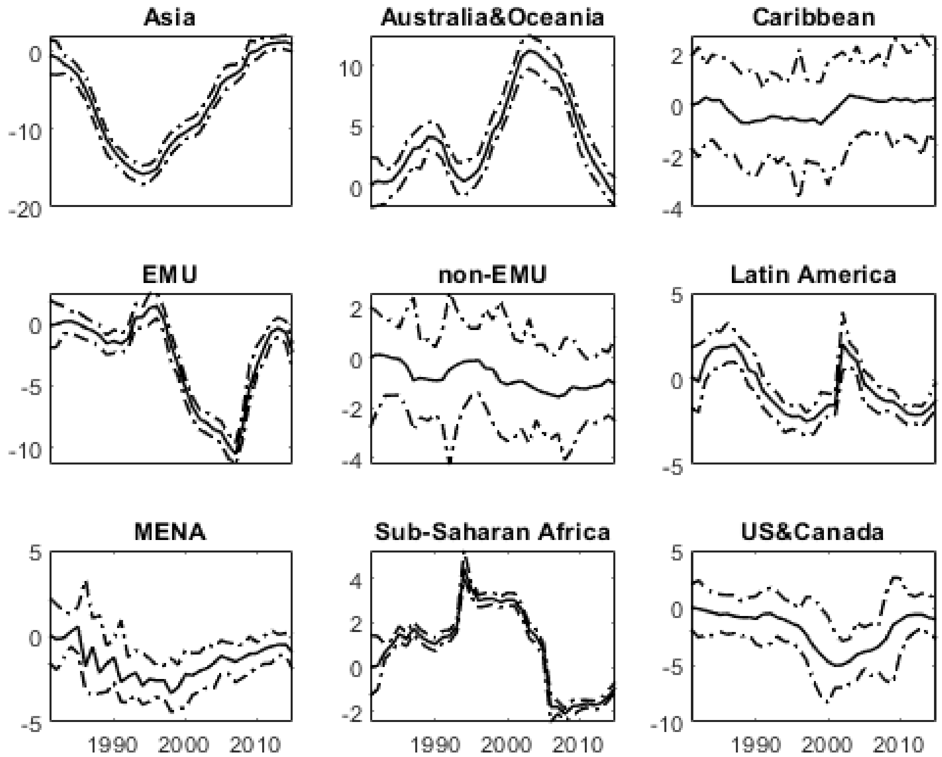

Figure 14: Estimated Regional Factors

ing into the 90s before going down. The sharp increase in the debt ratio in the 1980s is partly due to the Latin American debt crisis, often referred to as “La Década Perdida” or “The Lost Decade,” which originated in the late 1970s. The downward trend was briefly halted around 1997, coinciding with the onset of the Asian crisis. Another steep decline took place in the early 2000s, which continued well into the doorsteps of the recent financial crisis before making an apparent reversal.

Looking at the regional factors, as shown in Figure 14, the EMU regional factor experienced a plunge towards the end of the 90s, which continued until the financial crisis. Thus, the Euro’s introduction in 1999 most likely prompted the member states to bring their debt ratios to sustainable levels. Such ambitions were short-lived since the EMU regional factor sharply increased after the financial crisis in 2007. However, the sharp increase in the regional factor caused by the financial crisis is only apparent in the EMU region. The regional factor of Asia, for instance, has been on the rise since the Asian crisis of the mid-90s. In contrast, Australia & Oceania region has its factor steadily dropping since the beginning of the 2000s. Sharp increases in debt ratios can be observed in the early 80s in Latin America and Sub-Saharan Africa.

One of the big advantages of the DFM is that it provides useful and unique information through the variance decomposition given in equation (21). The variance decomposition from the DFM allows us to evaluate the time-varying contributions of each of the global, regional, and idiosyncratic components to the variation of the debt-to-GDP ratio of each country. Two questions are of major interest to us: (i) To what extent is each country's debt ratio explained by the global and regional factors? (ii) Are there any distinguishable patterns in the relative contributions of the factors in major countries or different regions?

We first want to examine the average values of the relative contributions of each of the global, regional, and country-specific factors, as they are changing over time. The relative contributions are the time-varying variance decomposition of each factor. Table 8 provides the summary results for the entire period and the two sub-sample periods of 1980–2000 and 2001–2015, respectively. Looking at the results with the full sample, we find that the global factor makes up, on average, about 30 percent of the variations in debt-to-GDP ratios in the world. The average relative contribution of the regional factor is 11.4 percent, whereas the country-specific factors' contribution is 52.2 percent. Among the regional averages, U.S. & Canada has the highest share explained by the global factor, which stands at 56 percent. In contrast, Sub-Saharan Africa has the highest share of the regional factor, followed by the EMU region. The results from using two sub-samples are similar, while the global factor's relative contribution is 24 percent. These results are lower than those from the PCA, but they show the presence of significant global and regional factors in public debt.

We present the plots of each factor's time-varying relative contributions in Figures 15a – 15e for each country by regions of Asia, EMU, Latin America, and the U.S. & Canada, respectively. For the sake of brevity, we report the plots of other regions in the Appendix (Appendix Figures A1.a   A1.d). We observe that the global factor's influence has been diminishing after the financial crisis period, reaching negligible figures in

Table 8 Variance Decomposition from the DFM

	Full Sample			1980-2000			2001-2015		
Regions	Global	Regional	Country	Global	Regional	Country	Global	Regional	Country
World	**0.30**	**0.11**	**0.52**	**0.34**	**0.1**	**0.49**	**0.24**	**0.13**	**0.55**
Asia	0.39	0.11	0.40	0.43	0.09	0.39	0.34	0.14	0.41
Australia & Oceania	0.44	0.08	0.41	0.50	0.07	0.37	0.35	0.10	0.47
Caribbean	0.14	0.05	0.73	0.18	0.05	0.7	0.09	0.06	0.77
EMU	0.23	0.18	0.5	0.28	0.16	0.48	0.15	0.22	0.54
non-EMU	0.2	0.10	0.63	0.24	0.10	0.56	0.12	0.09	0.72
Latin America	0.25	0.10	0.59	0.25	0.08	0.62	0.24	0.12	0.55
MENA	0.33	0.07	0.53	0.35	0.06	0.55	0.32	0.09	0.52
Sub-Saharan Africa	0.13	0.23	0.59	0.15	0.23	0.57	0.09	0.25	0.61
U.S. & Canada	0.56	0.07	0.27	0.64	0.06	0.22	0.44	0.09	0.34

some countries. In Asia, for instance, as noted in Figure 4a, countries like South Korea, Japan, Singapore, and Sri Lanka have been experiencing a decline in the share of the global factor. During the "Lost Two Decades," Japan has gone through an endless fiscal expansion and unprecedented monetary easing. The results show that the regional debt factor is not pronounced for Japan. However, for counties like Indonesia, Malaysia, and Thailand, the global factor share has slightly picked up during the late 90s. There were heightened efforts by all three countries during the 90s to establish integrational programs to boost the economic growth, which lead to the establishment of IMT-GT (stands for Indonesia-Malaysia-Thailand-Growth Triangle).

We present the plots of each factor's time-varying relative contributions in Figures 15a – 15e for each country by regions of Asia, EMU, Latin America, and the U.S. & Canada, respectively. For the sake of brevity, we report the plots of other regions in the Appendix (Appendix Figures A1.a A1.d). We observe that the global factor's influence has been diminishing after the financial crisis period, reaching negligible figures in some countries. In Asia, for instance, as noted in Figure 4a, countries like South Korea, Japan, Singapore, and Sri Lanka have been experiencing a decline in the share of the global factor. During the "Lost Two Decades," Japan has gone through an endless fiscal expansion and unprecedented monetary easing. The results show that the regional debt factor is not pronounced for Japan. However, for counties like Indonesia, Malaysia, and Thailand, the global factor share has slightly picked up during the late 90s. There were heightened efforts by all three countries during the 90s to establish integrational programs to boost the economic growth, which lead to the establishment of IMT-GT (stands for Indonesia-Malaysia-Thailand-Growth Triangle).

The results on the relative contributions are very different for EMU countries (Figure 15b). In particular, there is a uniform decline in the relative importance of the global factor. For Greece and Ireland, the global factor share reaches as low as 0.03 and 0.05, respectively, towards the end of the sample. These two countries were at the center of the European debt crisis. Remarkably, the core countries, such as Germany and France, also have relatively low shares explained by the global factor. Instead, the regional fac-

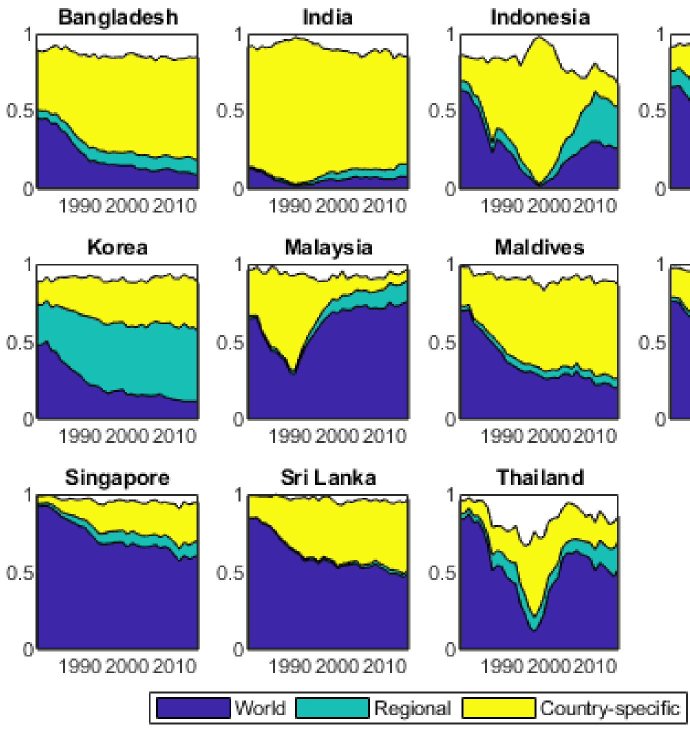

Figure 15a: Variance Decomposition Results – Asia

tor plays a more important role in their debt ratios, a phenomenon that can be referred to as the "EMU integration effect."

On the contrary, it is clear from Figure 15c that the regional factor plays a much less significant role for non-EMU countries, such as Norway and Switzerland. The country-specific factor dominates the regional factor in explaining fluctuations in the debt ratio. A series of policy rules and agreements on the part of EU and Eurozone countries, such as the *European Stability Mechanism* and the Fiscal Stability Treaty, may have impacted Eurozone countries' debt ratios. In contrast, countries outside of the Eurozone and especially the EU, remained unaffected.

Considering Latin America, as shown in Figure 15d, the region's general trend is consistent with the overall behavior across countries: the global factor share has been decreasing. The exceptions are Bolivia, Brazil, and El-Salvador, where there is an upsurge in the global factor's share around the time of the financial crisis. Further, the trend seemingly reversed after the crisis. The heightened share of the global factor in El-Salvador starting around 2000 coincides with its government's decision to peg its

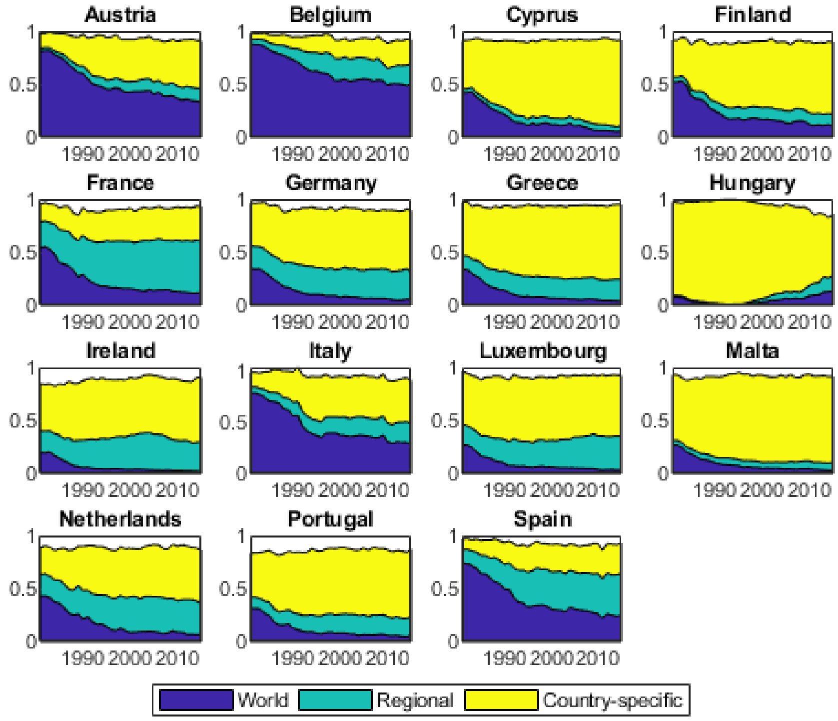

Figure 15b: Variance Decomposition Results – EMU

currency against the U.S. dollar. The pegged currency might have consequently limited the government's ability to inflate away from its ever-rising debt. The results for U.S. & Canada (Figure 15e) very closely emulate each other, as expected, but the U.S. has a lot more idiosyncrasies compared to Canada. The results regarding variance decomposition also reflect in the degree of dispersion in explained variances, as shown in Figure 16. The figure shows how the amount of variance explained by global, regional, and idiosyncratic components vary across countries throughout our sample period. Accordingly, we can see that variance explained by the global factor has undergone a nearly monotonic decline in dispersion. The same is true for the idiosyncratic part of the explained variance. Conversely, the regional factor's share has not changed significantly over time. Lower volatility of the international business cycle over the *Great Moderation* period might be lying behind the observed decreasing trend in the significance of the global factor [*].

[*]See for example Kose et al.[50] and Del Negro & Otrok[37] for the discussion on the phenomenon of the Great Moderation.

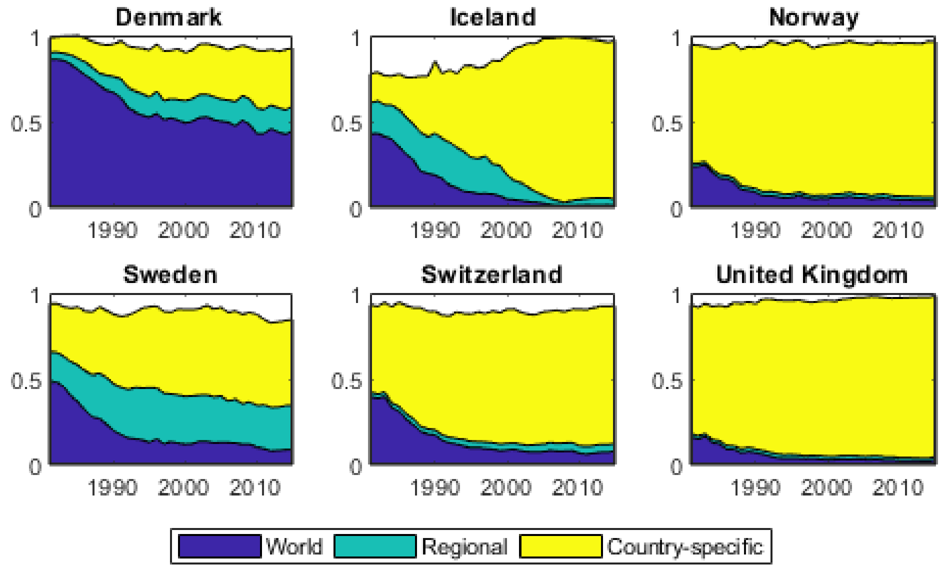

Figure 15c: Variance Decomposition Results – non-EMU

Determinants of Public Debt

In this section we examine the determinants of public debt while paying attention to the role of the global and regional factors of public debt. We adopt three different approaches.

Panel data models

We first address this issue using panel data models. The motivation of our analysis is in line with the literature on panel data models with a factor structure, which attempts to correct for cross-sectional dependence. Consider a panel data model with a factor structure.

$$y_{i,t} = \alpha_i + \gamma_t + \mathbf{X}_{i,t}\beta + \varepsilon_{i,t} \tag{23}$$

$$\varepsilon_{i,t} = \lambda_i' F_t^G + u_{i,t} \tag{24}$$

where $y_{i,t}$ denotes the public debt-to-GDP ratio of country i at time t. $\mathbf{X}_{i,t}$ is a vector of independent variables, and α_i and γ_t reflect country and time fixed effects. The error term $\varepsilon_{i,t}$ can be cross-sectionally correlated through a factor structure in equation (21), where F_t^G is a common factor and $u_{i,t}$ is an *iid* error term. We consider three different

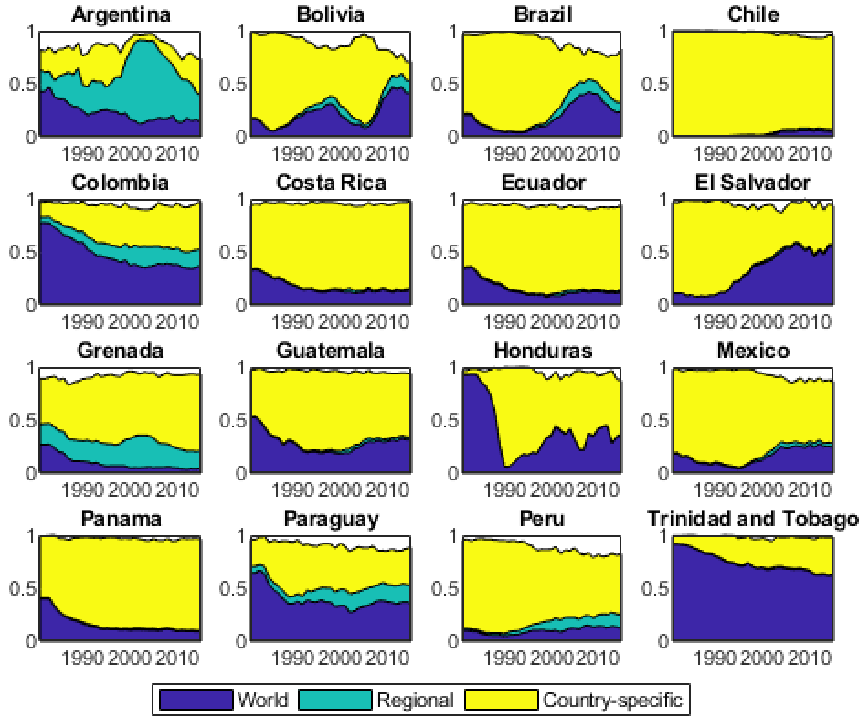

Figure 15d: Variance Decomposition Results – Latin America

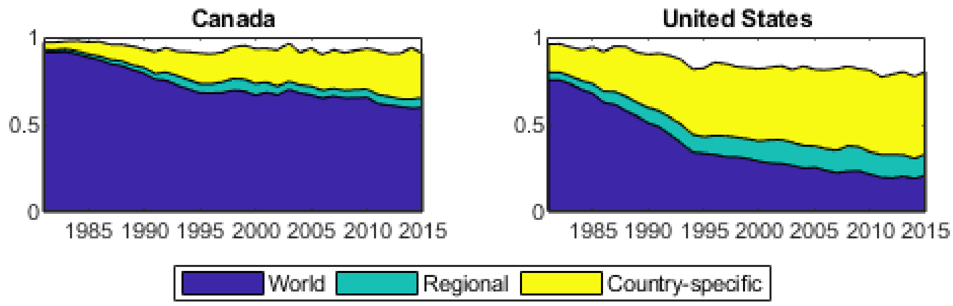

Figure 15e: Variance Decomposition Results – U.S.& Canada

estimation procedures to estimate equation (23). The first estimator is the usual fixed effects (FE) estimator, which does not account for a potential cross-sectional correlation; we refer to this estimator as FE-0. The second estimator includes the factor terms $\lambda_i' F_t^G$ by using the estimated global factor interacted with country-specific dummy variables, such that the factor loading coefficient (λ_i) of F_t^G of an individual country can differ over different cross-sectional units; we refer to this estimator as FE-I. For the third estimator, we consider Bai & Carrion-I-Silvestre[19] interactive fixed effects approach, denoted as IFE, which jointly estimates the regression coefficients and the factor loading parameters in an iterative procedure, while the factor is estimated by prin-

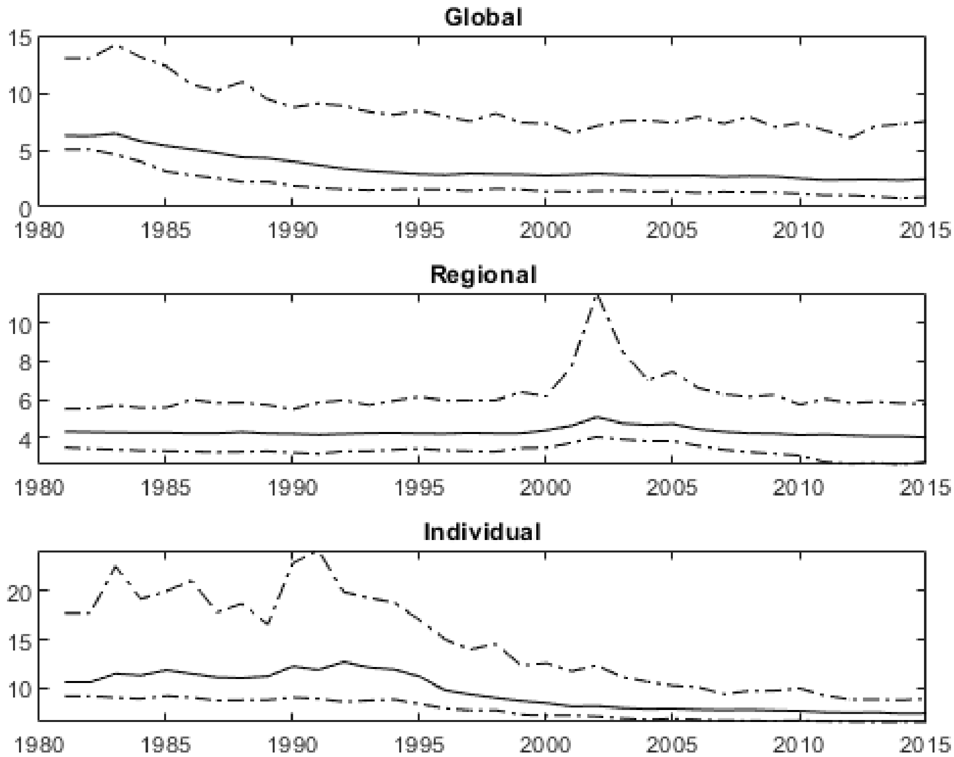

Figure 16: Stochastic Volatility

cipal components analysis.

We follow the theoretical models of Barro[23] and Roubini & Sachs[64] for the model specification. As such, we include primary surplus, real interest rates, GDP growth, inflation, GDP per capita, employment, productivity, and the current account. Higher real interest rates should increase debt because of rising repayment costs. Likewise, the primary surplus and GDP growth should decrease public debt through different channels. Theoretically, inflation has two opposite effects on public debt. One may expect that higher inflation can reduce the real value of government debt, but countries with high inflation can have higher nominal interest rates (Afonso[2]). Therefore, the effect of inflation is ambiguous. GDP per capita measures the level of development, and employment captures labor market conditions. Higher productivity can ensure competitiveness and thus indirectly decrease public debt (Afonso & Jalles[3]). The current account measures the competitiveness of the country. It is related to the twin deficit hypothesis, where government deficit can induce trade deficit and vice versa through interest rate and exchange rate channels.

Table 9 Panel Data Models with and without a Factor Structure

Variables	(1) FE-0	(2) FE-I	(3) IFE
Prim. Surplus	-0.412	-0.773***	-0.103
	(0.43)	(0.21)	(0.18)
Real Int. Rate	0.072	0.054	0.081
	(0.21)	(0.07)	(0.07)
GDP Growth	-0.977***	-0.320**	-0.914***
	(0.32)	(0.14)	(0.18)
Inflation	0.115	0.02	0.106***
	(0.14)	(0.03)	(0.04)
GDP per Capita	-13.836	-17.829**	-48.165***
	(20.50)	(8.01)	(6.57)
Employment	-1.152***	-1.144***	-1.106***
	(0.38)	(0.19)	(0.18)
Productivity	-2.873	11.412	-10.798**
	(18.43)	(7.00)	(4.90)
Current Acc.	0.138	0.287**	0.015
	(0.32)	(0.11)	(0.11)
Constant	275.523***	480.771***	523.696***
	(75.52)	(74.61)	(30.55)
Observations	1593	1593	1593
R-squared	0.09	0.90	0.23
N	118	118	118
Factor	No	Yes	Yes

Note: Figures in parenthesis represent robust standard errors.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The estimation results are provided in Table 9. From the results obtained using FE-0, we observe that only the coefficients of GDP growth and employment are significant. All other coefficients have expected signs, but they are not statistically significant. Among others, primary surplus, GDP per capita, and productivity tend to decrease public debt. Real interest rate, inflation, and current account tend to increase it. However, these effects are not significant. The results from FE-I and IFE are similar to the results using FE-0 in terms of expected signs. Still, they are different in the magnitudes and significance of the estimated coefficients. These estimators control the effects of the factor terms by using either the estimated global factor of the DFM or the principal components. Although only two coefficients are significant from FE-0, five out of eight coefficients are significant once we include the factor term to address the cross-sectional dependence. In the FE-I model with individual factor loadings, the coefficients of more variables (primary surplus, GDP per capita, and current account) become significant. The IFE estimator also yields more significant coefficients, compared to FE-0. Essentially, these two estimators of FE-I and IFE give more significant results when they account for cross-correlations using the factor structure.

Global factors of driving forces

Next, we examine the question of what would be the major driving sources of the global factor of public debt. This analysis relies on the approach of Crucini et al.[33]. They examine the driving force of the world global factor of growth rates from the global factors of its determinants, such as productivity, fiscal and monetary policy variables, the terms of trade, and oil prices. For this, we first estimate the dynamic factor model for each determinant and obtain the global, regional, and country-specific components. The determinant variables are organized into three groups: (i) fiscal variables: primary surplus, government revenues, and surplus, (ii) economic activity indicators: GDP growth, employment growth, and GDP per capita growth, and (iii) interest rates. We run a regression using the estimated global factors of these variables. All variables in the regression are standardized with zero mean and unit variance. Then, the estimated coefficients could be interpreted as partial correlation coefficients. Due to the limited number of time-series observations, we analyze partial correlation with only three variables, one from each group. As the variables can be highly persistent, we take the first difference. We present the results in Table 10. Different combinations of control variables yield nine models in total.

The first three models, (1) to (3), use primary surplus as the main fiscal variable but consider different economic activity indicators. Models (4) to (6) and (7) to (9) use government revenues and surplus as the main fiscal variables, respectively. All nine models include the global factor of the real interest rate. Results show that all three fiscal variables are negatively correlated with the global debt factor. The estimated partial correlation coefficient is not very high, but it is significant in more than half

Table 10 Multiple Linear Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.: ΔF_t^{Debt}									
$\Delta F_t^{Prim.Sur.}$	0.024	-0.046**	0.032						
	(0.06)	(0.02)	(0.03)						
$\Delta F_t^{Gov.Rev.}$				-0.027**	-0.037***	-0.013			
				(0.01)	(0.01)	(0.01)			
$\Delta F_t^{Surplus}$							-0.038*	-0.042*	-0.028
							(0.02)	(0.02)	(0.02)
$\Delta F_t^{GDPGrowth}$	-0.067*			-0.046**			-0.047***		
	(0.03)			(0.02)			(0.02)		
$\Delta F_t^{Employment}$		-0.065			-0.090*			-0.064	
		(0.06)			(0.05)			(0.06)	
$\Delta F_t^{GDPPerCapita}$			-0.193***			-0.151**			-0.140**
			(0.06)			(0.07)			(0.06)
$\Delta F_t^{InterestRate}$	0.047**	0.039	0.036**	0.023	0.016	0.018	0.022	0.02	0.017
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Constant	-0.094***	-0.103***	-0.094***	-0.098***	-0.103***	-0.100***	-0.092***	-0.095***	-0.094***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	24	24	24	25	25	25	25	25	25
R-squared	0.444	0.359	0.541	0.45	0.415	0.511	0.494	0.384	0.546

Note: All variables were standardized such that the estimated coefficients can be viewed as the partial correlation coefficients. Figures in parenthesis represent robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of the considered models. Economic activity indicators are also negatively correlated with the global debt factor. Correlation is stronger and statistically significant in more cases in comparison to fiscal variables. This result can be related to the existence of the global business cycle, as shown in Kose et al.[50]. The global business cycle can, in turn, affect the global debt level. The global factor of the real interest rate is positively correlated with global debt, but the correlation is statistically significant only in two out of nine models. Overall, we find that the global factor of public debt can be explained well by the global factors of government fiscal soundness and economic activities.

Cross-country regressions

Lastly, we explore the relative importance of the global and regional factors in explaining the variation of public debt in each country, compared to the effects of major domestic economic variables. A similar analysis is done in Longstaff et al.[53], who show that the global factor plays a predominant role in explaining the change in sovereign credit spreads. They note that the effect of the factor estimated from PCA is greater than that of domestic economic variables. Similarly, we want to measure the relative contribution of global and regional factors from the DFM in the presence of major domestic variables explaining the variation of each country's public debt. Consequently, we consider a country-by-country regression and evaluate the partial correlation coefficients in the following model, where all variables are standardized with zero mean and unit variance.

$$y_t^i = \alpha_0 + \alpha_1 F_t^G + \alpha_2 F_t^R + \delta' \mathbf{B}_t^i + v_t^i, \quad for i = 1, \ldots, N \tag{25}$$

where y_t^i is the debt-to-GDP ratio of individual country i, F_t^G and F_t^R are the estimated global and regional factors, respectively; $\mathbf{B}_t^i$ is a vector of country-specific variables including government revenues as a fiscal indicator, GDP growth rate as a real indicator, and the real interest rate.

The summary of the average values of the partial correlation coefficients by regions is given in Table 11. Looking at the world average, we find that country's public debt is more strongly associated with the global and/or regional factors of public debt, on average, than country's domestic variables such as government revenues, GDP growth, or interest rate. However, the regional factor is more pronounced in Eurozone. In non-Eurozone and Asian countries, the global factor is more strongly related to public debt than the regional factor, and interest rates have the strongest correlation with public debt. Global and regional factors are especially pronounced in Sub-Saharan Africa, Eurozone countries, South America, and partially in the MENA. Among the country-specific variables, interest rates show the strongest correlation with public debt. These findings further recognize the importance of global and regional factors in many countries.

Table 11 Average of the Partial Correlations

Region	Global Factor	Regional Factor	Fiscal Indicator	Real Indicator	Interest Rates
Asia	0.176	-0.003	-0.004	-0.071	0.238
Australia & Oceania	0.041	-0.005	0.030	-0.060	-0.150
Caribbean	0.112	0.028	-0.130	-0.066	0.203
EMU	-0.003	0.141	-0.035	-0.076	0.058
non-EMU	0.107	-0.018	-0.077	-0.073	0.199
Latin America	0.083	0.232	0.015	-0.087	0.065
MENA	0.158	0.000	-0.005	-0.048	0.142
Sub-Saharan Africa	0.513	0.188	-0.259	-0.129	-0.147
U.S. &Canada	0.156	0.005	-0.330	-0.078	0.288
World Average	0.212	0.112	-0.099	-0.089	0.033

Concluding Remarks

This chapter examined international comovements and public debt dynamics using data from 1980 to 2015 for 115 countries. We provide evidence for the existence of significant global and regional comovements of public debt. Our results show that there is a distinct global factor in the debt-to-GDP ratio. The patterns of the estimated global factor from the dynamic factor model are comparable to those from the principal component analysis or common nonlinear breaks using the Fourier function. The factor accounts for a significant share of the variation in public debt in many countries. We find that the global factor explains, on average, 30 percent of the variation of the debt ratio in the world.

The estimated global factor exhibits a downward trend while the pattern of regional factors differs across regions. Regional factors are the most important for the Eurozone member states. On the other hand, the relative importance of the idiosyncratic country-specific factors increases in most countries and regions. In particular, in Japan, the USA, and non-EU European countries, the country-specific debt component dominates other factors.

The contributions of regional factors are significant, especially in Europe, South America, and Sub-Saharan Africa. The global and regional factors of public debt are strongly correlated with the debt-to-GDP ratio of individual countries. The correlation with the global factor is even stronger than the correlation with some country-specific variables in many countries. This finding again highlights the importance and significance of global and regional debt factors. We also analyze the driving sources of the global and regional factors of public debt. We find that panel regression on the determinants of public debt yields more precise results when we account for the global debt factor's effects.

Our findings provide an important policy implication relating to a plethora of spillover effects. Since the global and regional common factors are significant in many countries' public debt, policymakers should be aware of their impact. The debt-to-GDP ratio is a key reference indicator of fiscal soundness, and many policies are designed deliberately accounting for their effects on this variable. Hence, if they ignore the influence of global and regional factors in the public debt, those policies may fail to be carried out efficiently. As with any topical analysis utilizing new methods, more future research is needed on these factors' inter-temporal effects.

PANEL ADL COINTEGRATION MODELS: AN APPLICATION TO THE DEFENSE GROWTH NEXUS

Introduction

Conventional views on the relationship between military spending and economic growth are built on the idea that defense spending will enhance growth in the short-run acting as a Keynesian-type stimulant. But, it will end up retarding the growth in the long-run as a result of crowding out capital formation in the economy. This argument has much support in the existing literature based on predetermined models of growth, where military spending is considered to be one of the right-hand side exogenous variables. However, it is equally plausible that military spending is endogenous to economics growth, since higher rates of growth provide governments more revenue to allocate for discretionary purposes.

Ever since the initiation of the debate about the potential endogeneity of the military expenditure by Joerding[47], a big number of studies followed in order to scrutinize the temporal causation between defense spending and growth. As a result, there is an ample evidence in the literature that supports causation running both ways (cf. Chowdhury[31], Dakurah et al.[35]). Among the recent studies, Chen et al.[29] studied a panel of 137 countries to examine the causality between military spending and growth. Their results show that there is a one-way causality that runs from military spending to economic growth in high-income countries, whereas the direction of causality is reversed for low-income income countries.

However, one of the critical limitations of most existing studies is that they tend to ignore the presence of a cointegrating relationship. It is very likely that there exists a long-run relationship between defense spending and growth. It is well established by now that in the presence of cointegration, the usual panel vector autoregressive (VAR) models can yield biased results, even when the traditional generalized method of moments (GMM) techniques are deployed to control for the feedback effects. Then, it will be reasonable to consider a panel cointegration model. As such, the present studies that consider the possibility of a long run relationship in most cases are limited to a single country *.

This chapter develops a new panel cointegration model. Our suggested procedure can overcome the difficulties found in the studies based on the panel vector auto-regressive (VAR) models, which can be biased in the presence of cointegration. We wish to adopt the ADL model in the panel data framework. In particular, unlike the usual cointegration approach using the pooling regression based on the estimate of the long-run variance, we adopt the GMM procedures of Arellano & Bond [11] and Arellano & Bover [12]. In fact, the panel ADL cointegration model is a special case of dynamic panel data models. Thus, we can potentially control for the effects of feedback effects, which are largely ignored in the previous studies.

Notably, we apply our suggested procedure to studying the highly debated topic of defense-growth relationship, while capturing the inter-temporal dynamic relation between military spending and economic growth. This chapter is most closely related to the study conducted by Lee & Chen [51]. They utilize Pedroni [60] panel cointegration methodology to investigate long-run relationship between GDP and defense expenditure in the panel of 89 countries for the period of 1988-2003. Their analyses show a long run bi-directional causality among developed and developing countries. Our study differs from theirs in several important ways. First, our study encompasses a much larger sample of countries (165) for a longer horizon (1960-2016). It is well known that panel cointegration tests tend to be more powerful as the number of cross-sections and time-series increase. Second, our cointegration test are based on the ADL specification, which, unlike Pedroni [60] approach, does not put any non-linear restrictions on the parameter estimates. Third, instead of using pooled ordinary least squares (OLS) procedure, we resort to GMM approach of Arellano & Bond [11] that can simultaneously

*Among a few studies, Chang et al. [28] study cointegrating relationship between defense spending and growth in Taiwan and Mainland China. Their result show no evidence of long run relationship. Similarly, Mehanna [55] studied the presence of cointegrating relationship in the U.S. and concluded that defense spending and growth have to long-run impact on each other.

control for potential feedback effects.

Our analyses reveal several important findings. First, our results based on the pooled sample show that there is a long-run causal relationship between defense spending and growth. However, once advanced and developing countries are considered separately, the long run relationship breaks down in the case of developing countries. Second, the short run analyses indicate that defense expenditure has an insignificant impact on the growth in the short run. In contrast, economic growth is found to be an important driver of defense spending based on our impulse- response analysis. These results largely undermine common beliefs that recognize defense spending as having a significant effect on economic growth.

The remainder of the chapter is organized as follows: the following section will give a brief review of the existing literature related the main topic of the chapter; Section 2 will summarize the data and methodology used; Next, section 3 discusses the empirical results obtained from our model which will be followed by section 4 that provides concluding remarks to the chapter.

Evidence from the Literature

The issue of defense growth relationship has been intensively studied since the initiation of the debate by Benoit [24], who analyzed 44 less developed countries (LDCs) over the period of 1950-1965 by deploying the Spearman rank order correlation analysis. His results showed strong positive relationship between defense spending and economic growth. The work by Frederiksen & Looney [43] revisited Benoit [24]'s analysis by dividing the set of 37 LDCs into resource constrained and unconstrained countries. They concluded that resource constrained countries face negative impact of military spending, since they must reallocate productive government spending towards military spending in order to maintain constant military budget.

A great deal of research followed the initiation of the topic of defense spending and economic growth in an attempt to find some meaningful definitive pattern between them. The diversity of conclusions, however, is rather discouraging: one part of them finding a positive relationship (Benoit[24]; Atesoglu & Mueller[14]) and another part pointing to a negative relationship (Loayza et al.[52]; Heo[45]; Chang et al.[27]). This divergence in the results can be related mainly to the inconsistency in theoretical and empirical methodologies used by authors. A number of them relied on neoclassical supply-side growth models arguing that military spending will have detrimental effect on economic growth because of crowding out civilian investment thereby diminishing productive government spending levels. Proponents of Keynesian-type approaches, on the other hand, assume that military spending, just like public expenditure, will stimulate aggregate demand, eventually leading to a growth in the economy.

An absence of definitive pattern among different countries was observed by Chowdhury[31]), who also investigated a presence of Granger causality between defense spending and growth by using the data for 55 LCDs (over 1961-87). He opted to running causality test for every country separately, allowing a variance in the periods chosen for each of them, due to unavailability of data for some countries. Diversity in his results of causality tests made him to conclude that the difference in socio-economic and political systems is a main constraint to generalization of estimation techniques.

The distribution of causality direction across countries leaves a little room for pooled estimation and creates favorable grounds for country-specific univariate approach. Employing variant of VAR modelling method and incorporating impulse response functions into VAR model, Masih et al.[54] discovered unidirectional causality from military spending to economic growth in the case of Mainland China. Also, economic growth was found to have short-term negative response to a one-time positive shock in military spending, which turns into persistent long-term positive growth afterwards. In contrast to Masih et al.[54]s results, Chang et al.[28] identified the output growth as a cause of surge in military spending in China after analyzing the data for the period of 1952-1995 related to both Mainland China and Taiwan. Moreover, they found a bidirectional feedback between military spending and output growth for Taiwan.

Chang et al.[27], for instance, proposed a dynamic panel model to estimate a one-way causality from military spending to growth by using GMM approach, proposed by

Arellano and Bond (1991). Their results showed that, if all 90 countries are pooled together, there are no signs of causality from defense spending to growth. The only case where causality observed was when the sample of low-income countries was tested. In addition, Chen et al.[29] used a two-step GMM estimation approach to study feedback affects from military spending to growth and vice versa. Their study of 137 countries indicated that there is a positive short run feedback from defense spending to growth but negative causality from economic growth to military spending.

Among country-specific approaches of defense growth analysis, the case of the United States is particularly popular (cf Ward & Davis[69]; Mueller & Atesoglu[56];), primarily due to both high volumes of national resources allocated towards defense and the role of the U.S. in geopolitical stabilization in different regions. Deploying cointegration analysis, Atesoglu[13], for instance, concluded that there is significantly positive relationship between military spending and economic growth in the U.S. Nonetheless, a study carried out by Mehanna[55] indicated about nonexistence of any relationship between defense spending and growth in the United States, who used Johansen's cointegration and error correction methodology along with VAR approach (for data over 1959-2001). Similar conclusion was suggested by Dunne & Smith[39], who made a critical review of deploying Granger-causality test. Using the relatively wider timeframe compared to Mehanna[55], he demonstrated how sensitive can the VAR approach be against the variables used, lag lengths and significance level used, also adding that Granger-causality often fails to establish the size of the effect, leaving the user with small information.

Although pooling a big number of countries in conducting causality test might seem promising, nearly every research developed in that framework fails to spot any universality in the direction of causalities among subject countries (see for example Chowdhury[31] or Dakurah et al.[35]). This trend is of course comprehensible, considering the difference in political and socio-economic regimes among countries. So, allowing for a certain homogeneity (e.g. region or income level) among countries allows to narrow down the focus of causality test. OECD countries, for instance, among other groups are often a subject of interest in the *milex* - *gdp* literature.

Overall, all the above-considered studies put remarkable effort to discover possible defense-growth causalities within and across countries and the main body of the literature seems to find the absence of general case across different countries. Thus, it only seems reasonably to conclude that Granger-causality based approaches are only useful when individual countries are analyzed, unless advanced dynamic panel data methods are used to account for any country specific differences. Accordingly, the latest advances in econometric techniques in estimating dynamic panel model together with availability of more consistent data for military spending is resulting in convergence in conclusions among panel data approaches. This certainly creates a possibility for reconsideration of works which have been done in the past in order to eliminate disagreements in conclusions.

Methodology and Data

Methodology

To estimate an inter-temporal dynamic relationship between defense spending and growth, one may consider the following reduced form bivariate panel VAR (P-VAR) system:

$$y_{i,t} = \alpha_{1i} + \sum_{j=1}^{k} \beta_{1j} y_{i,t-j} + \sum_{j=1}^{k} \gamma_{1j} mil_{i,t-j} + \sum_{j=1}^{k} \delta_{1,j} inv_{i,t-j} + \phi_{1,t} + \varepsilon_{1,i,t} \tag{26a}$$

$$mil_{i,t} = \alpha_{2i} + \sum_{j=1}^{k} \beta_{2j} y_{i,t-j} + \sum_{j=1}^{k} \gamma_{2j} mil_{i,t-j} + \sum_{j=1}^{k} \delta_{2,j} inv_{i,t-j} + \phi_{2,t} + \varepsilon_{2,i,t} \tag{26b}$$

where, $y_{i,t}$ is the natural log of per capita GDP of country i at time t; $mil_{i,t}$ represent the natural log of per capita military spending; $inv_{i,t}$ is the total investment as a ratio of GDP, a proxy for gross fixed capital formation, which is assumed to be exogenous to both military spending and growth; ϕ_t measures time-fixed effects. The term α_i in both equations introduced to capture unobserved heterogeneity that might be present across countries*. It is assumed to be uncorrelated with the idiosyncratic term $\varepsilon_{i,t}$, i.e. $E[\alpha_i, \varepsilon_{i,t}] = 0$. Both $\varepsilon_{1,i,t}$ and $\varepsilon_{2,i,t}$ are assumed to be normally distributed, with $E[\varepsilon_{i,t}] = 0$ and $Var[\varepsilon_{i,t}] = \sigma_i > 0$.

The setup of the model given by equations (26a) and (26b) gives a rise to an obvious problem of endogeneity due to the unobserved heterogeneity term, which can result in parameter estimates being biased. To bypass this problem, we apply forward orthogonal deviation (FOD) method, proposed by Arellano & Bover[12], in order to eliminate the constant and unobserved heterogeneity terms. According to the method of FOD, the average of all future observations is deducted from each observation to get rid of any fixed effects in the model. Thus, in actuality we will be estimating the following transformed bivariate model:

$$\Delta y_{i,t} = \sum_{j=1}^{k} \beta_{1j} \Delta y_{i,t-j} + \sum_{j=1}^{k} \gamma_{1j} \Delta mil_{i,t-j} + \sum_{j=1}^{k} \delta_{1,j} \Delta inv_{i,t-j} + \Delta\phi_{1,t} + \Delta\varepsilon_{1,i,t} \tag{27a}$$

$$\Delta mil_{i,t} = \sum_{j=1}^{k} \beta_{2j} \Delta y_{i,t-j} + \sum_{j=1}^{k} \gamma_{2j} \Delta mil_{i,t-j} + \sum_{j=1}^{k} \delta_{2,j} \Delta inv_{i,t-j} + \Delta\phi_{2,t} + \Delta\varepsilon_{2,i,t} \tag{27b}$$

where Δ indicates the FOD transformation of the variable. Also, both transformed error terms are assumed to hold orthogonality requirements.

The transformed model, on the other hand, contains another endogeneity issue. Namely, we have $E[\Delta y_{i,t-k}, \Delta\varepsilon_{i,t-l}] \neq 0$ and $E[\Delta mil_{i,t-k}, \Delta\varepsilon_{i,t-l}] \neq 0$, for every $l > k$. Traditional way of dealing with this issue is using the GMM technique proposed by Arellano & Bond[11] where moment conditions $E[y_{i,t-k}, \Delta\varepsilon_{i,t}] = 0$ for $k = 2 \ldots t-1$ is used to obtain consistent GMM estimators. In our current setup it is done by using previous lags as instrumental variables based on the given moment condition. We then conduct the Granger causality test by estimating the significance of lagged dependent variables in respective equations.

Panel VAR model is a convenient estimation tool when it comes to examining short-

*Here, the unobserved heterogeneity term can arise due to specific time-invariant characteristics each country has, which are hard to observe through numeric data. Also note, that $E[\alpha_i] = \alpha$ holds.

run dynamics of any given set of variables, but it lacks conclusiveness when the question is about long- run relationship between variables. Therefore, in this study we adopt an autoregressive distributed lag (ADL) model onto a panel setup to estimate any possible long-run cointegrating relationship between military spending and economic growth. This seemingly straightforward rearrangement of ADL model is expected to perform better compared to other tests for cointegration, since unlike other tests, it does not put nonlinear restrictions on the parameters. Furthermore, the family of ADL models are known to deliver better results when T is relatively small. So, our tests for cointegration is based on the following unrestricted error correction model:

$$\Delta y_{i,t} = \alpha_0 + \sum_{j=1}^{k} \alpha_{1j} \Delta y_{i,t-j} + \sum_{j=1}^{k} \alpha_{2j} \Delta mil_{i,t-j} + \sum_{j=1}^{k} \alpha_{3,j} \Delta inv_{i,t-j} \tag{28a}$$

$$+ \gamma_1 y_{i,t-1} + \gamma_2 mil_{i,t-1} + \gamma_3 inv_{i,t-1} + \mu_{1,i,t} \tag{28b}$$

$$\Delta y_{i,t} = \beta_0 + \sum_{j=1}^{k} \beta_{1j} \Delta y_{i,t-j} + \sum_{j=1}^{k} \beta_{2j} \Delta mil_{i,t-j} + \sum_{j=1}^{k} \beta_{3,j} \Delta inv_{i,t-j} \tag{28c}$$

$$+ \eta_1 y_{i,t-1} + \eta_2 mil_{i,t-1} + \eta_3 inv_{i,t-1} + \mu_{2,i,t} \tag{28d}$$

where tests for cointegration are based on the joint F-statistics of the lagged level variables with null hypothesis of no-cointegration being $(H_0 : \gamma_1 = \gamma_2 = \gamma_3 = 0)$ and $(H_0 : \eta_1 = \eta_2 = \eta_3 = 0)$ for equations (28b) and (28d) respectively. The proposed panel ADL (P-ADL thereafter) model is then estimated using GMM technique, similar to the previously stated P-VAR model.

In case if we find no cointegrating relationship based on our P-ADL model, our analysis will be limited to the short-run dynamic relationship according to P-VAR model. However, if we do end up finding cointegrating relationship between our variables, then the estimations will follow the restricted panel error-correction model (P-ECM) based on the following setup:

$$\Delta y_{i,t} = \alpha_0 + \sum_{j=1}^{k} \alpha_{1j} \Delta y_{i,t-j} + \sum_{j=1}^{k} \alpha_{2j} \Delta mil_{i,t-j} + \sum_{j=1}^{k} \alpha_{3,j} \Delta inv_{i,t-j} + \lambda_1 EC_{i,t-1} + \varepsilon_{1,i,t} \tag{29a}$$

$$\Delta mil_{i,t} = \beta_0 + \sum_{j=1}^{k} \beta_{1j} \Delta y_{i,t-j} + \sum_{j=1}^{k} \beta_{2j} \Delta mil_{i,t-j} + \sum_{j=1}^{k} \beta_{3,j} \Delta inv_{i,t-j} + \lambda_2 EC_{i,t-1} + \varepsilon_{2,i,t} \tag{29b}$$

where the error correction term $EC_(i, t-1)$ is simply the lagged residual from the regression of $y_{i,t}$ on $mil_{i,t}$, which is believed to capture the magnitude of long-run disequilibria and both λ_1 and λ_2 represent the speed of adjustment towards the equilibrium in the model. Based on this setup, the analysis of short-run causality can be performed by testing the significance of respective lagged endogenous variable, whereas the results of t-test on error correction term can be used to gauge on the long run behavior of the model. The regression of $y_{i,t}$ on $mil_{i,t}$ performed based on fixed effects estimation.

The optimal lags of variables to be considered for the model are determined based on the Andrews & Lu[8]'s moment and model selection criteria, which uses Hansen's J-statistics to estimate modified Bayesian information criterion (MBIC), modified Akaike information criterion (MAIC) and modified Quinn information criterion (MQIC) for each lags. The model with the least estimate of each criteria is deemed optimal.

Although there are no certain requirements in terms of order of integration of the variables for our P-ADL and P-ECM models, P-VAR does require the variables to be stationary in order to avoid spurious results. Thus, we used both Im-Pesaran-Shin (IPS) and Augmented Dickey-Fuller (ADF) tests to check for existence of a unit-root in our series. IPS was used due to its feature of considering each country individually and ADF is known to be compatible with even unbalanced panels. Based on the results shown in Table 12, the existence of unit root is rejected in all cases for all variables at 1% significance level, the only exception being military spending of OECD countries, which was rejected at 5% significance level.

Table 12 Panel Unit Root Test Results

Variable	Test	Full Sample	OECD	Non-OECD
$y_{i,t}$	IPS	-20.85*	-10.56*	-18.00*
	ADF	1141.85*	268.65*	873.19*
$mil_{i,t}$	IPS	-10.62*	-2.30	-10.81*
	ADF	709.15*	121.74*	587.40*
$inv_{i,t}$	IPS	-	-4.41*	-
	ADF	482.36*	129.38*	352.98*

Note: IPS = Im et al.[46] test statistics, ADF = Augmented Dickey-Fuller test statistics; The asterisk * denotes statistical significance at 1% level. $y_{i,t}$ denotes real economic growth per capita, $mil_{i,t}$ denotes the log of military spending per capita and $inv_{i,t}$ denotes gross fixed capital formation as percentage of GDP.

Data

In this study we look at data for 165 countries that cover the period of 1960-2016. Both per capita real GDP and gross capital formation (investment) data were obtained from the World Development Index (WDI) database of the World Bank. GDP data is normalized based on the prices for 2010. In order to decrease a heterogeneity within the data, we divide our sample of countries into two groups: OECD (advanced) countries and non-OECD (developing) countries*. The military spending data was obtained from Stockholm International Peace Research Institute (SIPRI) database and was also normalized based on 2010 prices.

Estimation Results

Panel Cointegration

We begin our discussion with estimates of the long-run relationship between military spending and economic growth based on the equations (28b) and (28d). Before deriving the main results, it is imperative to select the optimal lag length to be included in the models. As such, we select 2 lags to be optimal based on the results of all three selection criteria we used, as it is presented in Table 13.

Moving on to the main results given in Table 14, our proposed cointegration test

*See Table 19 in the Appendix section for the full list of countries

Table 13 Optimal Lag-selection Criteria Results

Lag	CD	J-statistic	p-value	MBIC	MAIC	MQIC
1	0.9335	85.4376	0.0121	13.43114	61.4376	34.8243
2	0.9340	19.3486	0.0132	-46.6006	3.3486	-14.3336
3	0.9145	16.9978	0.0019	-15.9567	8.9943	0.1288

is indicating that there are multiple cointegrating vectors in the relationship of military spending and growth, since the lagged level terms are jointly significant in both equations in the system. This essentially means that military spending and economic growth are highly important in explaining each other in the long run and keeping each other within the bounds of attainable equilibrium level. The existence of equilibrating adjustment in the relationship is further underlined by the significance of the error-correction term in equations (29a) and (29b), which are given in the last two columns of Table 14. Additionally, negative sign of the error-correction term is a clear indication of the fact that both series are quick in responding to the disequilibria brought to the model as a result of a sudden shock.

Our estimates take a slightly different turn once the sample is divided into non-OECD and OECD countries, reported by Table 15 and Table 16 respectively. Although non-OECD sample exhibited the same properties as the full sample, singling out OECD countries resulted in a loss of long-run relationship in the equation (29b), leaving us with a unique cointegrating vector. Hence, in the long-run, per capita growth in the economy of advanced countries is partially explained by military spending, along with other constituents. This result is perhaps due to the long-run spillover effects of military spending in the economy caused by civilian safety and technological advancement, as described by a number of studies in the literature*.

Panel VAR

The existence of a long-run cointegrating relationship between variables means that there is a short-run causality running at least in one direction, but it does not point to the direction of the causality. So, to reveal the direction of causality, we resort to

*See for example Ward & Davis [69], Chang et al. [27].

Table 14 Estimation Results – Full Sample

	P-VAR		P-ADL		P-ECM	
	Lag=1	Lag=2	Lag=1	Lag=2	Lag=1	Lag=2
Dep. var.: $\Delta y_{i,t}$						
$\Delta y_{i,t-1}$	0.431***	0.360***	0.385***	0.326***	0.407***	0.289***
	(10.911)	(8.779)	(9.026)	(7.292)	(7.997)	(4.45)
$\Delta y_{i,t-2}$		0.042*		0.021		0.039
		(1.687)		(0.849)		(1.278)
$\Delta mil_{i,t-1}$	0.006	0.004	0.005	0.004	0.006	0.004
	(1.468)	(0.843)	(1.163)	(0.777)	(1.359)	(0.797)
$\Delta mil_{i,t-2}$		0.002		0.004		0.003
		(0.555)		(1.125)		-0.697
$y_{i,t-1}$			-0.011***	-0.012***		
			(-2.977)	(-3.251)		
$mil_{i,t-1}$			0.006	0.005		
			(1.291)	(1.096)		
$EC_{i,t-1}$					-0.014*	-0.026***
					(-1.932)	(-3.241)
Dep. var.: $\Delta mil_{i,t}$						
$\Delta y_{i,t-1}$	0.707***	0.599***	0.599***	0.501***	0.707***	0.480***
	(7.315)	(5.956)	(5.686)	(4.657)	(5.878)	(3.651)
$\Delta y_{i,t-2}$		0.189**		0.139		0.151
		(2.17)		(1.56)		(1.517)
$\Delta mil_{i,t-1}$	0.045	0.045	0.028	0.015	0.053*	0.011
	(1.551)	(1.435)	(0.888)	(0.395)	(1.941)	(0.286)
$\Delta mil_{i,t-2}$		-0.029		0.001		-0.014
		(-1.305)		-0.055		(-0.612)
$y_{i,t-1}$			0.014	0.012		
			(1.151)	(1.005)		
$mil_{i,t-1}$			-0.053***	-0.045**		
			(-2.980)	(-2.320)		
$EC_{i,t-1}$					-0.046*	-0.072**
					(-1.847)	(-2.319)
N	4,164	3,962	4,059	4,029	4,229	4,029
Short-run causality						
$\Delta mil \Rightarrow \Delta y$	2.15	0.92			1.84	0.58
$\Delta y \Rightarrow \Delta mil$	52.52***	42.66***			29.98***	14.97***
Long-run causality						
$\Delta mil \Rightarrow \Delta y$			11.22**	13.20**	3.73*	10.50***
$\Delta y \Rightarrow \Delta mil$			8.99**	6.34*	3.41*	5.38**

Note: Numbers in parentheses reported are t-statistics for model coefficient estimates and p-statistics for both Hansen's J-statistics and Granger causality test; *, ** and *** indicate statistical significance at 5%, 1% and 0.1% respectively.

Table 15 Estimation Results – non-OECD Sample

	P-VAR		P-ADL		P-ECM	
	Lag=1	Lag=2	Lag=1	Lag=2	Lag=1	Lag=2
Dep. var.: $\Delta y_{i,t}$						
$\Delta y_{i,t-1}$	0.408***	0.333***	0.366***	0.300***	0.362***	0.278***
	(9.397)	(7.582)	(8.379)	(6.827)	(6.348)	(5.136)
$\Delta y_{i,t-2}$		0.050*		0.046*		0.050*
		(1.891)		(1.815)		(1.692)
$\Delta mil_{i,t-1}$	0.006	0.003	0.005	0.001	0.004	0.001
	(1.273)	(0.582)	(1.028)	(0.221)	(0.768)	(0.262)
$\Delta mil_{i,t-2}$		0.003		0.003		0.002
		(0.691)		(0.617)		(0.55)
$y_{i,t-1}$			-0.010*	-0.012**		
			(-1.656)	(-1.991)		
$mil_{i,t-1}$			0.004	0.005		
			(0.656)	(0.808)		
$EC_{i,t-1}$					-0.019*	-0.021**
					(-1.942)	(-2.307)
Dep. var.: $\Delta mil_{i,t}$						
$\Delta y_{i,t-1}$	0.691***	0.605***	0.559***	0.503***	0.626***	0.487***
	(6.60)	(5.41)	(5.01)	(4.26)	(4.92)	(3.84)
$\Delta y_{i,t-2}$		0.173*		0.142*		0.132
		(1.88)		(1.65)		(1.39)
$\Delta mil_{i,t-1}$	0.038	0.038	0.056*	0.045	0.033	0.037
	(1.26)	(1.17)	(1.91)	(1.39)	(1.09)	(1.14)
$\Delta mil_{i,t-2}$		-0.033		-0.015		-0.034
		(-1.443)		(-0.683)		(-1.491)
$y_{i,t-1}$			0.045**	0.039*		
			-2.232	-1.852		
$mil_{i,t-1}$			-0.074***	-0.059**		
			(-3.400)	(-2.515)		
$EC_{i,t-1}$					-0.05	-0.060*
					(-1.457)	(-1.665)
N	3,786	3,602	3,786	3,602	3,786	3,602
Short-run causality						
$\Delta mil \Rightarrow \Delta y$	1.62	0.73			0.59	0.34
$\Delta y \Rightarrow \Delta mil$	43.50***	34.08***			24.20***	16.37***
Long-run causality						
$\Delta mil \Rightarrow \Delta y$			6.99*	6.52**	3.77*	5.32**
$\Delta y \Rightarrow \Delta mil$			12.44**	6.81*	2.12	2.77**

Note: Numbers in parentheses reported are t-statistics for model coefficient estimates and p-statistics for both Hansen's J-statistics and Granger causality test; *, ** and *** indicate statistical significance at 5%, 1% and 0.1% respectively.

Table 16 Estimation Results – OECD Sample

	P-VAR		P-ADL		P-ECM	
	Lag=1	Lag=2	Lag=1	Lag=2	Lag=1	Lag=2
Dep. var.: $\Delta y_{i,t}$						
$\Delta y_{i,t-1}$	0.553***	0.553***	0.339***	0.379***	0.418***	0.416***
	(10.54)	(10.59)	(7.13)	(6.91)	(6.88)	(6.45)
$\Delta y_{i,t-2}$		0.008		-0.054		-0.052
		(0.19)		(-1.257)		(-1.097)
$\Delta mil_{i,t-1}$	0.014	0.013	0.023*	0.019	0.019	0.02
	(0.93)	(0.83)	(1.69)	(1.35)	(1.26)	(1.29)
$\Delta mil_{i,t-2}$		-0.01		-0.008		-0.006
		(-0.730)		(-0.640)		(-0.414)
$y_{i,t-1}$			-0.022***	-0.021***		
			(-6.204)	(-5.367)		
$mil_{i,t-1}$		-0.002	-0.001			
			(-0.404)	(-0.225)		
$EC_{i,t-1}$					-0.017***	-0.019***
					(-3.148)	(-3.206)
Dep. var.: $\Delta mil_{i,t}$						
$\Delta y_{i,t-1}$	0.669***	0.401***	0.286**	0.221*	0.438***	0.332**
	(5.61)	(3.35)	(2.30)	(1.66)	(3.01)	(2.06)
$\Delta y_{i,t-2}$		0.296**		0.202*		0.263**
		(2.52)		(1.74)		(2.21)
$\Delta mil_{i,t-1}$	0.175***	0.161***	0.190***	0.166***	0.200***	0.178***
	(3.96)	(3.40)	(4.65)	(3.73)	(4.51)	(3.73)
$\Delta mil_{i,t-2}$		0.059*		0.058*		0.061*
		(1.65)		(1.71)		(1.76)
$y_{i,t-1}$			-0.002	0.004		
			(-0.152)	-0.357		
$mil_{i,t-1}$			-0.051**	-0.046**		
			(-2.534)	(-2.146)		
$EC_{i,t-1}$					-0.017	-0.006
					(-1.099)	(-0.337)
N	1,335	1,304	1,335	1,304	1,335	1,304
Short-run causality						
$\Delta mil \Rightarrow \Delta y$	0.86	1.17			1.59	0.34
$\Delta y \Rightarrow \Delta mil$	31.44***	22.56***			9.06**	16.37***
Long-run causality						
$\Delta mil \Rightarrow \Delta y$			40.12***	30.68***	9.91**	10.28**
$\Delta y \Rightarrow \Delta mil$			6.02	5.86	1.21	0.11

Note: Numbers in parentheses reported are t-statistics for model coefficient estimates and p-statistics for both Hansen's J-statistics and Granger causality test; *, ** and *** indicate statistical significance at 5%, 1% and 0.1% respectively.

the technique of Granger causality by testing the joint significance of lagged dependent variables in our P-VAR model. Following the results presented in the Table 1, we can clearly see that military spending has very little significance in the equation of economic growth, which is supported by insignificant F-statistics in the Granger causality test. These findings are consistent with initial arguments made Joerding[47]. At the same time, the results of military spending equation are revealing that economic growth has a lot to do in defense spending habits of the countries we studied. These results act against the arguments of many studies, who stated that military spending is the one which promotes economic growth in the short-run, going hand-in-hand with other types of government spending. A closer look at the magnitudes of the parameter estimates are telling us that higher growth in the economy results in positive changes in military spending in the short run, which is contrary to the results obtained by Chen et al.[29], who spotted negative causality from growth to defense spending.

A bigger picture of the relationship can be seen by looking at impulse-response functions given by Figure 17. Accordingly, a plot of dY:dM in lower-left sub-panel is indicating about a significant short run positive response from military spending for a given shock in economic growth which dies out within a few years. In fact, as much as 13 per cent variation in military spending is explained by shocks incurred by economic growth, based on the results of forecast error-variance decomposition. The same story, however, does not apply to the responses of economic growth to the shocks to military spending, which is depicted by considerably large confidence intervals in the upper-right panel of Figure 17.

The robustness of above-reported results can be further backed by considering the estimates for advanced and developing countries separately. Short-run causality results for both subgroups are consistent with the results reported above (see Figure 18). These finding undermine our suspicions about the cross-sectional heterogeneity to some extent, but the possibility of variance in results after further sub-sampling cannot be ruled out either.

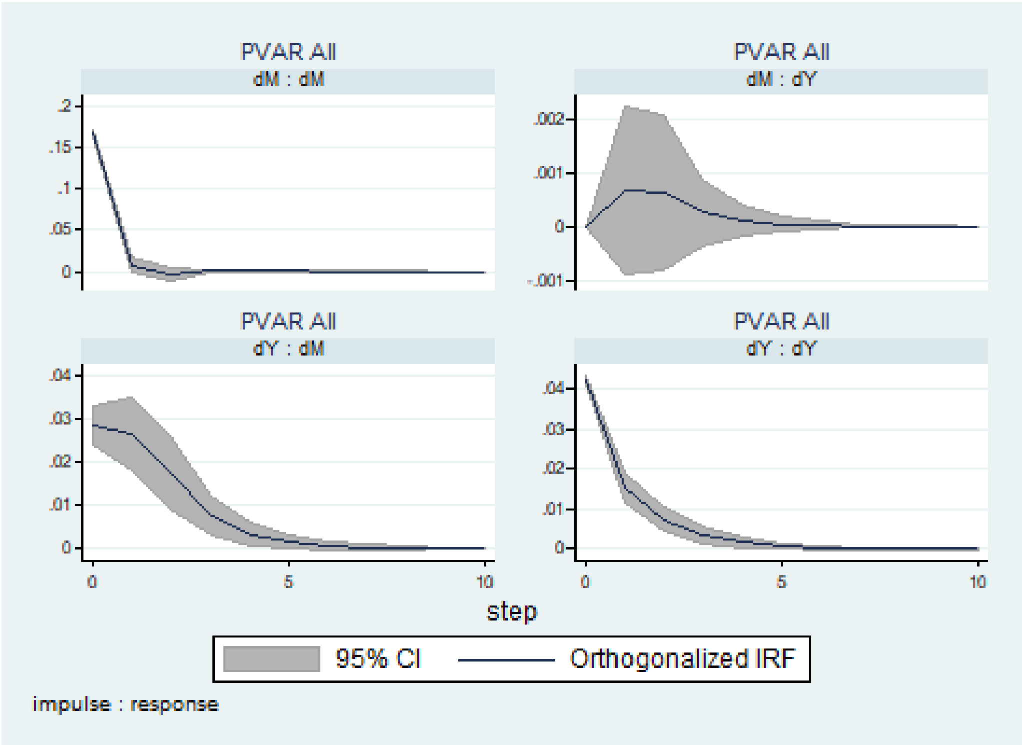

Figure 17: Impulse-response Functions – Full Sample

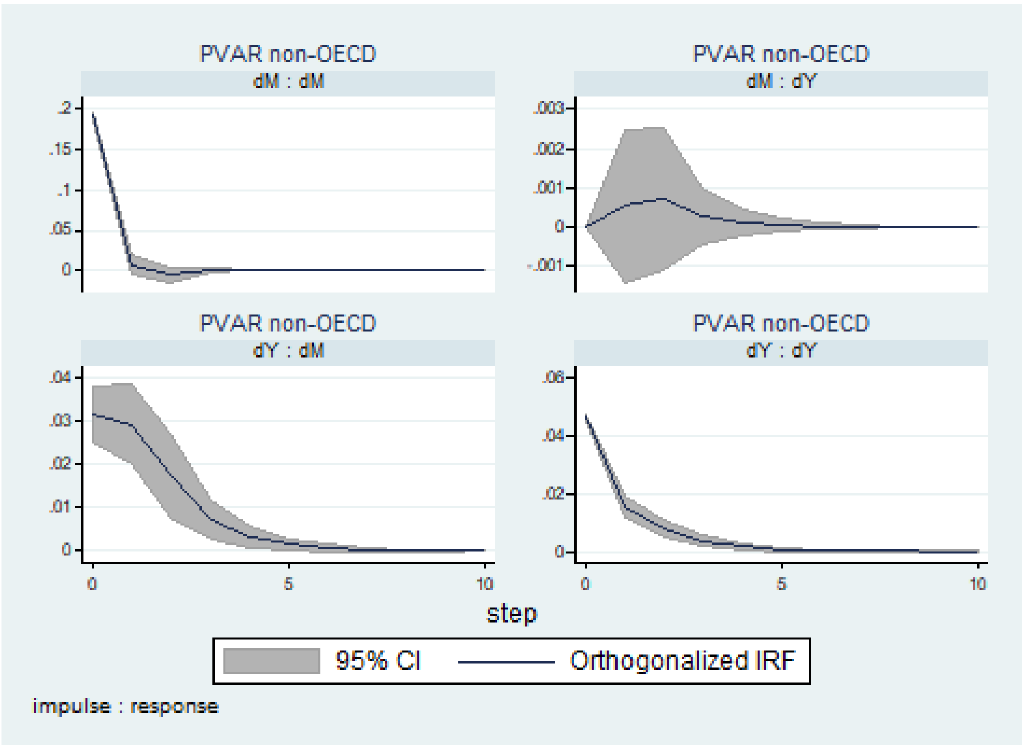

Figure 18: Impulse-response Functions – Non-OECD Sample

Concluding Remarks

In this study we revisited the highly contested topic of defense-growth relationship within the framework of panel vector autoregressive (VAR) model to capture any possible dynamic inter-temporal relationship. The study develops a traditional autoregressive distributed lag (ADL) model into a panel setup to estimate a long-run cointegrating relationship between the variables of interest in an unrestricted fashion. Full sample of data, which covers 165 countries for the period of 1960-2016, was further divided into two subcategories, in the hopes of mitigating adverse effects of any possible cross-sectional heterogeneity. The results reveal several interesting insights to the relationship of military spending and growth which undermine findings reported by several previous studies. Firstly, the long-run analysis revealed that there are multiple cointegrating vectors in the relationship of military spending and growth which signaled about the high importance of both series adjusting towards the equilibrium in the event of a shock. Secondly, when the advance group of countries studied separately, there happened to be a unique cointegrating vector within the relationship, where economic growth was deemed to be trivial in the long-run adjustment of military spending. This phenomenon is very likely a result of long-run spillover effects of military spending to the civilian sector, a finding reported by several studies in the past. Finally, an examination of short-run dynamics between our variables indicated about a high significance of economic growth in the equation of military spending, which turned robust even after splitting the data into two different subgroups.

The findings reported above could turn out to be useful when it comes to making policy-related decisions. After all, military expenditures play an important role in approving final draft of government budget for any given fiscal year. And, when it comes to positive statements in approving any military spending hikes, the argument about military spending being a short-run Keynesian-type growth stimulus should not be one.

The literature regarding this topic has been extensively adding to its body with the proliferation of new econometric techniques as well as availability of more data series, and perhaps will keep evolving. Along the several others, the literature could benefit if the current study is replicated by further dividing cross-sectional units into multiple subcategories based on the geographical positioning. In addition to that, an incorporation of spatial analysis techniques could also help reduce cross-sectional dependence within the sample and significantly improve the reliability of outcomes.

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Appendix 1

Appendix 1A

Table 17 Contribution of the first PC: Country rankings

Full Sample		Pre-Crisis		During Crisis		Post-Crisis	
Croatia	0.948	Slovakia	0.997	Colombia	0.975	Spain	0.948
Latvia	0.940	Czech Rep	0.995	Estonia	0.967	Ireland	0.947
Czech Rep.	0.911	Estonia	0.994	South Korea	0.959	Latvia	0.946
Estonia	0.908	Indonesia	0.993	Sweden	0.946	Poland	0.946
Sweden	0.883	Colombia	0.993	Indonesia	0.942	Lithuania	0.944
Austria	0.855	Spain	0.991	China	0.940	Belgium	0.943
	⋮		⋮		⋮		⋮
Netherlands	0.446	Mexico	0.821	Spain	0.032	Malaysia	0.193
Slovakia	0.413	Ireland	0.807	Netherlands	0.012	Peru	0.130
Mexico	0.356	Cyprus	0.804	Philippines	0.008	Chile	0.068
Spain	0.345	Chile	0.756	Cyprus	0.004	South Korea	0.041
Cyprus	0.213	Brazil	0.733	Germany	0.003	Panama	0.008
Chile	0.065	Austria	0.711	Belgium	0.000	Mexico	0.000

Appendix 1B

Consider the following panel data model with a factor structure:

$$y_{it} = \lambda_i' F_t + e_{i,t}, \quad i = 1, \dots, N, \quad t = 1, \dots, T \tag{1}$$

where F_t is $k \times 1$ vector of latent factors and Λ is $N \times k$ matrix of associated factor loadings. Equation (1) can be expressed in the following stacked form:

$$Y_t = \Lambda F_t + \mathbf{e}_t \tag{2}$$

where $Y_t = [y_{1,t}, y_{2,t}, \dots, y_{N,t}]'$, $\Lambda = [\lambda_1, \lambda_2, \dots, \lambda_N]'$ and $\mathbf{e}_t = [e_{1,t}, e_{2,t}, \dots, e_{N,t}]'$. The principal component estimator then minimizes the following sum of squared residuals:

$$V(k) = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}(Y_t - \Lambda F_t)^2 \tag{3}$$

where k is the number of unknown common factors. We use the following information criterion of Bai & Ng[20] to determine the optimal number of latent factors in our model:

$$IC(k) = ln(V(k)) + k\Big(\frac{N+T}{NT}\Big)ln(C_{NT}^2) \tag{4}$$

where, $C_{NT} = min\{N^{1/2}, T^{1/2}\}$. It can be shown that the estimate for the factor term, $\hat{F}_t$, is given by the first k leading eigenvectors of YY' multiplied by $T^{1/2}$ and $\hat{\Lambda} = Y'\hat{F}_t/T$. Bai[17] shows that under the general condition $\sqrt{N}/T \rightarrow 0$, $\sqrt{N}(\hat{F}_t - HF_t) \rightarrow N(0, V_F)$, where H is the rotation matrix and V_F is the asymptotic variance matrix.

After PCs are estimated, the next task is to determine the percentage of variation in sovereign CDS explained by each PC. To do so, we let y_{it}^* and e_{it}^* denote standardized y_{it} and e_{it} respectively, from equation (1). Since $y_{it}^* = \frac{1}{\sigma_i}(\lambda_i' F_t + e_{it}^*)$, assuming the orthogonality of the factors and the error term, the variance of the standardized sovereign CDS spreads (y_{it}^*) can be expressed as:

$$V(y_{it}^*) = \frac{\lambda_i^2 V(F_t)}{\sigma_i^2} + \frac{V(e_{it}^*)}{\sigma_i^2} = 1 \tag{5}$$

where $\lambda_i^2 V(F_t)/\sigma_i^2$ denotes the variance explained by the factor term and $V(e_{it}^*)/\sigma_i^2$ captures the unexplained portion of the variance. If the variance of the factor term is assumed to be a unity, as it is commonly done in such setup, the explained variance by the common factor can then be computed simply through λ_i^2/σ_i^2. Instead of computing the explained variance this way, one can also run a regression of sovereign CDS against the estimated factor. The resultant R-square value from the regression will be identical to $\lambda_i^2 V(F_t)/\sigma_i^2$ term[67].

Appendix 2

Table 18 Variables and their sources

Description	Source	# of countries
Gross Government Debt-to-GDP ratio	Historical Public Debt, IMF	187
Central Government Debt, % of GDP	Global Debt Database, IMF	172
GDP (constant LCU)	World Bank	208
GDP per capita (constant 2005 US$)	World Bank	203
CPI (2010=100)	World Bank	184
Total reserves including gold (% of GDP)	World Bank	53
Government Effectiveness: Estimate	World Bank	208
Expense (% of GDP) (Government)	World Bank	163
Interest payments (% of expense)	World Bank	160
Revenue, excluding grants (% of GDP)	World Bank	163
Tax revenue (% of GDP)	World Bank	163
Employment-to-Population ratio	World Bank	201
Official exchange rate (LCU per US$)	World Bank	196
Current account balance (% of GDP)	World Bank	187
Real interest rate (%)	World Bank	171
Interest Rates, Government Securities	IMF	78
Brent Crude Oil, US Dollars per barrel	FRED Database	184

Appendix 3

Table 19 The list of countries used in the estimations.

OECD	non-OECD			
Australia	Afghanistan	Djibouti	Lebanon	Russia
Austria	Albania	Dominican	Lesotho	Rwanda
Belgium	Algeria	Ecuador	Liberia	Saudi Arabia
Canada	Angola	Egypt	Libya	Senegal
Chile	Argentina	El Salvador	Lithuania	Serbia
Czech Republic	Armenia	Guinea	Macedonia	Seychelles
Denmark	Azerbaijan	Eritrea	Madagascar	Sierra Leone
Estonia	Bahrain	Ethiopia	Malawi	Singapore
Finland	Bangladesh	Fiji	Malaysia	Somalia
France	Belarus	Gabon	Mali	South Africa
Germany	Belize	Gambia	Malta	South Sudan
Greece	Benin	Georgia	Mauritania	Sri Lanka
Hungary	Bolivia	Ghana	Mauritius	Sudan
Ireland	Bosnia	Guatemala	Moldova	Swaziland
Israel	Botswana	Guinea	Mongolia	Syria
Italy	Brazil	Guinea-Bissau	Montenegro	Tajikistan
Japan	Brunei	Guyana	Morocco	Tanzania
Latvia	Bulgaria	Haiti	Mozambique	Thailand
Luxembourg	Burkina Faso	Honduras	Myanmar	Timor-Leste
Mexico	Burundi	Iceland	Namibia	Togo
Netherlands	Cabo Verde	India	Nepal	Trinidad
New Zealand	Cambodia	Indonesia	Nicaragua	Tunisia
Norway	Cameroon	Iran	Niger	Turkmenistan
Poland	CAR	Iraq	Nigeria	Uganda
Portugal	Chad	Jamaica	Oman	Ukraine
Slovak Republic	China	Jordan	Pakistan	UAE
Slovenia	Colombia	Kazakhstan	Panama	Uruguay
Spain	DPR Congo	Kenya	Papua	Uzbekistan
Sweden	Congo	Korea	Paraguay	Venezuela
Switzerland	Cote d'Ivoire	Kosovo	Peru	Vietnam
Turkey	Croatia	Kuwait	Philippines	Yemen