Assessing Asymmetric Effects of Oil Price Shocks on Emerging Markets securities

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Abstract

The volatility of crude oil prices presents a significant concern for investors and firms, particularly in emerging markets such as Brazil. This study delves into the asymmetric effects of oil price shocks on securities within emerging markets. Using a Structural VAR (SVAR) framework, we investigate the dynamic relationships among oil supply, oil consumption demand, and oil inventory demand shocks on three distinct emerging market proxies: iShares Ibovespa Index Fund (BOVA), Vanguard Emerging Markets Stock Index Fund (VWO), and iShares MSCI Emerging Markets ETF (EEM). Our analysis reveals that while oil supply and oil inventory demand shocks have an insignificant impact on stock returns, oil consumption demand shocks exhibit substantial effects. Furthermore, we employ a Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model to explore the asymmetric nature of these shocks. The findings indicate that positive oil shocks have positive effects on returns, and negative shocks have negative effects.

Keywords: GJR-GARCH, SVAR, Financial Time Series, Volatility

1 Introduction

The volatility of crude oil prices is a critical concern for both investors trading in crude oil derivatives and firms relying on oil as a raw material for production, particularly in the context of the Brazilian financial landscape. Disruptions in oil supply and demand, often stemming from geopolitical and natural factors, can trigger significant oil price shocks that reverberate through global financial markets. These shocks can have far-reaching consequences for various economic sectors, especially in emerging markets like Brazil. Understanding the relationship between oil price shocks and financial markets is crucial for risk management, investment decisions, and policy formulation. In fact, a prevailing trend has emerged whereby the majority of economic recessions have been heralded by an unanticipated surge in oil prices Hamilton (2011).

The literature on the relationship between oil prices and stock market returns is multifaceted, with various strands of research shedding light on this complex interaction. One strand of research, represented by Chen, Roll, and Ross (1986), argues against a straightforward connection between oil price changes and aggregate stock market returns, suggesting that the oil price index may not adequately describe equity market movements. Conversely, other studies, including those by Sadorsky (1999), Driesprong, Jacobsen, and Maat (2008), Park and Ratti (2008) provide compelling evidence of a negative and significant relationship between oil prices and stock market returns. For instance, Sadorsky (1999) highlights how positive oil price shocks can lead to negative returns in the U.S. stock market, while Nandha and Faff (2008) identifies a negative relationship between oil prices and global indices at the industry level. In a different strand of literature, researchers like Killian and Park (2009) and Wei and Guo (2017), and Benkraiem, Lahiani, Miloudi, and Shahbaz (2018) delve into the nuanced effects of oil price shocks on stock market returns. They discern that the U.S. stock market responds differently to oil price shocks driven by supply and demand factors, with supply-side oil price shocks having little relevance to the U.S. stock market. Instead, shocks resulting from increased real economic activity tend to exert a positive effect, while oil-market-specific demand shocks can negatively impact U.S. stock returns. Moreover, these studies explore the role of various oil market shocks, such as supply-side, precautionary demand, and aggregate demand shocks, in influencing stock returns across different regions and timeframes, providing valuable insights into the dynamics of stock markets in response to energy price fluctuations.

While previous research has explored the connection between oil prices and financial markets, there is little to no evidence on research about emerging market securities and how those securities compare to main US stock tickers such as the $S\&P500$. Additionally, there exists a vacuum in the literature to explore the asymmetric impact of oil shocks in Emerging market proxies. This study examines how the market volatility of three emerging markets investments respond to oil shocks using Baumeister and Hamilton (2019) decomposed oil shocks. To the best of my knowledge, this is the first paper doing such analysis in emerging markets using Baumeister and Hamilton (2019) framework and oil data.

In our examination of the interplay between oil-related factors and stock returns, SVAR models indicate that the impact of oil supply and inventory demand shocks is insignificant. However, a notable exception emerges with a 1-standard deviation shock in oil consumption demand, which induces a +1% change in stock volatility. Furthermore, our analysis reveals compelling evidence of statistically significant effects arising from oil supply, oil demand, and inventory demand shocks, as examined through an asymmetric lens with GJR-GARCH. Specifically, positive shocks engender positive effects and negative shocks prompt negative effects. This sets the stage for a comprehensive analysis of the intricate dynamics between oil-related shocks and stock market behavior.

2 Data

2.1 Data Sources

In this paper, I use monthly data from 2009:9 until 2021:2 totaling 142 observations. We use data from two main sources. All historical price data were collected from Yahoo Finance for the following securities: iShares MSCI Emerging Markets ETF (EEM), Vanguard Emerging Markets Stock Index Fund (VWO), iShares Ibovespa Index Fund (BOVA11.SA). In this study, we examine four distinct metrics for assessing global oil shocks. These metrics encompass economic activity shocks (EAS), shocks related to oil consumption demand (OCDS), shocks in oil inventory demand (OIDS), and oil supply shocks (OSS). We obtained an updated version of the detailed data on these oil shocks, which had been previously examined by Baumeister and Hamilton in 2019, as well as by Salisu and Gupta in 2021. This updated data was retrieved from Professor Christiane Baumeister's website at the following URL: https://sites.google.com/site/cjsbaumeister/research. Professor Christiane Baumeister sourced the data from the U.S. Energy Information Administration (EIA), and these datasets are publicly accessible on their website. The calculations used to generate this data are transparently presented in the accompanying Excel file, and the researcher regularly updates the data. Therefore, authors should have no concerns about using the sourced data as shocks. Note, the shocks estimated by Baumeister and Hamilton (2019) are all calculated using US data. However, this should not be an issue since all emerging markets stocks used in this analysis are publicly traded stocks in the USA and therefore reflect the perspectives of mostly US investors into the US and emerging markets.

3 Methodology

3.1 Structural VAR framework

We examine the dynamic relationship among oil consumption demand, inventory demand, and supply shocks on emerging market financial securities, using the SVAR framework.

The structural representation of the VAR model of order p takes the following general form:

$$A_0 y_t = c_o + \sum_{i=1}^{p} A_i y_{t-i} + \epsilon_t \tag{1}$$

where, y_t is a 4×1 vector of endogenous variables, i.e ,$y_t = [OSS_t, OIDS_t, OCDS_t, \gamma_t]$ such that γ represents the financial security in analysis, A_0 represents the 4×4 contemporaneous matrix, A_i are 4×4 autoregressive coefficient matrices, ϵ_t is a 4×1 vector of structural disturbances, assumed to have zero covariance and be serially uncorrelated. The covariance matrix of the structural disturbances takes the following form $E[\epsilon_t \epsilon_t'] = D = [\sigma_1^2 \sigma_2^2 \sigma_3^2 \sigma_4^2] \times I$. In order to get the reduced form of our structural model (1) we multiply both sides by A_0^{-1}, such as that:

$$y_t = a_o + \sum_{i=1}^{p} B_i y_{t-i} + e_t \tag{2}$$

where $a_0 = A_0^{-1} c_0$, $B_i = A_0^{-1} A_i$, and $e_t = A_0^{-1}$, i.e $\epsilon_t = A_0 e_t$. The reduced form errors e_t are linear combinations of the structural errors ϵ_t, with a covariance matrix of the form $E[e_t e_t'] = A_0^{-1} D A_0^{-1}$

The structural disturbances can be derived by imposing suitable restrictions on A_0. The short-run restrictions that are applied in this model are the following:

$$\begin{bmatrix} \epsilon_{1,t}^{oss} \\ \epsilon_{1,t}^{ocds} \\ \epsilon_{1,t}^{oids} \\ \epsilon_{1,t}^{\gamma} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \times \begin{bmatrix} e_{1,t}^{oss} \\ e_{1,t}^{ocds} \\ e_{1,t}^{oids} \\ e_{1,t}^{\gamma} \end{bmatrix}$$

The restriction in the given model can be explained as follows. We take Oil supply shocks as independent from all variables. Additionally, we acknowledge the undeniable impact of supply on the demand side of the oil market. However, in order to determine the order the inventory demand and consumer demand shocks, we run a Granger causality test: Notice, we find way

Table 1: Granger causality Wald tests

Equation	Excluded	F	df	df_r	Prob $> F$
OSS	OCDS	6.8258	1	135	0.0100
OSS	OIDS	0.19944	1	135	0.6559
OSS	γ	12.366	1	135	0.0006
OSS	ALL	5.2778	3	135	0.0018
OCDS	OSS	0.00064	1	135	0.9798
OCDS	OIDS	0.34535	1	135	0.5577
OCDS	γ	4.1035	1	135	0.0448
OCDS	ALL	1.3756	3	135	0.2529
OIDS	OSS	14.19	1	135	0.0002
OIDS	OCDS	7.3268	1	135	0.0077
OIDS	γ	0.30081	1	135	0.5843
OIDS	ALL	5.2566	3	135	0.0018
γ	OSS	2.9277	1	135	0.0894
γ	OCDS	1.1e-05	1	135	0.9973
γ	OIDS	0.00646	1	135	0.9360
γ	ALL	1.2927	3	135	0.2795

stronger test statistics for a relationship where OIDS impacts OCDS than OCDS to OIDS. In detail, for an equation with OIDS excluding OCDS we find a $F-stat = 7.3(p-value : 0.0007)3$ as opposed to $F - stat = 0.345(p - value : 0.56)$ for an equation with OCDS excluding OIDS. Hence, we have a Granger test favoring an SVAR with OCDS impacting OIDS.

To proceed to the estimation of the reduced form of model (1), it is first necessary to establish the stationarity of the variables. The ADF and PP unit root tests suggest that all variables are I(0). The order of the VAR model was identified using the Akaike Information Criterion (AIC) and the Bayesian information criterion(BIC). The AIC and BIC suggested a VAR model of order one as shown in table 2.

Table 2: AIC and BIC for VAR Models

	VAR(1)	VAR(1/2)	VAR(1/3)	VAR(1/4)
AIC	1203.108	1199.681	1206.016	1207.557
BIC	1261.941	1305.322	1358.233	1406.116

3.2 Assymetric GARCH framework: GJR-GARCH

Beyond exploring the dynamic relationship among oil consumption demand, inventory demand, and supply shocks on emerging market financial securities using the SVAR framework, we also explore the asymmetric effects of each shock.

There is a stylized fact that the Glosten-Jagannathan-Runkle GJR-GARCH model by Glosten, Jagannathan, and Runkle (1993) captures that is not contemplated by the standard GARCH model, which is the empirically observed fact that negative oil shocks have a different impact on the variance than positive shocks. This asymmetry used to be called the leverage effect because the increase in risk was believed to come from the increased leverage induced by a negative shock. Notice that the effective coefficient associated with a negative shock is $\alpha+\gamma$. In financial time series, we generally find that γ is statistically significant.

The specific model just described can be generalized to account for more lags in the conditional variance. A $GJR-GARCH(p,q)$ model assumes the following form:

$$\sigma_t^2 = w + \sum_{i=1}^{p}(\alpha_i + \gamma_i I_{t-i})\epsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 \tag{3}$$

where

$$I_{t-i} = \begin{cases} 0 & \text{if } r_{t-i} \geq \mu \\ 1 & \text{if } r_{t-i} < \mu \end{cases}$$

Note that $r_t = \mu + \epsilon_t$, where μ is the expected return and ϵ_t is a zero mean white noise. Nevertheless, also note that this model just like GARCH, captures stylized facts in financial time series: volatility clustering. In fact, if $\alpha+\gamma+\beta<1$, the volatility is mean reverting, and it fluctuates around σ, the square root of the unconditional variance. The regular GARCH model is, in fact, a restricted version of the GJR-GARCH, with $\gamma=0$ without the component that accounts for the asymmetry.

In order to determine the best model by optimizing p,q, we proceeded and ran all possible models and calculated their respective BIC and AIC.

Table 3: AIC and BIC for GJR-GARCH models

	arch1	arch2	arch3	arch4	arch5	arch6	arch7
aic	−410.1858	−430.5185	−429.2782	−431.127	−429.4283	−419.4676	−417.7757
bic	−390.5957	−403.9797	−399.7906	−407.5369	−402.8895	−395.8775	−391.2368
L.arch	✓	✓	✓	✓	✓		
L2.arch						✓	✓
L.tarch	✓	✓	✓	✓	✓	✓	✓
L2.tarch		✓	✓		✓		✓
L3.tarch			✓				
L.garch	✓	✓	✓			✓	✓
L2.garch				✓	✓		

Note that the model with the smallest BIC and AIC was the specification 7 with $arch(1)$, $garch(1)$, and $tarch(1)$. Thus, this specification is then used for all results discussed later in this paper.

4 Results

4.1 SVAR Empirical Findings

Table 4 summarises the contemporaneous coefficients for the financial securities under investigation. Given the structure of our model, it becomes clear that supply shocks a_{41} don't directly impact the return on emerging markets stocks with statistically insignificant coefficients. On the other hand, Inventory demand(OIDS) and consumption demand(OCDS) had strong coefficients. OCDS across all proxies demonstrated a negative coefficient with a_{42} averaging at -0.012. OIDS across all proxies demonstrated a negative coefficient with a_{43} averaging around -0.0049. Thus definitely we see a stronger impact in the magnitude of OCDS on returns over OIDS. This follows the theoretical background in oil shocks for the general literature for US securities.

Table 4: SVAR contemporaneous coefficients.

Coefficient	BOVA	VWO	EEM
a_{11}	1	1	1
a_{21}	-0.0596382	-0.0625079	-0.0666266
a_{31}	1.390008***	1.360914***	1.356378***
a_{41}	0.0029687	0.0023523	0.0032456
a_{12}	0	0	0
a_{22}	1	1	1
a_{32}	1.369252***	1.368426***	1.375334***
a_{42}	-0.0135622**	-0.0117215**	-0.0097144*
a_{13}	0	0	0
a_{23}	0	0	0
a_{33}	1	1	1
a_{43}	-0.007098***	-0.0040521***	-0.0036504**
a_{14}	0	0	0
a_{24}	0	0	0
a_{34}	0	0	0
a_{44}	1	1	1

$*p < 0.10, **p < 0.05, ***p < 0.01$

Notes: Table 4 presents all baseline results from our SVAR model presenting all contemporaneous coefficients for three different proxies of emerging markets stocks. iShares Ibovespa Index Fund (BOVA), Vanguard Emerging Markets Stock Index Fund (VWO),iShares MSCI Emerging Markets ETF (EEM).

In summary, we see a strong empirical result that emerging market stocks just like US stocks are demand-derived. Also, note that generally the contemporaneous coefficients' magnitude and sign did seem to be consistent across the different stock proxies, which shows that our results are also robust for data changes- thus strengthening our findings.

4.2 Accumulated lagged responses(Impulse Response Functions)

The results in Figure 1 supply side shocks present negative impacts on the returns on stocks and demand side present positive impacts. More specifically, we have that a standard deviation shock of Oil supply would lead to about a -1% change in returns. On the demand side, one standard deviation shock in OCDS and OIDS led to about 1% and 0.5% respectively. However, note that for both OSS and OIDS our 95% confidence lies very close to 0, which makes both conclusions weaker and shows us that such shocks are close to insignificant relative to OCDS. In fact, such results align with a major portion of the literature. Bastianin, Conti, and Manera (2016) found that oil supply shock does not affect the stock market volatility of G7 countries while oil demand shock does. More specifically, while Oil inventory demand is a factor of demand by definition, this indicator can also be interpreted as a factor anticipating shock on the supply side: precautionary. In theory, inventory demand would increase as if there is a risk of negative oil supply shock, which also aligns with the impact directions.

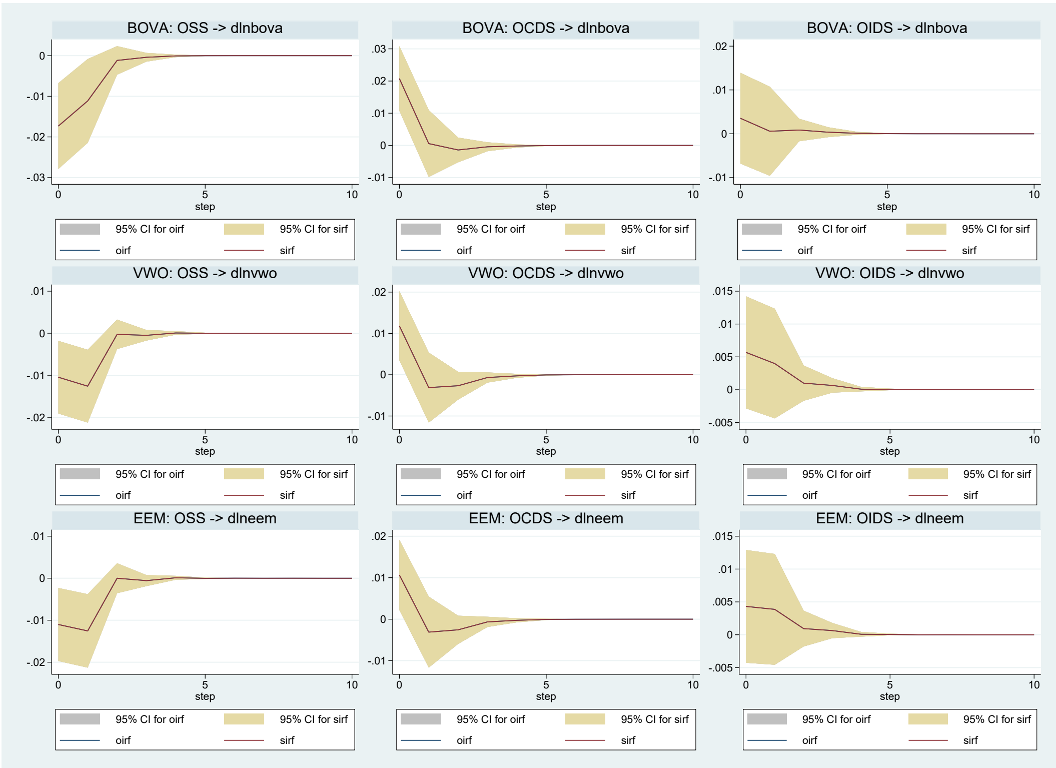

Figure 1: IRF for all specifications: $\sigma \pm 1.96SE$

Finally, we conclude that Oil consumer demand as a shock impacted returns on stock across all specifications the most. Thus, we can conclude that just like developed countries (G7), emerging markets are demand-derived and almost insensitive to oil supply.

4.3 GJR GARCH: Asymmetric impact on shocks

After having found conclusions about the sign and magnitude of demand and supply shocks on emerging market stocks, we further explore the asymmetry of the shocks on whether the sign of the shock would change the impact on stock or potentially the average effect has hidden something.

Since GARCH has a completely different specification than our initial SVAR model, we need to first estimate the best model. As shown in Table 3, we found that the best model that was able to converge its optimization had an order: $arch(1), garch(1), tarch(1)$. In Table 5 we have all coefficients of our given specification run across all proxies and all different shocks individually so that we can spot the impact of the asymmetric nature of each shock by itself. To interpret our GJR-GARCH model we first need to specify exactly how to combine our arch and tarch coefficients. Note that since we run all specifications with a GJR-GARCH(1,1), essentially our model follows as below:

$$\begin{aligned}\sigma_t^2 &= w + \sum_{i=1}^{1}(\alpha_i + \gamma_i I_{t-i})\epsilon_{t-i}^2 + \sum_{j=1}^{1}\beta_j\sigma_{t-j}^2 \\ &= w + (\alpha_1 + \gamma_1 \cdot I_{t-1})\epsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2\end{aligned}$$

$$\sigma_t^2 = w + \alpha_1 \cdot \epsilon_{t-1}^2 + \gamma_1 \cdot I_{t-1}\epsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$$

Now, note that if we want to find the impact of the given shock on out stock return variables, then can simple look for α_1, γ_1 since we have that:

$$\frac{\partial\sigma_t^2}{\partial\epsilon_{t-1}^2} = \alpha_1 + \gamma_1 I_{t-1}$$

Thus, by definition as decribed in the methodology section, if we have a positive shock, then $I_{t-1} = 0$ and the impact is simply α_1 and if we have a negative shock, then $I_{t-1} = 1$ and the impact is simply $\alpha_1 + \gamma_1$. Thus, lets then proceed to assess whether asymmetric effects exist across our shocks.

Let's first look into Oil supply shock models (3) and (6).

Table 5: Glosten-Jagannathan-Runkle GARCH

	(1) BOVA[1]	(2) BOVA	(3) VWO	(4) VWO	(5) VWO	(6) EEM	(7) EEM	(8) EEM
SHOCK								
OIDS	✓			✓			✓	
OCDS		✓			✓			✓
OSS			✓			✓		
ARCH								
L.arch	0.842***	0.184	0.662**	0.684**	0.834**	0.582*	0.409*	0.761**
	(0.197)	(0.254)	(0.310)	(0.306)	(0.380)	(0.305)	(0.242)	(0.374)
L.tarch	-0.797***	-0.238	-0.770***	-0.814***	-0.923**	-0.716**	-0.611***	-0.867**
	(0.223)	(0.250)	(0.299)	(0.290)	(0.375)	(0.292)	(0.222)	(0.368)
L.garch	0.108	-0.0349	0.0178	0.0413	0.0392	0.0346	0.141	0.0465
	(0.176)	(0.436)	(0.102)	(0.136)	(0.205)	(0.176)	(0.211)	(0.229)
Constant	0.00247***	0.00363**	0.00215***	0.00213***	0.00185***	0.00233***	0.00239***	0.00202***
	(0.000921)	(0.00176)	(0.000441)	(0.000519)	(0.000515)	(0.000621)	(0.000677)	(0.000638)
Obs.	141	141	141	141	141	141	141	141

$*p < 0.10, **p < 0.05, ***p < 0.01$

Notes: Table 5 presents all baseline results from our GJR-GARCH model. iShares Ibovespa Index Fund (BOVA), Vanguard Emerging Markets Stock Index Fund (VWO),iShares MSCI Emerging Markets ETF (EEM).

[1] Specification using OSS and BOVA was omitted because it did not converge, while optimizing the parameters for the GJR model.

Note that for both specifications, we find coefficients to be statistically significant at least in 10% level. For specification (3), we found that for positive shocks there exists an impact of 0.662 and for negative shocks we have change in returns of $-.108$.For specification (6), we found for positive shocks there exists an impact of 0.582 and for negative shocks we have change in returns of $-.134$. Thus, for all specifications in oil shocks were found to have a positive effect on positive shocks and negative effect on negative shocks. Lets now look into specifications (1),(4),(7) that describe Oil inventory demand shocks. For specification (1), we found that for positive shocks there exists an impact of 0.842 and for negative shocks we have change in returns of 0.045. For specification (4), we found that for positive shocks there exists an impact of 0.684 and for negative shocks we have change in returns of -0.13. For specification (7), we found that for positive shocks there exists an impact of 0.409 and for negative shocks we have change in returns of -0.202. Generally, OIDS shocks had different results across specifications but majority of them showing a similar result to OSS.

Finally, we look into Oil consumer demand shocks (OCDS) on specifications $(2), (5), (8)$. Specification (2) did not yield any significant results. For specification (5), we found that for positive shocks there exists an impact of 0.834 and for negative shocks we have change in returns of -0.089.For specification (8), we found that for positive shocks there exists an impact of 0.761 and for negative shocks we have change in returns of -0.106. Just like all other shocks, we found a strong evidence for asymmetry here with opposite signed effects. Additionally, across all specifications OCDS did seem to have the largest coefficients for positive shocks.

5 Conclusion

Overall, using our SVAR model we find very strong evidence for a shock in Oil consumption demand shock to impact positively the returns on stocks by +1%. Do note that the shocks data were already decomposed into standard deviations, which means the 1% find in the IRF only really show the impact on stocks for an even smaller shock than $1\sigma_{OCDS}$. We find little to no evidence on the impact of Oil supply and inventory demand shocks on emerging market stock returns. I then hypothesize that potentially by estimating the average effect of a shock on returns would be omitting the true impact of demand and supply shocks. Thus, we implement a GJR GARCH to account for this asymmetry. We find statistically significant results across all shocks, and we find mostly positive coefficients for positive shocks and negative coefficients for negative shocks. Additionally, we highlight the oil consumption demand being the largest impact on returns. such finding could be interpreted using the logical idea that positive shocks would be a sign for positive and growing and same logic for negative.

Further studies could be conducted with different specification of asymmetric GARCH such T-GARCH and EGARCH to assess the robustness of our results. Additionally, it would be interesting to incorporate the sequential/ordering nature of SVAR within the GARCH model, so that we could avoid potential over or under estimation of our results.

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