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Green bonds, conventional bonds and geopolitical risk

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ABSTRACT

This paper analyses linkages between green, conventional (corporate and sovereign) bond markets and geopolitical risk in high and low volatility periods between 2014 and 2022 using a Markov-switching VAR (MS-VAR) framework. The results indicate that geopolitical risk significantly affects green bonds in periods of high volatility, but does not do so to conventional bond markets. Green bond markets are significantly affected by sovereign and corporate bonds in both regimes, with stronger effects from corporate bonds evident in high volatility periods. This suggests that green bonds behave differently to conventional bonds and may be more susceptible to geopolitical risk and contagion.

1. Introduction

The United Nations Environment Programme Emissions Gap Report (2022) highlights that current strategies aimed at fighting climate change remain insufficient to achieve global temperature increases at or below 1.5 °Celsius relative to pre-industrial revolution levels by the end of the century, with estimates of 2.5 °Celsius cited as more realistic. The report states that the financial system must be transformed and used to enable the '*…sectoral transitions required to address the current climate crises*' (United Nations Environment Programme, 2022). Green finance is increasingly being cited as a powerful weapon in the fight against climate change (Sachs et al., 2019). Green bonds, bonds that fund environmentally friendly projects and initiatives, are one such green finance tool that have gained popularity in recent years (Tolliver et al., 2020). Indeed green bond issuance reached a new milestone of $2 trillion in the third quarter of 2022 (Climate Bonds Initiative, 2022).

The increase in climate-related risks has occurred during a period of increasing geopolitical risks, one of the most recent being the February 2022 Russian invasion of Ukraine. Geopolitical risks influence financial sectors both domestically and internationally, for example via economic sanctions. Caldara and Iacoviell (2022) define geopolitical risk as '*..the threat, realization, and escalation of adverse events associated with wars, terrorism, and any tensions among states and political actors that affect the peaceful course of international relations*' and highlight that it influences investment decisions by market participants and stock market behavior.

There is a body of work discussing the effect of geopolitical risk on financial markets (Balcliar et al. (2018); Yang et al. (2021); Smales (2021)) and a growing strand of literature analysing linkages between geopolitical risk, green bonds, and conventional bonds. Bouri et al. (2019) find geopolitical risks predict returns and volatility measures of Islamic bonds by analysing the geopolitical risk index utilised in this paper. Ma et al. (2022) also analyze this index to predict stock returns, finding that the geopolitical threats index can help prediction. Nguyen and Thuy (2023) find that geopolitical risk, also measured using this index, increases the cost of bank loans and Phan et al. (2022) find that an increase in geopolitical risk is associated with a decline in bank stability.

In terms of linkages between geopolitical risk and green bond markets Lee et al. (2021) analyze the relationship between green

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bonds, oil prices and geopolitical risk from 2013 to 2019 using quantile analysis finding Granger-causality from geopolitical risk to green bonds at lower quantiles. Sohag et al. (2022) analyze the response of green assets, including green bonds, to geopolitical risk measures using cross-quantilogram and quantile and quantile methods finding that they transmit positive shocks to the green equities and bonds. Cepni, et al. (2022) find that green bonds exhibit consistently positive time-varying correlations with both physical and transition climate risk indexes.

Tang et al. (2023) investigate the asymmetric effects of U.S. Economic Policy Uncertainty, geopolitical threats, geopolitical acts, and West Texas Intermediate Crude oil on green bond returns finding that, for the short run, green bond returns are negatively affected by economic policy uncertainty and geopolitical acts but positively by geopolitical threats and oil. In the long run, green bond returns are negatively affected by economic uncertainty and geopolitical acts but positively affected by oil. Dong et al. (2023) investigate the impacts of geopolitical, economic and climate policy on the long-term correlations between energy and stock markets and conventional and green bond markets. They find that both conventional and green bonds have a safe-haven function when geopolitical risk is high, while green bonds outperform conventional bonds as a safe haven when economic policy uncertainty and climate policy levels are high.

The literature discussed above analyses the relationship between geopolitical risk and a range of markets, including green and conventional bonds. This paper will add to the literature by empirically investigating the relationship between the green bond market, conventional bond markets and geopolitical risk across two periods, namely tranquil market conditions and in a relatively higher volatility period. In this way we aim to identify potential contagion channels, following the Forbes and Rigobon (2002) definition of contagion as a significant increase in market dependencies between normal and crisis periods. To our knowledge this is the first paper that employs this methodology and focusses on the topic of contagion within these markets. The Securities Industry and Financial Markets Association (SIFMA) estimates that in 2022 the outstanding value of global bond markets was €129.8 trillion, eclipsing that of equities, which was estimated to be €101.2 trillion for the same period (Kolchin et al., 2023). Apart from their size, well developed bond markets perform several important functions such as increasing the competitiveness, efficiency and stability of the financial system and enhancing communication between policy-makers, financial markets and society (Sokoler, 2002). Therefore it is important to gain insights into how these markets may interact with each other, particularly in times of stress such as high geopolitical risk, which is cited by many as the top risk facing global markets in 2023 (SandP Global, 2023).

This work is intended to inform investment strategy and policy discussions regarding the rapidly growing and relatively new green bond market. In terms of investment strategy literature suggests employing alternative portfolio choices in the presence of contagion (Aït-Sahalia and Hurd, 2015) so this work could form a first step towards informing investors whether they may need to consider changing strategies by aiding the identification of contagion in these markets.

In terms of policy increasing calls for regulation of green assets and the financial crisis of 2007/08 highlighted the importance of understanding risk transmission channels between assets and markets at a systemic level (Kavonius and Castrén, 2009). Therefore the results should contribute to policy discussions and lay the foundation for further analyses.

The empirical analysis is described in Section 2, while Section 3 discusses the results. Section 4 concludes.

2. Data and methodology

Green bond, corporate bond and sovereign bond data have been obtained from Bloomberg, with daily log differences used in the analysis, while daily observations of the geopolitical risk index (GPR) of Dario and Iacoviello (2022) serves to proxy for geopolitical risk.[1] The sample ranges from July 31, 2014 to October 31, 2022, thus capturing both the onset of the COVID-19 pandemic in early 2020 and the war in Ukraine on 24th February 2022.[2] As no crises originated in the financial markets analysed during that time, but events like the COVID-19 pandemic affected markets such as equities, regimes will be defined as low- and high-volatility. During the latter we expect general volatility to have an impact on financial markets but that volatility does not necessarily originate in those markets.

The S&P Green Bond Index, launched in 2014, is a multi-currency rules-based benchmark that serves to proxy for the performance of the green bond market. The bonds included are globally issued bonds labelled ‘green’ by the Climate Bonds Initiative. Kanamura (2020) investigates the ’greenness’, i.e. correlations between green bond prices as environmental value and crude oil prices as fossil fuel value, of green bonds, finding that S&P green bonds, as well as Bloomberg Barclays MSCI, do indeed carry greenness. Due to some MSCI data gaps the S&P Green Bond Index is analysed.

The Bloomberg US Corporate Bond Index measures the investment grade, fixed-rate, taxable corporate bond market, thus representing the corporate bond market. The 10-year Treasury yield serves to proxy for the performance of sovereign bond market and as an indicator of investor confidence. The GPR is produced using news from ten major national and international newspapers based on a search for words from eight word categories, namely War Threats, Peace Threats, Military Buildups, Nuclear Threats, Terror Threats, Beginning of War, Escalation of War, Terror Acts.

Barros et al. (2022) uses the international GPR to analyze the effects of shocks on the Brazilian economy. Gozgor et al. (2019) utilize the GPR, along with other uncertainty measures, to analyze their role on return and volatility of gold, finding that the GPR and the U.S. real effective exchange rate significantly affect gold returns. Zhang et al. (2022) use the GPR to analyze co-movements between geopolitical risk and returns of global defense and aerospace companies, finding significant co-movements around the onset of the war

[1] GPR index levels are stationary at 1 % level of significance.

[2] The sample period begins in 2014 due to availability of green bond data.

in Ukraine. Table 1 reports summary statistics for the variables.

Table 1 suggests that normality is rejected in all cases, evidenced by excess kurtosis. Green bond and corporate bond returns display negative skewness while sovereign bond yields are positively skewed, reflecting the lower level of risk associated with this asset.

While statistics for the GPR are included for completeness intuitively these cannot be compared to those for the bond markets given as they are obviously not a proxy for a financial market. Fig. 1 presents the GPR data.

The effect of the pandemic and the war in Ukraine are clear in as the GPR spikes in early 2020 and February 2022.

We employ a two-state Markov-Switching vector autoregression (MS-VAR) to observe direct and indirect bilateral relationships between the variables, enabling us to address the research question as we are concerned with interactions between the markets considered. The regime switching component is appropriate given that we are testing for contagion and thus require low- and high-volatility regimes to analyze the aforementioned relationships in both states, given our definition of contagion. This method endogenously models the regime-switching behavior of the variables, which reduces the risk of incorrectly selecting regimes by exogenously selecting them. Also, the model assumes that the transition probabilities have a preference for staying in the current state thus capturing the volatility-clustering behavior of financial markets discussed by Cont (2007).

We choose two regimes due to the relatively short length of the sample. Bai-Perron Break Point Analysis also supports imposing one structural break. The model takes the following form:

$$y_{i,t} = \alpha(s_t) + \sum_{k=1}^{2} \beta_k(s_t) y_{i,t-k} + \varepsilon_{i,t}^{st}, \quad s_t \in \{1,2\}, \quad \varepsilon_{i,t}^{st} \sim i.i.d.N\left(0, \sigma_{st}^2\right) \tag{1}$$

in which $y_{i,t}$ is an n dimensional time series vector of dependent variables, α is a matrix of state dependent intercepts, $\beta_1 \ldots \beta_k$ are matrices of the state dependent autoregressive coefficients, $\varepsilon_{i,t}^{st}$ is a state dependent noise vector and s_t is an unobserved random variable that causes the system to change from regime to another. We assume s_t follows a first-order Markov process in which the current regime, s_t relies only on the regime one period in the past, s_{t-1}. We therefore examine two discrete states, denoted as s_1 and s_2. s_1 represents a low-volatility regime while s_2 represents a high-volatility regime.

The regime follows a first order Markov-chain:

$$\begin{aligned} p[s_t = 1 | s_{t-1} = 1] &= p_{11}, \\ p[s_t = 2 | s_{t-1} = 2] &= p_{22}, \\ p[s_t = 2 | s_{t-1} = 1] &= p_{12}, \\ p[s_t = 1 | s_{t-1} = 2] &= p_{21}, \end{aligned} \tag{2}$$

in which p_{11} denotes the probability of the system remaining in state 1 at time t, given that the system was in state 1 at time $t-1$; p_{21} denotes the probability of the system switching to state 2 from state 1; p_{22} denotes the probability of the system remaining in state 2 at time t, given that the system was in state 2 at time$t-1$; p_{12} denotes the probability of the system switching to state 1 from state 2. Two lags are suggested by the Akaike Information Criterion (AIC).

3. Results

We begin by plotting the smoothed probabilities of the system being in a crisis regime. These are calculated as follows:

$$P(s_t | F_T; \theta), \ i = 1, 2, \tag{3}$$

in which F_T denotes the collection of all observed variables up to and including time T, in other words all information in the sample, and θ is the vector of parameters $(\alpha(s_t),\ \beta_k(s_t), \sigma_{st}^2, p_{11}, p_{22}, p_{12}, p_{21})$. Smoothed estimates are then computed via the backward recursion algorithm as presented by Hamilton (1994). Fig. 2 illustrates these.

$$y_{i,t} = \alpha(s_t) + \sum_{k=1}^{2} \beta_k(s_t) y_{i,t-k} + \varepsilon_{i,t}^{st},$$

Table 1
Summary statistics.

Variable	Obs.	Mean	St. Dev.	Skewness	Kurtosis	Min.	Max.
Green bond	2153	-0.0001	0.0035	-0.6009	4.6010	-0.0241	0.0201
Sovereign bond	2153	0.0002	0.0332	0.2174	32.8358	-0.3415	0.4059
Corporate bond	2153	0.0001	0.0035	-1.3965	13.1556	-0.0393	0.0182
Geopolitical risk index	2153	112.8336	54.1241	2.2611	10.1464	9.4916	539.5826

Notes: This table reports summary statistics for the daily log returns for the indicated Bond variables. Geopolitical Risk Index reports daily levels. Std. Dev. denotes standard deviation; Min. denotes minimum; Max. denotes maximum. The sample period ranges from July 31, 2014 to October 31, 2022.

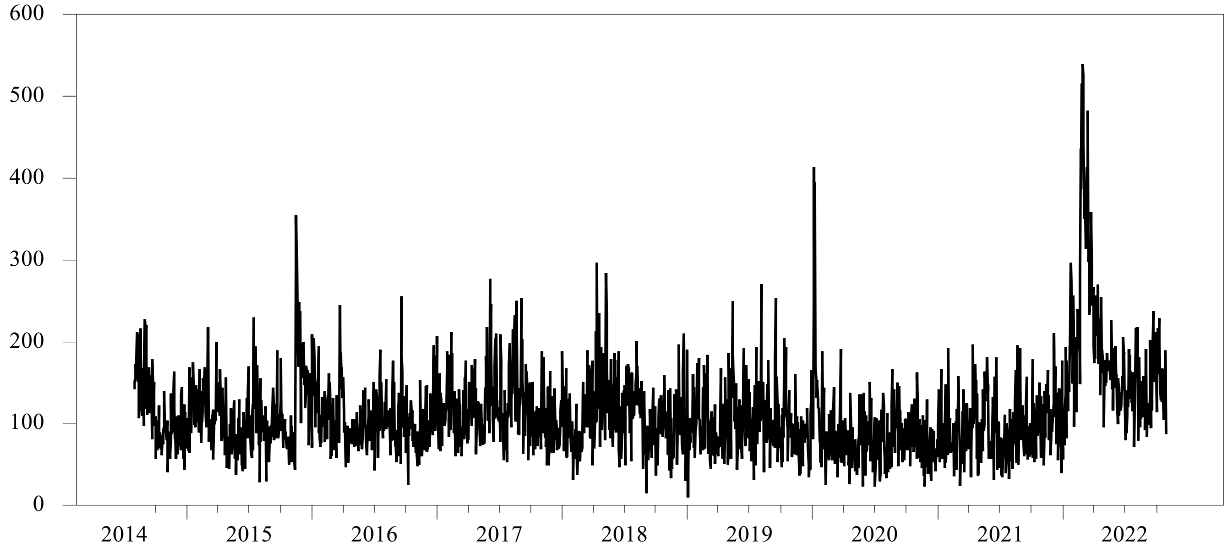

Fig. 1. Geopolitical risk index.
Notes: This Figure illustrates the geopolitical risk index (GPR). The sample runs from July 31, 2014 to October 31, 2022.

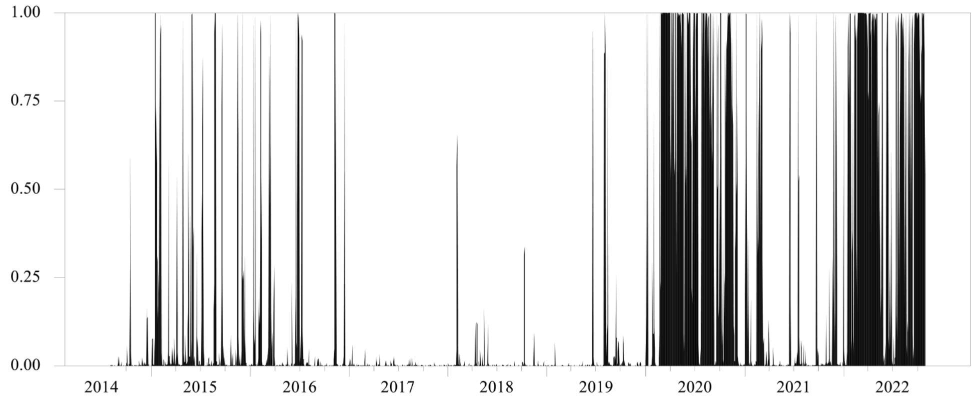

Fig. 2. MS-VAR smoothed probabilities probability of smoothed probabilities probability of high volatility regime.
Notes: This Figure illustrates the smoothed probabilities of the system being in a high volatility regime for the following MS-VAR equation.

$$s_t \in \{1,2\},$$

$$\varepsilon_{i,t}^{st} \sim i.i.d.N\left(0,\sigma_{st}^2\right)$$

in which $y_{i,t}$ is an n dimensional time series vector of dependent variables, α is a matrix of state dependent intercepts, $\beta_1 \ldots \beta_k$ are matrices of the state dependent autoregressive coefficients, $\varepsilon_{i,t}^{st}$ is a state dependent noise vector and s_t is an unobserved random variable that causes the system to change from regime to another. Two lags are suggested by the Akaike Information Criterion (AIC). The sample runs from July 31, 2014 to October 31, 2022.The subscript * denotes significance at the 10 % level; the subscript ** denotes significance at the 5 % level; the subscript *** denotes significance at the 1 % level.

Fig. 2 indicates that the system is likely to be in a high volatility regime briefly between 2014 and 2016, which coincides with events such as the annexation of Crimea and the October 2014 US Treasury bond flash crash. There is another spike in 2020 which corresponds with the COVID-19 pandemic, before a final increase in early-2022 which aligns with the onset of the war in Ukraine. High volatility prevails until the end of the sample which intuitively makes sense given events such as the global energy crisis, the continued war in Ukraine and political instability in countries such as the UK.

Table 2 reports mean and standard deviation results from the MS-VAR presented in Eq. (1).

Table 1 enables the identification of two regimes. The standard deviation of each variable increases following the switch in regimes, and standard deviations are statistically different from zero in both regimes. Also, significant coefficients on the indicated transition probabilities suggest that regimes are persistent.

Table 2
MS-VAR estimation results 1.

	Low Volatility Regime		High Volatility Regime	
	μ	Σ	μ	σ
Green bond	-0.0000	0.0000	-0.0002	0.0000
	(0.92)	(0.00)***	(0.58)	(0.00)***
Sovereign bond	0.0004	0.0039	0.0030	0.0004
	(0.57)	(0.00)***	(0.55)	(0.00)***
Corporate bond	0.0001	0.0000	-0.0006	0.0000
	(0.38)	(0.00)***	(0.19)	(0.00)***
Geopolitical risk index	48.8063	1367.4339	14.6392	2151.4536
	(0.00)***	(0.00)***	(0.00)***	(0.00)***
	$\theta_{p1} = 0.79$***		$\theta_{p2} = 0.95$***	
	$\theta_{q1} = 0.21$***		$\theta_{q2} = 0.05$***	

Notes: This table reports results for the following MS-VAR equation:.
$y_{i,t} = \alpha(s_t) + \sum_{k=1}^{2}\beta_k(s_t)y_{i,t-k} + \varepsilon_{i,t}^{st}, s_t \in \{1,2\}, \varepsilon_{i,t}^{st} \sim i.i.d.N(0,\sigma_{st}^2)$,
in which $y_{i,t}$ is an n dimensional time series vector of dependent variables, α is a matrix of state dependent intercepts, $\beta_1 \ldots \beta_k$ are matrices of the state dependent autoregressive coefficients, $\varepsilon_{i,t}^{st}$ is a state dependent noise vector and s_t is an unobserved random variable that causes the system to change from regime to another. Two lags are suggested by the Akaike Information Criterion (AIC). The sample runs from July 31, 2014 to October 31, 2022. The subscript * denotes significance at the 10 % level; the subscript ** denotes significance at the 5 % level; the subscript *** denotes significance at the 1 % level. Θ denotes the coefficient on the indicated transition probability.

Table 3 reports the coefficients on the indicated variable in each of the indicated VAR equations in order to ascertain if there any change in the relationships between these assets occurs after the switch in regimes.

Table 3 indicates that geopolitical risk significantly affects green bond returns in the high volatility regime, thus suggesting that these assets are susceptible to this type of risk. This corresponds with Sohag et al. (2022), Cepni et al. (2022), Lee et al. (2021). It is noteworthy that the conventional bonds analysed do not experience this, indicating that green bonds behave differently. This is in line with literature such as Hachenberg and Schiereck (2018) who find that green bonds trade tighter than non-green bonds and Baker et al. (2018) who conclude that green municipal bonds are issued at a premium compared to similar non-green bonds.

There is evidence of Granger-causality from both conventional bonds to green bonds in low volatility regimes, with more significance evident in high-volatility which again indicates that green bonds are prone to changes in these markets. This corresponds to Ferrer et al. (2021) who find that green bonds display linkages to government and high-quality corporate bonds. However these results conflict with those of Dong et al. (2023) who find that conventional and green bonds become less correlated, thus displaying safe-haven features, when geopolitical levels are high. That research analysed long-term stock-bond correlations using a DCC-MIDAS model while the methodology employed in this work investigates contemporaneous relationships between assets to analyze potential shock transmission channels. The estimation period in Dong et al. (2023) also ends in March 2022, six months before that of this research, which may also influence results.

Sovereign and corporate bonds are significantly impacted by each other, and green bonds, in both regimes providing insight into the interactions between these markets in tranquil and higher volatility periods.

While we report results for the GPR for completeness it would not add value to comment on these given that intuitively bond markets should not affect this, apart from perhaps indirectly through news stories on another matter of geopolitical importance.

4. Conclusion

This paper seeks to contribute to the ongoing academic, policy and industry discussions on the relatively new green bond market. We find that the green bond market is more susceptible to geopolitical risk in times of high volatility, while corporate and sovereign bonds are not. This indicates differences between green and conventional bonds which will be relevant in coming years when it is likely that geopolitical risk will continue to be high and something that policy makers should take into consideration while designing regulations for green assets.

From a political perspective international initiatives such as the Paris Agreement and the United Nations Sustainable Development Goals require large-scale, long-term global green investment and green bonds provide one way of achieving this (Tolliver et al., 2020). As the problems associated with climate change continue to increase it is likely that governments will come under more pressure to increase their efforts to address these and as Green, Social, Sustainability, Sustainability-linked and transition (GSS+) bonds accounted for just 5 % of total global bond markets in 2022 (Jones, 2023) it is expected that there will be a push to increase the issuance of such securities. Given that our results suggest that green bonds are more susceptible to geopolitical risk in times of high volatility this could lead to unintended financial market consequences in times of stress, which should be considered from a financial stability perspective. From an investment viewpoint the results suggest that employing alternative portfolio choices in the presence of contagion, as outlined by Aït-Sahalia and Hurd (2015), should be considered given that potential contagion channels have been identified.

These results provide a starting point for further research. Possible avenues include adding other financial markets to the analyses,

Table 3
MS-VAR estimation results 2.

Dependent	Independent	Low volatility regime		High volatility regime	
		β1	β2	β1	β2
Green bond	Sovereign bond	-0.0108	0.0050	0.0075	-0.0024
		(0.00)***	(0.20)	(0.03)**	(0.56)
	Corporate bond	0.0333	0.0703	0.3617	0.1198
		(0.30)	(0.02)**	(0.00)***	(0.03)**
	Geopolitical risk index	0.0000	-0.0000	-0.0000	0.0000
		(0.32)	(0.53)	(0.08)*	(0.23)
Sovereign bond	Green bond	0.2313	0.2150	-1.2170	0.5267
		(0.07)*	(0.04)**	(0.03)**	(0.33)
	Corporate bond	1.4721	-0.0942	-1.4856	1.0455
		(0.00)***	(0.64)	(0.00)***	(0.05)**
	Geopolitical risk index	-0.0000	-0.0000	0.0000	-0.0000
		(0.34)	(0.55)	(0.95)	(0.96)
Corporate bond	Green bond	-0.0143	-0.0328	0.0033	0.1635
		(0.33)	(0.01)***	(0.93)	(0.00)***
	Sovereign bond	-0.0142	0.0049	0.0183	0.0080
		(0.00)***	(0.10)*	(0.00)***	(0.05)**
	Geopolitical risk index	0.0000	0.0000	-0.0000	0.0000
		(0.59)	(0.13)	(0.83)	(0.74)
Geopolitical risk index	Green bonds	-295.3958	324.2152	335.7098	722.8085
		(0.31)	(0.29)	(0.51)	(0.11)
	Corporate bond	-587.4438	-542.9972	-753.3602	-236.7251
		(0.14)	(0.25)	(0.12)	(0.63)
	Sovereign bond	18.0854	-70.5906	-54.7988	-57.7467
		(0.75)	(0.21)	(0.20)	(0.16)

Notes: This table reports results for the following MS-VAR equation:.
$y_{i,t} = \alpha(s_t) + \sum_{k=1}^{2} \beta_k(s_t) y_{i,t-k} + \varepsilon_{i,t}^{st},\ s_t \in \{1,2\},\ \varepsilon_{i,t}^{st} \sim i.i.d.N(0, \sigma_{st}^2),$
in which $y_{i,t}$ is an n dimensional time series vector of dependent variables, α is a matrix of state dependent intercepts, $\beta_1 \ldots \beta_k$ are matrices of the state dependent autoregressive coefficients, $\varepsilon_{i,t}^{st}$ is a state dependent noise vector and s_t is an unobserved random variable that causes the system to change from regime to another. Two lags are suggested by the Akaike Information Criterion (AIC). The sample runs from July 31, 2014 to October 31, 2022. The subscript * denotes significance at the 10 % level; the subscript ** denotes significance at the 5 % level; the subscript *** denotes significance at the 1 % level.

supplementing the methodology with regime-dependent impulse response functions (IRFs) and utilizing country-specific GPRs.

Author statement

All work presented in this paper was conducted by the author, Lisa Sheenan.

Data availability

Data will be made available on request.

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