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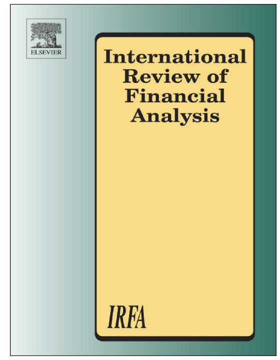

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Interbank Liquidity Risk Transmission to Large Emerging Markets in Crisis Periods

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Abstract

In this paper, we conduct two investigations regarding funding liquidity risk in large emerging economies: Brazil, Russia, India, China, and South Africa — BRICS. In the first, we track the relevance of monetary policy decisions originating in developed economies for interbank funding liquidity risk in BRICS economies during crisis periods by applying a time-varying parameter model in a Bayesian framework. The results indicate weak associations between interbank credit market and US monetary policy and market conditions. In contrast, the Federal Reserve's National Financial Conditions Index (NFCI) — a representative of the health of both real and financial sectors in the US — matters more. The temporal patterns of the results imply that key central banking decisions precede or coincide with low degrees of associations. In the second, we examine whether interbank credit crunch exerts an influence on market liquidity risk in BRICS economies using a Granger causality approach. The results reveal that interbank credit crunch depresses market liquidity in the corresponding domestic market and that the state of fear and credit market conditions in the US exert some influence in this regard. Overall, our findings hint at judicious market intervention and liquidity management by BRICS central banks.

Keywords: Credit Risk; Liquidity Risk; Bond Market; Stock Market; BRICS; TED; US VIX

1. Introduction

This paper examines the role of the US as a source of macro-financial risk transmission to interbank credit markets in large emerging economies while considering various crisis periods, namely the Global Financial Crisis (GFC), the European Sovereign Debt Crisis (ESDC), and the COVID-19 pandemic induced crisis (CPIC). Specifically, we verify the existence and extent of funding liquidity risk spillover from multiple channels to BRICS (Brazil, Russia, India, China, and South Africa) economies in response to exogenous shocks. We further visit an attendant hypothesis in funding liquidity risk literature: the transmission to market liquidity risk. We study this phenomenon using Granger causality tests to discover whether interbank credit crunch has an influence on market liquidity risk in BRICS economies.

Several practical and theoretical concerns motivate this paper. Foremost, the ongoing COVID-19 pandemic has imposed unprecedented economic hardship in the form of disruptions to production and supply chains (Renko, 2020; Song et al., 2021), loss of net capital flows and trade (Kejzar & Velic, 2020), increase in the unemployment rate (Kawohl & Nordt, 2020), and diminished real economic growth. Under a conventional monetary policy regime, the response of financial markets to such economic fundamentals would have been strongly negative. Yet, the economic downturn during the pandemic inherits a legacy of post-taper monetary policy from the Federal Reserve, and a lagging quantitative easing from the European Union. Faced with the unforeseeable challenge of supporting the global economy, all central banks injected record levels of liquidity into the financial system through open market operation, which was further aided by massive fiscal stimulus. Though markets are arguably efficient enough to understand the ad hoc nature of these interventions, asset prices continued to rally and — importantly — began to reflect less the economic reality on the ground. In the course of this, uncertainty persists on the timing, extent, and shape of economic recovery, aggravated by fears of prolonged inflation. Indeed, the asset management noticed a rise in investors' risk aversion. Speculation is at an all-time high regarding how public fear, uncertainty and corporate profitability will play out in the markets in the coming years[5]. In theory, the credit spread on debt securities is a forward-looking indicator that reflects these market expectations. The fact that these spreads have repeatedly

[5] https://www.forbes.com/sites/investor/2021/07/08/stock-market-crash-coming-soon-you-need-to-see-these-2-charts/?sh=1b0708055887; https://markets.businessinsider.com/currencies/news/big-short-michael-burry-warns-meme-stocks-crypto-crash-coming-2021-6

widened abruptly since 2020 substantiates the claim of progressive shrinkage in investors' risk appetite. Moreover, with extended periods of monetary policy rate cuts, numerous corporations across many G20 countries continue to capitalize on low rates to issue debt and buy back shares. The downside is that increasing leverage makes these firms more vulnerable to declines in operating earnings and jeopardizes long-run solvency[6]. Similar concerns exist on the macro-prudential front, especially with respect to commercial banking, corporate- and sovereign-lending operations. The level of exposure faced by these entities is known far less due to a lack of studies addressing this matter. We address that gap in this paper and provide comparative insights between multiple financial crisis periods. We accomplish this via the angle of credit conditions in the interbank markets, concentrating on the variable funding liquidity risk.

There is growing body of literature that recognizes the importance of funding liquidity risk transmission. For instance, using call report data, Spiegel (2021) has shown for American foreign subsidiary banks that monetary-policy spillover during the pandemic was active through the bank lending channel. Similar results, albeit to a lesser magnitude, have been reported by Yilmazkuday (2020) for the foreign exchange channel[7]. Unlike the traditional transmission channel, however, this paper finds the disease outbreak conduit to be more salient. China is the most economically important member of the BRICS club, and its transmission of US-led policies to China's economy has consequences for the global recovery from the pandemic. Not only has China been the first country to show signs of fast recovery from the pandemic, her economic size and trade channels ripple through to economic performances and rebound potential of a large number of developing (and in certain cases developed countries, e.g., Australia). For example, Wang and Zhang (2021) have shown this to be true for energy consumption patterns of a large number of countries. Unlike previous crises that were of financial origin, during the COVID-19 pandemic, US banks heavily benefited from the Fed's liquidity injection and a heavy capital buffer — a legacy of the preceding crises. Consequently, American banks scarcely struggled to meet the surging liquidity demands from concurrent calls on corporate credit lines (Li et al., 2020). This shows that the banking industry (and arguably the Fed) learned from the global financial crisis ordeal when many banks exposed to credit-line drawdowns were forced to suspend their

[6] Much recently, news that the world's most indebted property developer, the Chinese Evergrande, is on the brink of default has led to a decline of at least 2% in the stock market indices of US, China and other emerging economies (https://www.kiplinger.com/investing/stocks/603465/china-evergrande-crisis-us-stock-market).
[7] For bank lending during crisis periods, see Shahin and El-Achkar (2017).

lending activities (Ivashina and Scharfstein, 2010). These results follow the initial shock to the banking sector which was poised to incur a harder blow than any other economic sector. Investors' unease regarding the banks were not assuaged by the prudential measures and recovery plans. Let us keep in mind that the velocity of stock price drop in banks mimicked the price plunge (and rising credit default swap (CDS) spreads) by proportions identical to that over the period of Lehman Brothers' fall. These concerns were reflected in dismal of credit rating outlooks. Demirguc-Kunt et al. (2020) also report evidence of such factors as banks' liquidity constraints amid the pandemic resulting in the sector's under-performance.

In addition to funding liquidity risk transmission, we attend to an adjacent but relatively less explored question of whether funding liquidity risk leads to depression of liquidity in asset markets in the BRICS countries. The majority of previous papers tend to address market liquidity (Broto and Lamas, 2020; Rösch and Kaserer, 2013; Schwarz, 2019) in isolation, which reflects the assets' (or collaterals') quick convertibility to cash. Among the few studies which examined the interplay between market and funding liquidity, notable are Boudt et al. (2017), Chung et al. (2018), Deuskar and Johnson (2021) and Macchiavelli and Zhou (2021). As stated earlier in the justification segment of our first investigation, researchers mostly concentrate on the developed world, particularly the US and the Eurozone. Hence, far less is understood about funding liquidity risk's propensity to trigger market liquidity risk in emerging economies such as BRICS; especially, if and to what extent the interbank credit conditions in these large emerging markets are influenced by the powerful policy-driving economies like the US. We find this gap puzzling given the significance of funding liquidity to institutional actors, who often shy away from taking large positions in high margin instruments or in financing cash outflow intensive projects when funding liquidity is tight. The studies quoted above shed light on the dynamics of such tightening spreads on their respective empirical settings, but the dynamics of funding liquidity risk is largely unaddressed in BRICS economies.

We build this motivation upon the findings of several important previous studies: Hui, Genberg, and Chung (2011) have indicated that during crisis, or financial stress, funding liquidity and market liquidity tend to have a close relationship. Likewise, Drehmann and Nikolaou (2013) have declared that funding liquidity risk was one of the main causes of historical banking crisis, thus finding that in this environment there is a downward spiral between funding liquidity and market liquidity risk. Aside from the preponderant focus on the empirics in the developed world, other existing works are theoretical in nature. Hence, there is a gap in empirical research on the relationship between funding and market liquidity risk in emerging economies (Dahir et al., 2018; Dahir et al., 2019). This relationship is important for all market participants to consider when they want to invest/trade in emerging markets as these markets have low liquidity and infrequent trading characteristics compared to developed markets (Antoniou, Ergul, & Holmes, 1997). We empirically test this hypothesis employing a modified Granger causality approach in the frequency domain which is capable of controlling for conditional variables. This allows us to not only test the direction of causal influence between funding liquidity in the interbank market and financial markets but also condition these results based on the prevailing macro-fundamental and market inferred sentiments in the developed economies. Since this modified Granger causality test operates in the spectral domain, it allows us to make inference on the short- and long-run dynamics of causal links between credit and financial markets. Importantly, we observe that the mediating influence of market uncertainty (proxied through VIX) is active in lower frequencies, whereas TED spread is active in higher frequencies. Our empirical attempts and the novel results constitute a timely contribution to financial and emerging markets literature.

The rest of this paper is organized as follows. We detail the background literature underpinning our motivation for this paper in Section 2, while Section 3 describes the data and methodology. We then present and analyze our empirical results in Section 4. Section 5 concludes with a recap of our salient findings and implications as well as potential paths for future research.

2. Relevant Literature

The essence of our investigation is determining the scale and significance of macro-financial risk transmission, via the US market, to the interbank credit sector of BRICS economies. Intensified risk transmission within financial and economic crisis literature is traditionally conceptualized as the migration of disturbances (e.g., fear, uncertainty, illiquidity) across international capital markets — stemming, in part, from trade, credit and financial interlinkages, and, more importantly, from a common thread of global macro-economic disruptions. A subdomain of this discussion is the transmission of liquidity shocks and spillovers in crisis times. Its effect is arguably found to have differential influences (unlike the normal trade-based linkages) on investors' behavioral attitudes and preferences. The strand of literature documents the evidence suggesting that the investors' collective (and often biased) responses, following the propagation of global crises, engender a greater level of market fluctuations as well as spur significant economic policy reforms. One example of this is Obstfeld (1984), who developed second-generation currency crises model to account for the heterogeneous investors' behavior. This model and its modern derivatives also account for the notion of 'sunspot crisis' which implies a phenomenon whereby investors' lack of incentives in gathering country-specific information leads to erroneous sentiments and overall economic disequilibrium (Calvo and Mendoza, 2000; Kodres and Pritsker, 2002). Such evidence was by and large discernible within the context of global financial crises (GFC), wherein a multitude of uniform responses by international investors coupled with asymmetric information exacerbated the adverse consequences of interdependence and liquidity spillover across developed and emerging markets. Likewise, the outbreak of COVID-19 precipitated sharp declines in the price performance of major stock indices such as Dow Jones, Nikkei's and Shanghai due to the prevailing investors' anxiety and sentiment across the international borders (Naseem et al., 2021).

Extant literature further features mixed evidence relating to the impact of major events in the history on the transmission of funding liquidity risk. In this respect, Karolyi (2011) has predicted the likely disastrous (spillover) implications of terrorist attacks on stocks and bonds once measured on a market-level basis within the context of CAPM. Likewise, Chesney et al. (2011) have highlighted the spillover effect of terrorist attacks on financial markets with findings that are at best mixed. Moreover, Leoni (2013) has provided an empirical evidence pointing to the banks' declining deposits and subsequent failure caused by severe strains on reserves following the spread of the HIV/AIDS disease in the early 1990s across the sub-Saharan countries. In the same vein, Lagoarde-Segot and Leoni (2013) have suggested, using a theoretical framework, that the spread of HIV/AIDS and tuberculosis, especially within the context of poor and developing countries, are contributing factors in the determination of banking reserves and stability. Their findings were particularly attributed to the large deposit withdrawals made by the people following the higher prevalence of the disease to afford the high cost of medications and treatments.

Notwithstanding the foregoing, theoretical literature also provides the evidence of remarkable developments concerning the explanation of crisis propagation via the financial market channels. Specifically, Garber and Grilli (1989) and Valdés (2005) have examined the role of liquidity shortages in crises spillovers by extending the Diamond and Dybvig (1983) bank-run model to an international setting. The basic premise of such models is that a bank run in one country can induce investors' fire sale of long-term assets. A direct implication is large outbound capital to a second (safer) country wherein the liquidity is replenished. Correspondingly, Allen and Gale (2000) have shown that significant regional contagion is explainable by overlapping claims within the international banking system. Such findings pertain largely to an indirect form of crisis transmission due to the portfolio rebalancing strategies of common international investors in response to global market shocks and instabilities.

There is also plenty of empirical literature on liquidity spillover effects, especially in the aftermath of the GFC. Such studies have typically focused on single market channels to determine the level of crises-induced financial market interdependencies in terms of assets' returns and volatilities (Diebold and Yilmaz, 2009; Forbes and Rigobon, 2002; King and Wadhwani, 1990). However, very little attention has been paid to the extent and transmission of interbank markets' liquidity spillover, especially concomitant with the periods of financial turmoil. In this respect, Xu et al. (2018) have only reported findings in support of illiquidity and volatility spillover effects via the global equity markets using a multiplicative error model during and after the GFC. Other studies have further contended that such spillover effects are traceable from: (i) simultaneous financial constraints affecting liquidity providers (Comerton-Forde et al., 2010) and (ii) capital inadequacy for financial intermediaries which are actively involved in trading high-risk securities (Kyle and Xiong, 2001). Nonetheless, in spite of the extensive literature, there are still significant uncertainties in relation to the sources of funding liquidity spillover within the emerging market economies and via multiple market channels.

With regard to the transmission of funding liquidity risk to market liquidity, Brunnermeier and Pedersen (2009) suggest that during periods of restrained liquidity crises, market liquidity is highly sensitive to the speculators' intent on taking capital-intensive positions in high-margin securities. In effect, this leads to a "margin spiral" phenomenon whereby the speculators' funding constraints are tightened and prices are predominantly determined by the funding liquidity considerations as opposed to the movements in fundamentals. The study also provides key policy recommendations suggesting that the central banks could mitigate market liquidity problems by controlling funding liquidity. Drehmann and Nikolaou (2013) have also provided the evidence in support of strong downward spirals of market and funding liquidity risk specifically during the crisis times. In essence, it is found that the banks facing lack of funding liquidity due to the inability in securing sufficient funding from the interbank market, tend to liquidate their assets leading to a downward pressure in the assets' prices as well as greater level of market depression.

In addition to the above literature discussed above, many scholars attribute systemic risk transmission from the developed economies to BRICS. The roles of the Fed and the European Central Bank (ECB), in particular, are heavily documented. The matter of monetary policy is also important as it pertains to central bank independence in emerging countries (Garriga & Rodriguez, 2020). Despite disparate structures and differences in mandates, the Fed and the ECB induce policy synchronizations in many non-OECD economies. As these economies grow more complex and pursue their own mandates, they also face challenges due to a lack of political and economic independence from the executive branches of the government. As such, experts have expressed fear about how effective localized monetary policy decisions are in many emerging economies. Our paper is one of the first attempts at quantifying this aspect, taking the BRICS as a case study. This is especially timeous considering that there have been talks of setting up an independent BRICS-based bank to relieve emerging economies from dependence on policies in the developed countries (Klomegah & Moscow, 2012). Lastly, the level of risk aversion is an important leading indicator of cross-border capital flows: both in direct investment and flows to financial assets. Yield chasing is a notable manifestation of this. These stylized facts and pre-existing concerns motivate our decision to consider these variables.

Finally, researchers have also shown a surge of interest on the role of the US as an originator of policy shocks and spillover risk during periods of economic turmoil. In this connection, Park and Shin (2020) have studied the contagion effect of the GFC on the level of direct and indirect exposure of foreign banks in the emerging countries. Likewise, Jin and An (2016) have examined the contagion effect of the GFC from the US market to the G7 and BRICS countries using multi-scale correlation approaches, with results suggesting that cross-market correlations are conditional on the time, scale, and recipient country. Correspondingly, many have studied different characteristics of crisis-spillover phenomenon for a variety of assets and markets. On the contrary, considerably less explored is the subject of liquidity in the banking system. The study by Frank and Hesse (2009) is particularly focused on the dynamic correlations between liquidity in the equity, debt, and credit markets during the GFC and established the dominance of US as a risk-transmitter. Moreover, Fratzscher et al. (2018) have expanded the scope further and demonstrated the role of the first round of QE by the Fed in buoying equity market performances in emerging market economies. Similarly, Georgiadis and Gräb (2016) have considered the same for the ECB, showing the signaling effect of dovish monetary policy announcement in propping up investor confidence within the emerging markets. Our analysis extends this stream of research by quantifying liquidity spillover characteristics of global and local origins. We identify not only episodes when such effects are pronounced, but also their time evolution and propagation during stress periods. We contextualize our findings by marrying the results with key central banking decisions.

3. Data and Methodology

3.1 Data

This study uses two datasets. The first comprises five variables per every BRICS country to capture short-term funding liquidity in BRICS and global markets. These are: 5-year sovereign credit default swap (CDS) spread, stock market benchmark, local government bond index, local corporate bond index, and the emerging economy liquidity spread (EELS). The CDS spread is an indicator of the actual sovereign default risk of each BRICS economy. The local stock market index is used to track the stock price performance of companies. These are the IBOVESPA, MOEX Russia Index, NIFTY 50, Shanghai Composite Index (SSE), and the JSE All Share Index representing the stock markets indices of Brazil, Russia, India, China, and South Africa, respectively. Similarly, the local government bond index measures the performance of fixed income securities issued by the BRICS government. The corporate-bond index likewise tracks the performance measure of corporate debts issued by investment-grade corporations (Hill and Schneeweis, 1983) denominated in each BRICS country. Moreover, we have artificially constructed the EELS as an analogue to the TED spread. It is calculated as the difference between selected BRICS economies' popular overnight interbank rates and their short-term risk-free rates. In this respect, we further sidestep the controversy of whether emerging markets' risk-free rates are genuinely riskless by focusing on BRICS — five productive and large economies that attract sizeable flow of global capital via real and financial investments[8].

[8] BRICS equity and debt markets enjoy appreciably higher liquidity than other smaller emerging economies.

The second dataset includes a representative class of mature market factors. These are: TED spread, S&P 500 composite index, CBOE US implied volatility index (VIX), EURO STOXX 50 volatility index (VSTOXX), Chicago Fed's National Financial Condition Index (NFCI), Global Economic Policy Uncertainty (GEPU), Cleveland Fed's Systemic Risk (SR) index, the Amihud's (2002) illiquidity measure, and Bloomberg Barclays Global Aggregate Bond (AGG) index. At the global scale, the TED spread (the price difference between three-month US Treasury bill and Euro Dollar future contracts) is a proxy for global markets' credit risk (Boudt et al., 2017). We also use the UK TED spread, defined as the difference between the 3-month LIBOR and the 3-month UK Treasury Bill (Benbouzid et al., 2018) that Kellard et al. (2021) used to control for market liquidity. Similarly, the EU TED spread is measured based on 3-month Euro LIBOR spread (Cerutti et al., 2017). The S&P 500 represents the performance of the US stock market (Balcilar and Ozdemir 2013) — and, by extension, the developed markets. The VIX and VSTOXX broadly reflect the forward-looking outlook of the global stock market uncertainty (Ben Amar and Carlotti, 2021; Hammoudeh and McAleer, 2015; Chiang, Li, and Yang, 2015). Moreover, the NFCI is used as a proxy for the US financial condition with its positive values indicating tighter-than-average financial conditions (drying liquidity) and negative values revealing the opposite conditions (ample liquidity) (Fink & Schüler, 2015; De Nicolò and Lucchetta, 2017). The index broadly serves as an indicator of the overall economic stress measuring the performance of both real and financial sectors. It is an evaluation of (i) debt and equity markets, (ii) the market liquidity state and credit condition as well as (iii) the shadow banking system. A value of the index being zero is an indication of a normal financial condition whereas the values below and above zero are representative of average economic stress and lower than average stress, respectively. The GEPU index (based on current-price GDP measures) is used as a proxy for the Global macroeconomic volatility (Li et al, 2020). Correspondingly, the Cleveland Fed's systemic risk variable is used as a proxy for markets' perception of the risk of widespread insolvency in the banking sector. The Amihud's (2002) illiquidity measure is used as a proxy for markets' liquidity risk. It is traditionally calculated as the average of daily absolute (close-to-close) returns per dollar traded over a given period. Meanwhile, we rely on a modified version of the Amihud illiquidity following intuitions from Barardehi et al. (2021) who proposed the measurement of absolute return between opening and closing prices of the trading day to exclude the overnight price movements. The exclusion of overnight returns considering that they are primarily information driven with little to no relevance for liquidity measurement, could potentially lead to a lower degree of measurement errors and estimation biases. Finally, we use the AGG as a representative of a widely accepted benchmark for fixed income securities and debt market performance (Lin and Niu, 2021).

Our data are at the daily frequency, and the sampling window begins at different times due to data availability. All data series, however, end in September 2021 and mostly cover the GFC, the ESDC, and the CPIC. Table 1 highlights the salience of our variables within macro-financial literature that deal with liquidity risk transmission across developed and developing markets, whereas Table 2 provides the summary statistics of the variables for each country in the BRICS. The reported statistics predominantly reveal sizeable cross-country variations, notably for the EELS spread and Amihud illiquidity. Notably, there is evidence of average negative EELS for China and Russia, reflecting countries' significant short-term interest-rate spikes especially attributable to periods of financial stress. Correspondingly, Brazil and Russia record higher relative average and standard-deviation values of Amihud illiquidity, which are broadly associated with the episodes of investors' dramatic sell-off of major securities over the sampled period. Meanwhile, the reported statistics relating to other benchmark indicators are within an identical range, with corporate debt securities revealing highest relative volatility specifically for South Africa and Brazil.

<Insert Table 1 Here>

<Insert Table 2 Here>

Table 3 likewise provides the summary statistics of the variables for mature markets. They are broadly representative of positive average values of the TED spread measures, VSTOXX, NFCI and the GEPU index. On the contrary, there are negative average values for the S&P500, VIX, systemic risk and the AGG indices. Collectively, there evidence of a relatively weaker US financial condition corresponding with the negative performance of stock and bond markets as well as higher levels of uncertainty during the period of the study.

<Insert Table 3 Here>

3.2 Methodology

3.2.1 A time-varying parameter model

Our interest in understanding the dynamics of an emerging economy's funding liquidity conditions vis-Ă-vis local and global transmission factors calls for a multivariate estimation technique equipped with time-varying parameters (TVP). Consequently, we adopt a time-varying parameter model with locally adaptive shrinkage properties (Kowal et al., 2019). The principal regression model with $X_t = \left[X_{1,t}, X_{2,t}, X_{3,t}, \dots, X_{n,t}\right]^j$ dynamic macro antecedents (for country c) of liquidity spread is as follows:

$$EELS_{t,c} = X_{(t,c)\beta_{t,c}} + \varepsilon_{t,c} \qquad (1)$$

$$\left[\varepsilon_{t,c}\right]\sigma_{t,c}^2 indepN(0, \sigma_\varepsilon^2) \qquad (2)$$

$$\Delta^{+\beta_{t+1,c}=\omega_{t,c}} \qquad (3)$$

$$\left[\omega_{j,t,c} \vee \tau_0, (\tau_{k,c}), (\lambda_{k,s,c})\right] indepN\left(\tau_0^2 \tau_{j,c}^2 \tau_{t,c}^2\right) \qquad (4)$$

In Equation (3), t represents the time-varying regression coefficients, while Δ+ stands for differencing. We incorporate priors (j, t, c) for innovations as follows:

τ_0 (global shrinkage parameter)

$\tau_{j,c}$ (covariate shrinkage parameter)

$\tau_{j,t,c}$ (covariate and time-based dependence parameter)

This approach benefits from an extra layer of time-varying dependence whereby the relative influence of the covariates can be inferred from the shrinkage parameters that are themselves dynamic. Hence, the model is apt for determining which (and how many) factors are relevant for EELS. Moreover, the dynamic components help reveal the relative importance of specific determinants which may be dormant in certain periods. Most crucially, the sparsity imposed by dynamic horseshoe priors (DHS) mentioned above enables identification of irrelevant factors, which, too, may vary over time. The utility of this aspect is visible in greater details in Section 4, where we observe certain results where the sparsity element reduces a particular factor's influence to triviality for extended (in some cases entire) time-spans. The simulation results reported by Kowal et al. (2019) reveal the outperformance of the Bayesian trend filtering (BTF)-DHS approach against competing models in a high-dimensional dynamic predictor context. Our application of the BTF-DHS model likewise outperforms the approach of Kalli and Griffin (2014) based on the RMSE scores. This is also consistent with demonstrations of Carvalho et al. (2010) regarding the suitability and flexibility of local-global priors in accommodating large signals (long time series) and sufficient noise shrinkage.

3.2.2. Granger Causality

To determine whether the past values of funding liquidity risk have a causal influence on liquidity in financial markets, we apply the spectral form of Granger Causality test. For a covariance-stationary pair of credit spread EELS at time t, $EELS_t$, and concomitant market liquidity as measured by Amihud illiquidity[9] L_t at time t, we define Z_t in the following $VAR(k)$ model as:

$$Z_t = A_1 Z_{t-1} + \cdots + A_k Z_{t-k} + \epsilon_t \quad (5)$$

The error term ϵ_t is $N_2(0, \sum_2^n k)$, where $\sum_2^n k$ is a two-by-two covariance matrix and $[A_1, A_2, A_3, \dots, A_k]$ is a two-by-two coefficient matrix. Transferring Equation (5) to the spectral domain necessitates the following transfer function:

$$P(\omega) = \frac{1}{(I - \sum_{j=1}^{k} A_j e^{-ij\omega})}, -\pi \leq \omega \leq \pi \qquad (6)$$

$$p(\omega) = P_{EELS\,EELS}(\omega)\; P_{EELS\,L}(\omega)\; P_{L\,EELS}(\omega)\; P_{L\,L}(\omega) \qquad (7)$$

As per Granger-Causality test, we can now define the spectrum of $EELS_t$ against L_t as:

$$h_{(L\rightarrow EELS)}(\omega) = ln(\frac{h_{(EELS\,EELS)}(\omega)}{\tilde{P}_{EELS\,EELS}(\omega)\sigma_2\tilde{P}_{EELS\,EELS}(\omega)*}) \qquad (4)$$

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[9] Amihud (2002) approach has been applied as it uses daily data on stock prices and trading volume to create a measure for stock or security illiquidity in a given period, $RiytVOLDiyt$. $Riyt$ is the return for stock i on month t of year y, and $VOLDiyt$ is the associated trading volume (in local currencies).

For regular frequency-domain causality, we start by simulating a stationary bootstrap ($n = 1{,}000$) series ($EELS_t*$, L_t*) from observed EELS and Amihud series ($EELS_t, L_t$). We then use BIC model selection criterion to estimate a VAR (k) model via Seemingly Unrelated Regression approach. For a frequency s, we execute a Fourier transform $f_s = \frac{s}{T}; s = 1, 2, 3, \dots, [\frac{T}{2}]$ to calculate $h_{L*\to EELS}(2\pi f_s)$. After computing the median of this series, we derive the $(1-\alpha)$-quantile of the bootstrap distribution 1,000 times where α denotes the traditional significance level of 5%. For each frequency, we mark the estimated value ($\hat{h}_{L*\to EELS}(2\pi f_s)$) as significant if it exceeds the unconditional quantile critical value. For the conditional version of this test, we repeat the same process with the following notable differences: (a) a bootstrap series ($EELS_t*$, C_t*, $MACRO_t*$) is simulated from observed series ($EELS_t$, C_t, $MACRO_t$), (b) the median value of $h_{L*\to EELS*|MACRO*}(2\pi f_s)$ is computed for each frequency s, and (c) $\hat{h}_{L*\to EELS|MACRO}(2\pi f_s)$ values are marked as significant if bigger than $q_{cond,\alpha}$.

4. Results and Analyses

We begin by presenting the posterior expectations of the regression coefficients from Equation (1). Figures 1 to 5 present the country-specific plots of coefficients. The estimation of the TVP model for each country is based on 25,000 Markov Chain Monte Carlo iterations. We then proceed to present and analyze our results on a country-by-country basis since there is little theoretical motivation to understand the risk transmission procedure *en masse;* hence, our disaggregated approach.

Broadly speaking, our findings demonstrate high degrees of prominence associated with the transmission of liquidity risk via the mainstream local and global market channels especially during crisis periods. Particularly revealing is the finding attributed to the trend behavior of selected indicators in response to major crises including the GFC, ESDC and CPIC.

4.1 Brazil

Figure 1 presents evidence of concomitant marked shifts pointing to notable liquidity transmission across key indicators namely IBOVESPA, Chicago's NFCI and the systemic risk within later episodes of the GFC. Such finding is by and large attributable to the transitory shocks stemming from commodity price fluctuations, stock market's slump, local currency devaluations and credit crunch in the mid-2008. Nonetheless, the market witnessed some positive movements in 2009 in light of the policy-maker's monetary and fiscal stimuli, stronger inflows of foreign capital, and an overall optimism of consumers and investors over the market's recovery.

We also uncover the evidence of significant liquidity spillover effect in relation to other Brazilian indicators specifically in the late 2009. Our findings are importantly analogous with the unfolding of the ESDC following the first rating downgrade of the Greece sovereign debts. Additionally, it is partly in line with the pre-eminent role of the Brazil's monetary authorities (MA) in refraining from adopting the pro-cyclic (restrictive) measures in line with the principles set out by the International Monetary Fund (IMF). Alternately, the MA operated countercyclical economic policies in an attempt to combat the crisis-induced exchange rate depreciation, credit squeeze, asset deflation and unemployment, to maintain higher price stability. Our observations also indicate the evidence of a drastic change in the pattern of key local and mature market indicators including the Brazilian government bond and CDS spread as well as economic policy uncertainty, VIX, VSTOXX, TED spread and AGG index in the last quarter of 2010. On the one hand, the global markets experienced unusually high volatility as well as thinning liquidity due to the eruption of the unsettling political and economic conditions arising from the ESDC. Contrarily, the Brazilian bond market witnessed a positive outlook over and above the performance of global fixed-income markets. The country experienced a record sale of high-yield bonds with lower relative risk level, in response to investors' search for flight to quality and liquidity. Another plausible explanation for the remarkable turnaround in the behavior of indices is pertinent with the concerns raised by the Brazilian finance minister in September 2010 with regard to *international currency war* induced by the net exporters' attempt to intervene in the currency market for securing their competitive position. Correspondingly, the existing literature further reveals a complementary evidence pointing to the Brazilian markets' commonality in liquidity, which is primarily driven from foreign investors' multitude of trading actions particularly during periods of market decline (Pilar & Veras, 2020).

<Insert Figure 1 Here>

Finally, in the course of the CPIC, there are clear signals affirming the evidence of liquidity spillover across the TED spread, VSTOXX, VIX, NFCI and the AGG indicators as well as by a smaller extent within the local equity and CDS sectors. A likely explanation for this observation is associated with a myriad of factors engendering higher scales of liquidity transmission. These factors include the adoption of less stringent containment responses constituting a supply shock to the economy, implementation of conventional monetary policies, a notable local government's budget deficit and significant external shocks within the local currency, investment, trade and travel sectors instigated by a reduced growth forecast and shrinkage of the developed economies.

4.2 China

For China, the results point to the spillover effect primarily attributable to the massive proliferation of sovereign debt at the global scale as the principal transmitter of liquidity risk; particularly in the course of the ESDC. More notably, Figure 2 uncovers evidence of intensified transmission across the local and global equity, bond and uncertainty indicators which re-emerges along the years 2018-19 as well as in the wake of the CPIC. Our findings are predominantly associated with the sovereign debt build-up of most European economies coupled with the pessimistic outlook from the US Fed in fear of second double-dip recession and the escalation of risk aversion. Moreover, the Chinese corporate debt gained widespread credibility among the international investors following the degradation of European credit outlook and the Chinese authorities' reforms aiming at the mitigation of US dollar exposure. Correspondingly, the aversion of investors toward the hardest-hit Eurozone economies triggered the intrusion of China-based companies in the search for considerable out-bound investment opportunities and acquisition of cheap assets, brand names and technologies.

<Insert Figure 2 Here>

Regarding the CPIC, the results are broadly inconsequential, with an exception of few intermittent pockets of mild variations spotted on the verge of the COVID-19 outbreak in the behavior of some local and mature market indicators. Our finding is partly intuitive given the country's high financial capacity and access to abundant liquidity to grapple with the economic impact of the outbreak.

4.3 India

Our empirical evidence on liquidity transmission in the case of India (Figure 3) is largely conspicuous both at local and international levels. We primarily find support for significant spillover effects during the ESDC. In this connection, we discern a considerable shift in the trend behavior of Nifty 50 stock exchange in February 2012. Such observation is predominantly associated with the market's unattractiveness for foreign investment banks in view of the Reserve Bank of India (RBI)'s stringent restrictions. The inflow of capital from international investors declined substantially in the early 2012 given the heightened level of risk aversion as represented by the fall-off of the VIX and VSTOXX indices coupled with the sharp dips in the performance of other key indicators in the preceding months reflecting growth shocks in the advanced economies. More to the point, we uncover a complimentary evidence resulting in a concomitant drop in the coefficient estimates of the NFCI.

<Insert Figure 3 Here>

We further trace patterns of abrupt shifts in the coefficient trends of mainstream markets in the midst of 2014. Several interesting observations arise from examination of events in the year 2014 including the formation of Modi-led government, RBI's inflation control, declining unemployment and export growth following the adoption of the 'Make in India' initiatives and educational reforms as well as refined labour laws, leading to significant recuperations in the markets' performance over the ensuing years. The Nifty 50 index surged past the 8000-mark in September 2014 in response to the election of Narendra Modi, whereas it eventually hit lower closes in subsequent months as a result of the investors' widespread selling pressures stemming in part from weaknesses in global bourses. Correspondingly, the bond market ran into a credit crunch given the investors' sustained selling pressures and huge outflows of capital in response to unclear market regulations as well as concerns around the monsoon.

Our observations also uncover signs of the liquidity transmission over the years 2015-16. Such observations are predominantly associated with the performance of the Nifty 50 index hitting a high of 8,834 in March 2015, as well as the impact of foreign portfolio investors' venture into the Indian market. Moreover, the role of industrial and manufacturing sectors was prominent in view of the government's initiatives for creation of world class infrastructure. Likewise, there was a remarkable surge in foreign institutional investors' demand for government securities by an excess of $10 billion over its preceding year. Nevertheless, the enactment of the Insolvency and Bankruptcy code in 2016 marked another significant turnaround in the behavior of key local and mature market indicators, leading to higher vibrancy and liquidity, strengthened investor confidence, as well as greater access to fund rising opportunities for infrastructure companies. Finally, 2018 witnessed an uncertain investment environment in India amid rising US interest rates with sharp declines of nearly 19 percent in the proceeds from government debt securities.

With regard to the CPIC, the experience of the country is broadly evident of a relatively less pronounced transmission of liquidity risk within the local and global market channels particularly akin to the economy's strong initial recovery from the pandemic effect as compared to its peers. Nonetheless, the situation altered drastically in the light of ferocious rise in infections and mortalities leading to severe capital losses, higher uncertainty, poor economic outlook, and more importantly a liquidity crisis.

4.4 Russia

In the case of Russia, Figure 4 shows evidence of sizeable variations in the trend behavior of the Russian MOEX and the NFCI indices particularly over the periods ensuing the eruption of the ESDC. The funding of liquidity spillover mainly ran through the Russian banking sector and correspondingly within the local-currency government bond market in the early months of 2010 and mid-2011 due to recoveries made in the Russian commodity exports. Moreover, a myriad of factors such as reduction of bank loan supplies for non-financial private sector as well as an overall slump in the credit demand facilitated means for banks' additional issuance of government debt securities. Consequently, the market witnessed a widespread demand surge by foreign investors for the Rubble-denominated government bonds following the stabilization of Russian foreign exchange market coupled with the introduction and qualification of new bonds. In a likely manner, a series of scandals and reforms in the LIBOR market and the global interest rate benchmarks triggered considerable adjustments within the Russian financial market.

<Insert Figure 4 Here>

We also uncover the evidence of some marginal divergence in the coefficient of most indicators particularly analogous with intensification of the ESDC. In addition, the local debt and CDS indicators levelled off as large external assistance flowed into the country via the IMF-EU programs leading to dramatic alignments of fiscal deficits, labour cost, and price level. Notwithstanding the foregoing considerations, the obtained ESDC betas reveal the evidence of liquidity transmission within the local debt and international equity, bond and uncertainty conduits in the mid-2013. Such evidence attributes the permeation of liquidity shocks to the growing influence of foreign investors within the Russian bond market context in light of several price discovery reforms such as removal of infrastructural and legal impediments for foreign access, consolidation of investor base, and adoption of inflation targeting framework by the Russian central bank. Another crucial finding pertains particularly to the pervasive impact of the economic sanctions and falling oil prices near the tail-end of 2014, causing significant balance of payment pressures and a consequent surge in capital outflows as well as local currency depreciation.

Considering the CPIC, Russian economy confronted three major problems including the lockdown's demand and supply consequences, increased asset price volatility and more importantly the oil price collapse as well as geopolitical tensions. Correspondingly, the market witnessed widespread net capital outflows in the ensuing months particularly germane to levels of portfolio investments and foreign direct investment.

4.5 South Africa

Finally, the empirical evidence corresponding to the South African economy (Figure 5) suggests an evidence of a notable interlinkage across the local and global financial market channels over the specified market turbulence episodes particularly the ESDC and CPIC. More specifically, our observations are by and large attributed to the bond market dynamics over the period ensuing the GFC as the South African economy entered a recessionary phase albeit having healthy public finances and lower debt levels. The government's issuance of bonds and bills gave rise to higher debt accumulation and elevation of implied volatility both locally and globally. Additionally, the credit market ran into an unstable territory with the CDS spread soaring in the light of mounting concerns over increased issuance, weak economic data and earnings reports as well as the consequent widespread expectation of rising defaults. Correspondingly, the eruption of the ESDC led to higher levels of unemployment, current account deficits and lower saving rates within the economy. Such events further exacerbated the deterioration of assets equality and profitability following the African Bank's record losses in the second half of 2014 from unsecured lending to low-income households. The South Africa's sovereign foreign currency debt was consequently downgraded by the Standard and Poor's to one notch above the speculative grade. Moreover, a greater scale of systemic risk spread over smaller institutions due to higher susceptibility and concentration.

<Insert Figure 5 Here>

The results also reveal an evidence of some marginal transmissions of liquidity risk across local and global equity and bond market indices during the CPIC. The principal argument behind such intensified transmission is associated with the announcement of the lock-down phase, which was followed by the government's adoption of several fiscal measures in favor of small businesses and vulnerable communities. The initiatives of the South African government were further coupled with an interest-rate cut of 100 basis points by the reserve bank to combat the inflationary strain and recessionary backdrops. The government finances were however more constrained, providing lesser stimulus unlike the case of other affected economies. Moreover, on March 27, 2020, Moody's downgraded the country into a sub-investment grade with the bond index suffering a 9.7 percent decline in mid-2020. Correspondingly, the JSE All Share Index traded down by 12.1 percent in the month of March resulting in an indiscriminate and severe selloff of foreign investors as well as an overall high-risk level within the market.

We further extended our analysis by examining the distributional pattern of the obtained regression coefficients of the selected BRICS economy indicators. Our findings are illustrated in the form of a series of country-specific box plots in Figure 6, specifying the upper edge, lower edge, median, and two quartiles of the datasets.

<Insert Figure 6 Here>

Our results predominantly reveal an identical coefficient range of all indicators across the BRICS economies. Moreover, all series are found to follow a standard normal distribution, with values ranging within the conventionally accepted confidence interval. Nevertheless, three major indicators namely NFCI, SR index and local stock market indices are found to exhibit wider degrees of dispersion of coefficient values. Particularly, the coefficient range and values of the NFCI series are larger for Russia, reflecting the country's higher level of funding liquidity risk in response to the changing financial condition in the US. Correspondingly, our findings suggest that the Brazilian IBOVESPA index followed by the Chinese SSE index are likely to be marginally prone to the spillover risk. Moreover, we find that, unlike the theoretical predictions, the obtained coefficient values of local stock market indices of Brazil and partly China and India are on average ranging within the positive territories. Finally, we uncover complementary evidence pointing to the relatively higher prominence of the SR index as a key channel of liquidity transmission to BRICS economies.

4.6 Results of the Granger Causality Test

Findings associated with the frequency-scaled Granger Causality (GC) test on selected pairs of country-based indicators are reported in this section. Figure 7 presents a group of GC spectral plots revealing primarily the causal associations of the EELS as a proxy for funding liquidity risk with the Amihud factor representing the market liquidity risk. Additionally, we conducted an augmented causal analysis that accounts for conditional cause and effect dynamics within the frequency-domain causality analysis to determine the conditional linkages with respect to additional explanatory factors; namely, the TED and VIX indicators. The results are shown in Figure 8. We report findings reflecting a re-scaled frequency range of [0, 0.5] for the daily frequency of our series.

<Insert Figures 7-8 Here>

The application of a varying parameter model is motivated by the fact that a large body of literature shows monetary policy decisions to transmit in different patterns and with diverging levels of intensity depending on the business cycle, level of uncertainty, and general macroeconomic fundamentals. As such, modeling in a static framework is unappealing to our analysis. Furthermore, given our intent to compare between different crises, it stands to reason that a dynamic model would serve our purpose better. Our application of Granger Causality in a frequency domain is an extension of the same line of thinking that motivates capturing the temporal elements of the interrelationships between the variables. Nonetheless, the key variables of interest here are funding liquidity risk and the market liquidity — the latter quantified as a 3-month rolling window of price impact captured by the popular Amihud measure. Our first set of results show a convincing causal influence of spread measures in the credit market holding a causal impact on price impact in the asset markets — on a domestic basis. This relationship is mostly unidirectional, meaning that the converse is not true. The economic interpretation is that an illiquid asset market does not generate panic or lead to widening spreads in the interbank market. This finding could be indicative of growing maturity of these emerging markets. One would suspect that such situations would be more prevalent in the frontier markets. However, given the size of the BRICS markets and the growth in sophisticated investor participation demonstrated by foreign capital flow, this result is unsurprising. The frequency domain information, in this regard is more revealing. The causal influence of the EELS flow ranges from low frequency in Brazil and India to high frequencies in Russia. China and South Africa show mixed patterns. Converting the frequencies to time (periods), we infer the following economic interpretations: credit market spreads in Brazil and India only have an effect over a very long-time horizon. This means that central banks in these countries have ample time to take corrective measures and intervene in the open market should illiquidity concerns arise. The Chinese and South African results show little room for such leeway. The Chinese results are difficult to interpret confidently given the high degree of significant results ranging from low to mid frequencies. This could be indicative of central bank challenges to mediate through open market operations. This finding also highlights the difficulties faced by the People's Bank of China in maintaining the health of the Chinese banking system, which is widely considered the main financier of the Chinese economic miracle.

Our observations of the results obtained for Brazil further point to a significant unconditional GC running from the Amihud measure to the EELS factor. We also found complementary evidence suggesting a decreasing GC pattern across lower frequencies and high prominence across the entire frequency range. On the contrary, we uncovered the evidence of an overall insignificant unconditional reverse causality with the exception of some pockets of high prominence within the lower scales. Likewise, conditioning on the TED spread and the VIX factor, our results are broadly indicative of modest degrees of significance particularly evident at lower scales. In other words, there is a strong annihilation power of the conditioning factors at lower frequencies. Moreover, the evidence relating to the Chinese market broadly reflects a remarkable degree of causation and prominence within the EELS-Amihud spectra especially after conditioning on the VIX factor. Conversely, the role of TED spread as a conditioner is predominantly inconsequential within the entire frequency array.

The findings attributed to the experience of Indian market in general reveal some notable degrees of unconditional causation for the couple EELS-Amihud. More importantly, we discern patterns of remarkable degrees of significance and annihilation power specifically within the lower frequency scales considering the predictive role of both conditional factors in the determination of market liquidity risk. Conversely, our evidence corroborates to an insignificant degree of reverse causation from Amihud to the EELS within the Indian market context. Moreover, findings associated with the Russian market liquidity dynamics indicate patterns of causation and prominence across the entire frequency range. The VIX exhibits marks of strong amplification power within the mid-range frequencies of the sample, whereas the TED spread presents remarkable annihilation power with high degrees of prominence across all frequencies. Finally, the evidence relating to the South African local market context reflect areas of significant unconditional causation running from the EELS to Amihud as well as prominence across the entire sample of frequencies. On the flip side, we spot decreasing GC patterns of the EELS-Amihud causation within the short-term frequencies upon conditioning on the VIX factor and a strong amplification power followed by an annihilation power of the TED spread within the mid-range scales.

Our results, taken altogether, can be interpreted as dual evidence of successful central banking and progressive learning from previous crises by the major emerging economy central bankers. Nearly all BRICS central banks responded to the CPIC by implementing measures to counter liquidity risk in the near-term, institution wide, and at the systemic level. For example, the RBI prohibited the use of unsecured fund markets for anyone but primary dealers. Other central banks imposed constraints on lending and borrowing in the interbank markets. These prudent measures helped ward off further escalation of banks' susceptibility to exogenous credit shocks by lowering dependence on borrowed funds. Our results broadly corroborate the findings of a great deal of the previous work in that the financial consequences of policy uncertainty are assessed (Baker et al., 2016; Donadelli & Gerotto, 2019) with implications pointing specifically to the liquidity spillover effect within the equity markets (Chen & Chiang, 2020; Luo & Zhang, 2020) as well as corporate and sovereign bond markets (Brogaard et al., 2019; Kaviani et al., 2020).

The forward-looking implications of our findings can have profound influences on financial markets' performance. Previously ongoing loosening of lockdown measures worldwide, coupled with expirations of loan moratoriums, had ameliorated the flow of loan receipts. Nonetheless, uncertainties over mass-administering vaccines recast doubts over whether the improved receipts flow would sustain. Even the most optimistic estimates predict the flow to remain depressed for a protracted period. Similar concerns afflict the corporate debt market as widening spreads persist in several major economies. Consequently, uncertainty is at an all-time high with respect to the banking sector's asset quality and liquidity assurance. In such a crucial and fragile macro prudential juncture, whether funding liquidity risk will continue to defy a dismal economic outlook is a matter of legitimate concern and speculation.

5. Implications of Findings

Details of the results described in the preceding section makes apparent that if we organize the most relevant indicators in a descending order of statistical significance, the Chicago Fed's NFCI and domestic stock markets emerge as the most pertinent conduits of interbank credit stress for BRICS economies. The organization pattern of the figures 1 to 5 attests to this discovery. At this stage, a caveat is warranted, however. To extend the statistical significance to economic significance, some more analysis is necessary. For instance, it is understandable that coefficient values for the stock markets would be high — given that an equity market nearly always shows greater dispersion than an interbank credit market where things move much slower. Moreover, emerging economy stock markets are, in general, more volatile than developed economies'. A less expected finding is the high values for the Chicago FED's NFCI. This is arguably our most major finding in this paper. From a theoretical standpoint, neither positive nor negative coefficient of NFCI is expected for large emerging markets — meaning that improved financial conditions in the US should not necessarily coincide with worsening or booming credit market conditions in the emerging economies. This should, in theory, be idiosyncratic and country-specific. Nonetheless, global capital would naturally opt for the safer US markets when conditions are good. We observe the opposite for Brazil and South Africa and occasionally for Russia — particularly during the Euro Sovereign Debt Crisis. The same applies to India only after COVID-19 hit, and the opposite for China. Likewise, for the stock market channel, theory would predict that when credit spread tightens — that is to say when EELS rises — institutions are expected to liquidate their positions in the asset markets, leading to a sell pressure. This should depress market performances. Therefore, the expected coefficient sign would be negative. First off, China is an exception here as well. Looking at other countries, patterns in Brazil stand out. This could be indicative of internal turmoil or foreign appetite for Brazilian assets. Future researchers may wish to evaluate this market deeper by matching this phenomenon to the Brazilian central bank intervention in the financial markets during this stage, like it happened with China multiple times recently. The Brazilian pattern is visible for India but with a distinct demarcation of regimes. In the latter half of the sample window, the relationship reversed from theoretical expectations. This could be a signal of increased attention to the Indian market by professional investors. It was probably around this time that large ETFs started to cover the Indian market more. It was also around the time when the Modi regime overcame the mismanagement scandals and consolidated its position — sending a strong signal of stability to the investment community. Most interestingly, for Russia, the market-EELS relationship runs opposite to the NFCI-EELS relationship. More research is needed to unravel the intricacies of this nexus.

The discussion above implicates the Chicago FED's NFCI indicator and provides empirical evidence of its utility in research beyond developed economy markets. Given the overwhelming statistical and economic association between NFCI and emerging economy liquidity spread (EELS) unraveled in this study, it is worth connecting this finding to prior research. Particularly, we compare our result with previous works addressing the predictive capacity of this indicator. Granziera and Sekhposyan (2019) investigate whether the relative forecasting performances of economic models are associated with financial conditions or not. They note that use of the conditioning information (NFCI) as a tool to select a model can lead to improvements of up to 20 percent in the root mean squared forecast error relative to a competitive autoregressive benchmark in a pseudo-real-time forecasting exercise. This is in line with the results of Dery and Serletis (2021) who declare that the NFCI risk index has the strongest predictive relationship with economic activities. These findings are consistent with the theoretical properties of the index's constituents and their weights. The NFCI is a weighted average of 105 measures of financial activity that are presented relative to their sample averages and scaled by their sample standard deviations. It was constructed to have an average value of zero and a standard deviation of one over a sample period back to 1971. To construct the index, weights are calculated to capture the relative importance of each indicator in explaining the index's historical fluctuations. After taking into account the mixed-frequency nature of these indicators, the NFCI is the single factor that could predict the group of indicators as a whole. In order to interpret movements in the NFCI, each of the 105 financial indicators classifies into one of three types: risk, credit, or leverage. Risk indicators are those measures that represent volatility and funding risk in the financial sector. The second type of indicators, credit ones, are measures of household and nonfinancial business credit conditions. Finally, leverage indicators are normally measures of debt relative to equity. Risk indicators tend to get positive weights but credit and leverage indicators tend to get negative weights. Hence, "tight" financial conditions are related to increasing risk and decreasing credit and leverage. As a result, this index has the following interpretation: its positive values have been historically related to tighter-than-average financial conditions, whereas its negative values have been historically related to looser-than-average financial conditions (Brave & Kelley, 2017). As such, the findings of our paper indicate that the NFCI index is not only an important variable for the US and developed economies, but carries weight as a global macro-economically significant variable as seen for the interbank credit environment in the BRICS economies. In this manner, our findings extend the liquidity-specific relevance of prior works. Dyskant and Silva (2020) consider the relationship between illiquidity and corporate bond spreads after the Fed tightening. They indicate that the Fed tightening has a higher impact on yield spreads than the time of the financial crisis. For example, during the 2008 financial crisis, a one standard deviation increase to a bond's illiquidity measure causes yield spreads to increase by 12 percent but during the monetary tightening period, they increase by 18 percent. To measure this important impact, they use the NFCI as a proxy for financial conditions. Their results also indicate that when financial conditions tighten, i.e. when the NFCI increases, corporate bond market liquidity declines.

Overall, our results indicate high degrees of prominence in the transmission of liquidity risk via the mainstream local and global market channels — particularly during crisis periods. An alternative approach worthy of considering here could have been adding break-point tests to ascertain if major events significantly impact the transmission. This line of investigation was considered by the authors in this paper but did not prove practical enough to proceed. There are several reasons for this, as explained below, which may assist future researchers to adopt and advance our findings further. For example, Kowal et al.'s (2019) method derives its strengths from applying two shrinkage parameters that force coefficient levels to stability and/or close to zero. This unique feature motivated us to adopt it to look for economic significance, which is otherwise not so straightforward to achieve in a static model. Nevertheless, applying the same technique in a break-point format is not so straightforward. Our attempts at quantifying that yielded low statistical power in the presence of breakpoint/regime-specific dummies. Furthermore, the Bayesian estimation approach means that our computations are heavily time-consuming. Hence, considering that very little additional economic insight is expected from adding new discrete models, we did not adopt this approach. Moreover, there is an over-hanging methodological issue: which variable should we apply in the breakpoint test? If we consider EELS, we should assume that credit market spreads exhibit slowly evolving patterns with sudden, discontinuous jumps. Moreover, they rarely coincide with monetary policy decisions or market responses either domestically or from the developed economies. Visually, we also observe a sudden reversion to the mean in the dynamic plots presented and discussed above. This phenomenon is unlike the slower reversion observed in the financial markets. Breakpoint identifications with such stylized facts can lead to a very high number of break-points and, by extension, over-parameterization. Therefore, generating sub-samples and re-running tests, similar to the frequentist tradition, does not promise enough marginal benefit for us to consider. Future researchers should try to investigate these questions, in the manners described above, using traditional/frequentist tools.

Another point to mention here is that this study was designed on a country-by-country basis since we found little theoretical motivation to understand the risk transmission procedure *en masse*. However, we concede that it may be difficult to get a consistent empirical conclusion from individual countries only. Therefore, future researchers should consider cross-country transmission of the liquidity risk. In this regard, we want to point out a few challenges that researchers should consider, especially related to trade-network and exchange rate relationships. For example, we considered generating a network based model with the US and China as core nodes and other emerging economies in the periphery. Yet, we ran into modeling challenges since it is difficult to anticipate theoretical channels through which such shocks could propagate. Furthermore, much of the trade within the BRICS economies is conducted with US Dollar. Additionally, funding liquidity risk is closely related to the credit conditions in the banking system. Upon searching interbank connections and lending within the BRICS countries, our preliminary literature search showed very minor linkages. If anything, more interconnectedness exists with the European Union. Therefore, future researchers can overcome these limitations by doing a preliminary investigation of pre-existing interbank and trade network linkages and model country specific transmissions accordingly.

6. Conclusion

In this paper, we dealt with two questions related to funding liquidity risk in emerging markets. First, we verified whether macro policies in the developed countries (proxied by the US) are transmitted to large emerging economies (proxied by the BRICS countries). Sub-questions within this question involve the identification of channels through which this transmission could occur, and, if so, to what extent. Though we generally found little evidence of monetary policy in the US being associated with funding liquidity risk in BRICS economies, we discovered that the economic conditions in the US (proxied by the Chicago Fed's NFCI indicator) represent a much more potent explanator. This suggests that credit market conditions in BRICS economies are associated with the US economic health but exhibit weak ties with monetary policy decisions. In other words, evidences point toward economic linkages as well as relative central bank independence. By virtue of applying a time varying model, we also observed that BRICS economies show an overall effective monetary intervention by means of adopting flexible policy frameworks and an active use of macro-prudential tools to address the threats of inadequate liquidity arising from the crises. The results for a distinct group of variables were economically meaningful and interpretable in a way that allowed us to timestamp the effects of multiple policy- and non-policy-based developments. In particular, we discovered the importance of aggregate health of the real and financial US economy to be more salient to BRICS economies' interbank markets compared to traditional policy-based variables. This highlights the importance of considering robust leading indicators of the economy like the NFCI in macroeconomic policymaking in emerging economies.

We also examined an attendant hypothesis of whether funding liquidity risk in large emerging economies triggers liquidity risk in the local financial markets. Our Granger causality results confirm this, although the direction of causality sometimes is bi-directional. We further account for the possible mediation role of the state of the global economy in driving the aforesaid causal influences by conditioning the causality results on the state of fear (VIX) and the prevailing credit market sentiments (TED) in the advanced economies. The results generally point to higher influence of the VIX in the short-run and the TED in the longer run. Taken together, our findings matter for the decision making of central bankers. By showing that credit conditions in large emerging economies are still tethered to global credit and market conditions, we highlight the importance of policy coordination and a re-evaluation of monetary policy transmission strategies and independent policy enactment by BRICS central bankers.

Widening our research scope is worthwhile both empirically (e.g., expanded dataset) and methodologically. More precisely, it would be interesting to examine whether our dynamic coefficient model with shrinkage priors outperforms other models when applied to various liquidity (and risk) constructs. Future researchers can carry this out using Bayes factors or Deviance Information Criterion. Another potential area for extension would be to include more emerging economies. While we were encumbered by resource constraints, future researchers may widen the gamut to capture funding liquidity risk dynamics of many more emerging economies (e.g., N11). As globalization does not show signs of abatement and global capital flows travel freely, and the fact that not many objections are pervasive putting an end to it in a post-COVID world, more emerging economies are expected to rise to prominence. Such an investigation with a protracted scope would be a welcomed addition to the academic literature.

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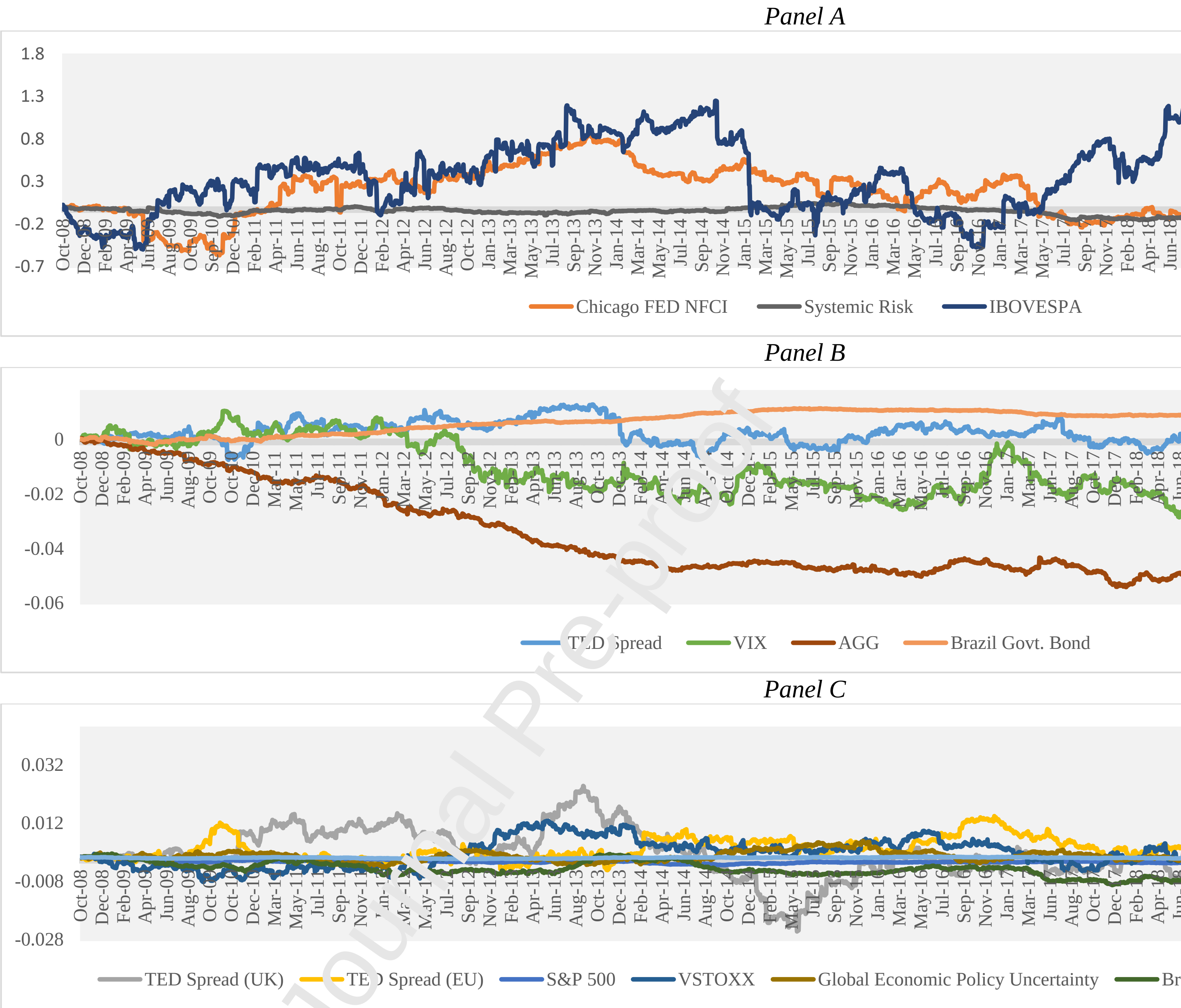


Figure 1: Time-varying Coefficients for Brazil

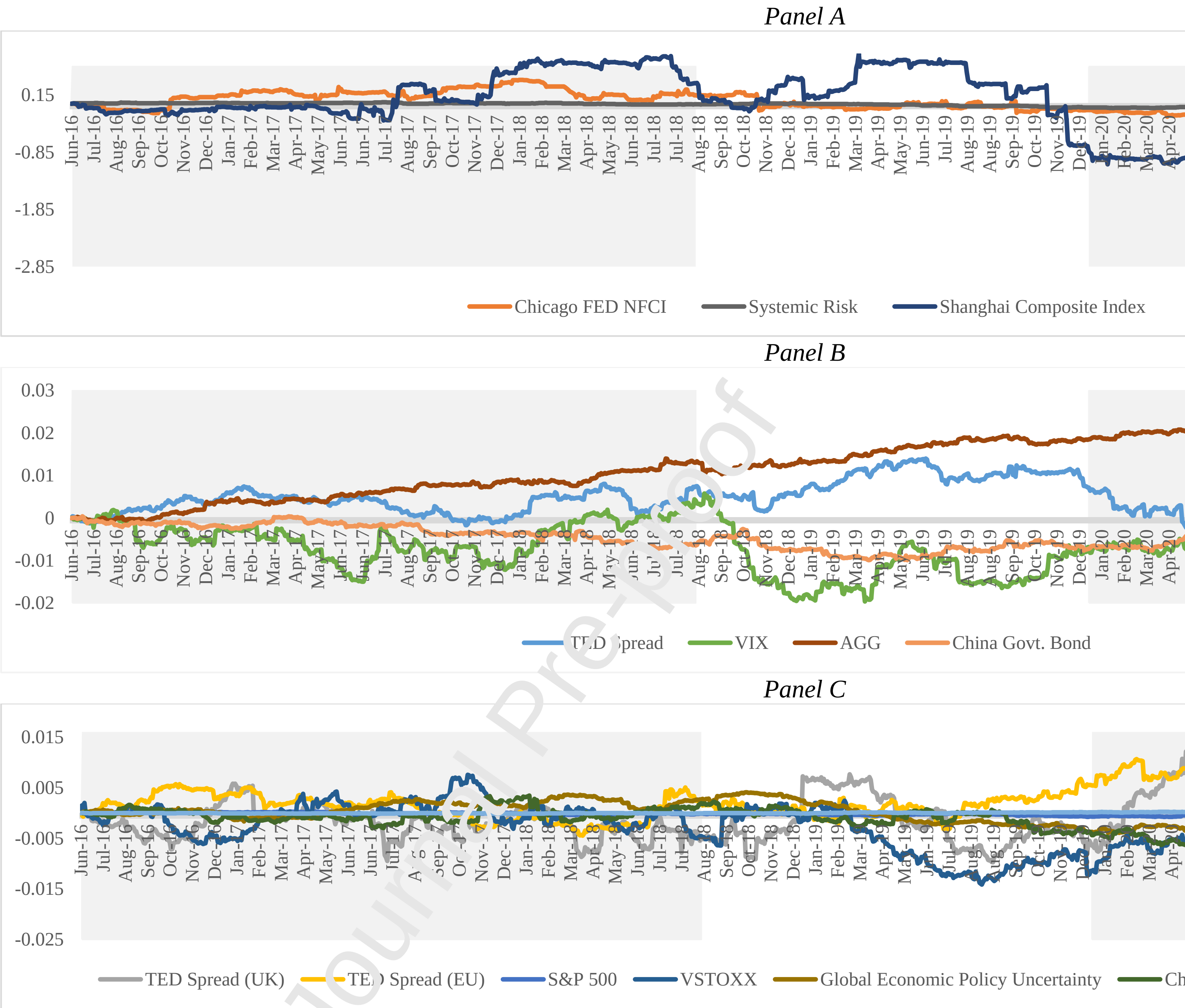
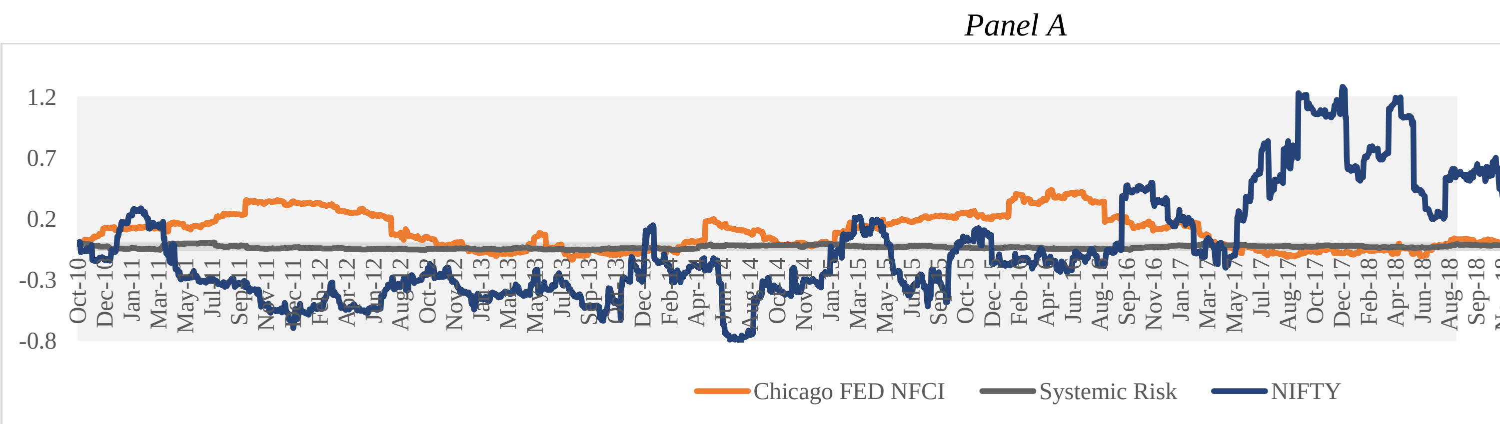
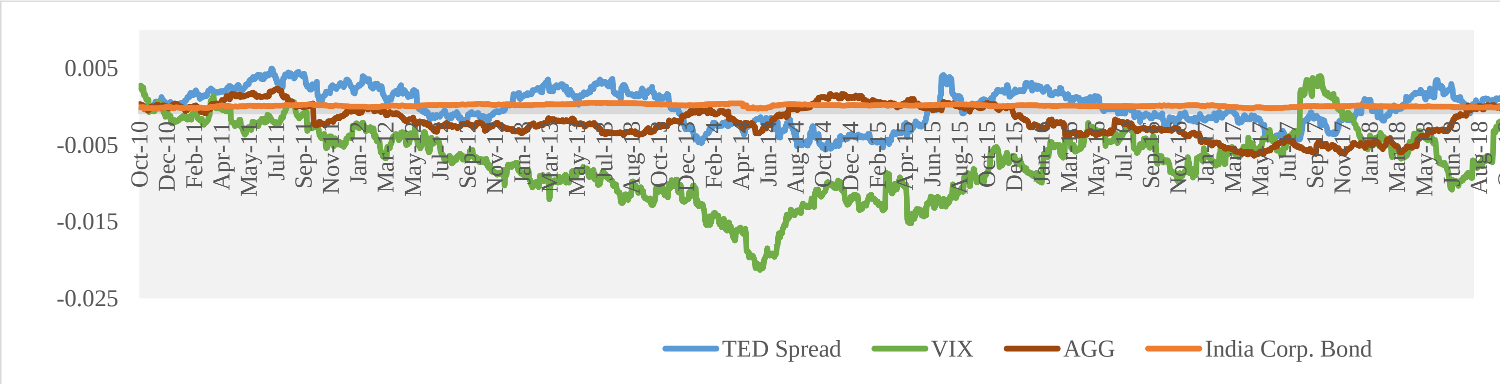


Figure 2: Time-varying Coefficients for China



Panel B



Panel C

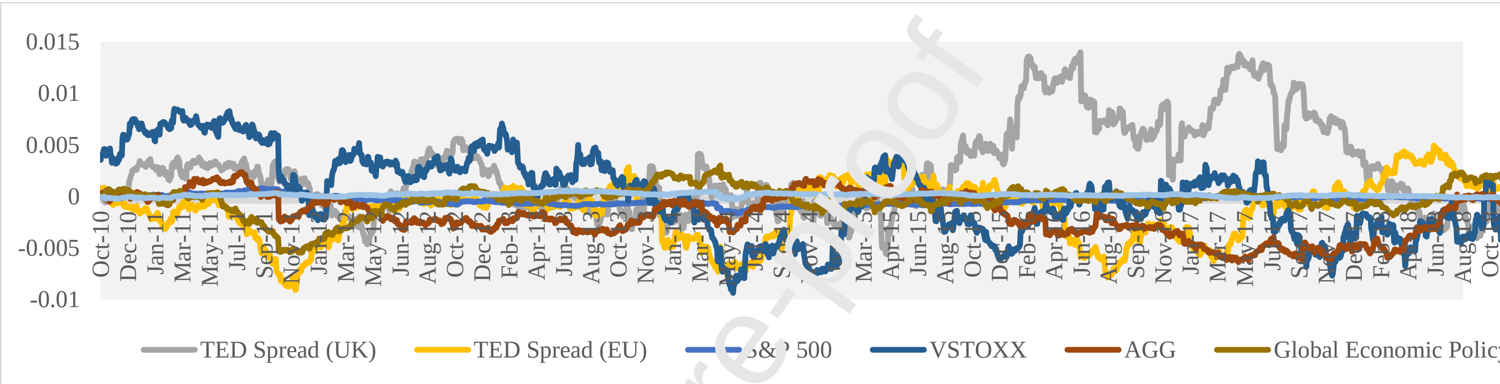
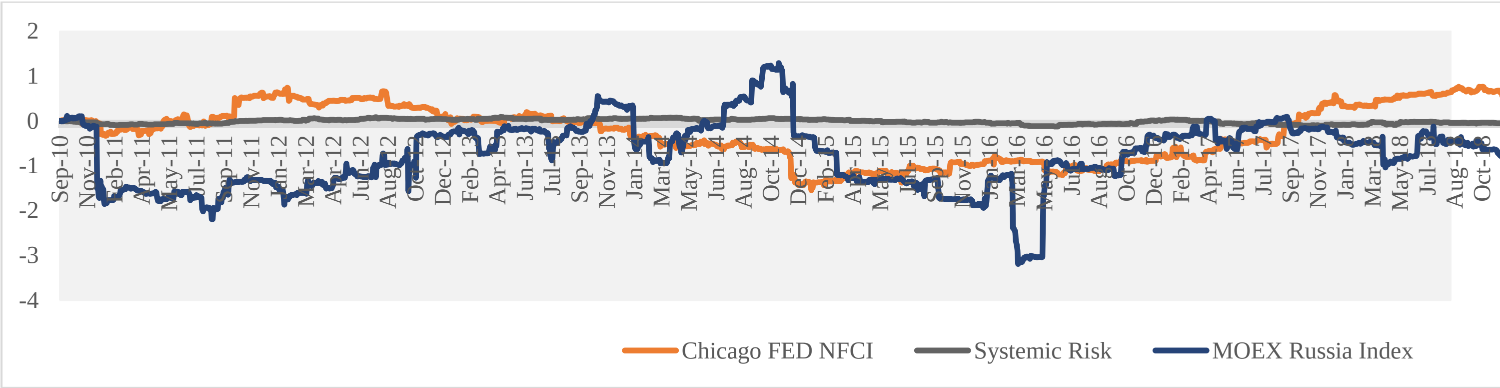
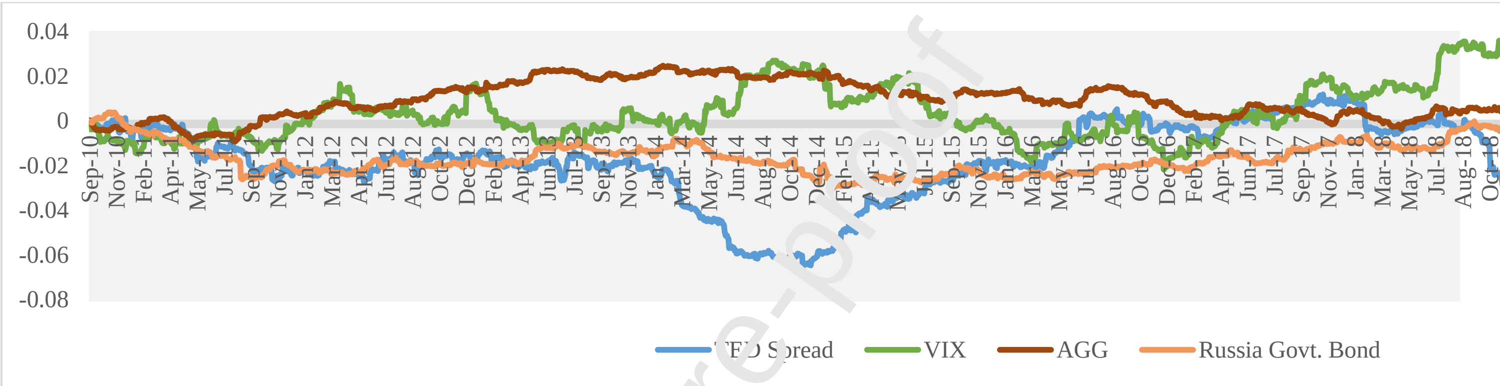


Figure 3: Time-varying Coefficients for India

Panel A



Panel B



Panel C

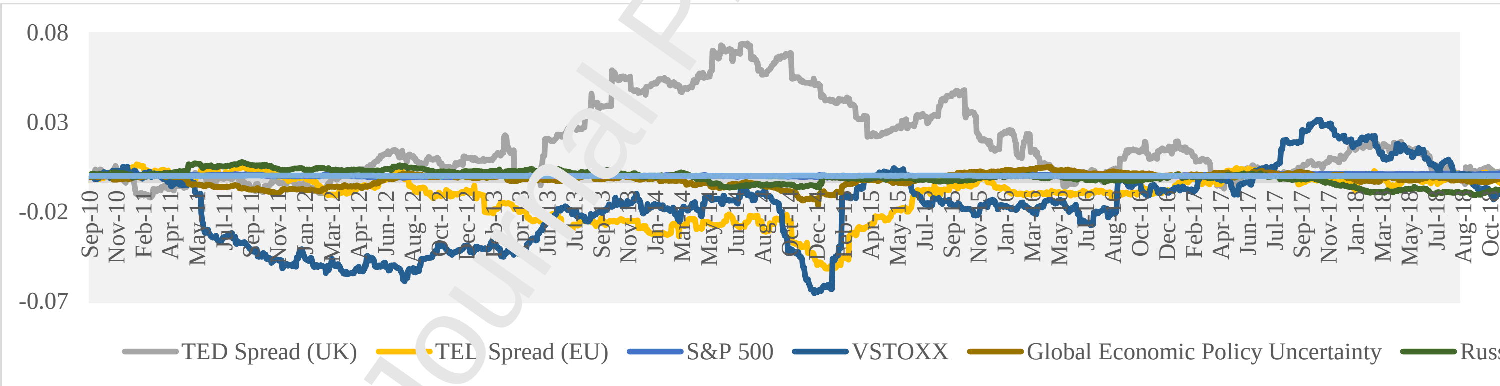
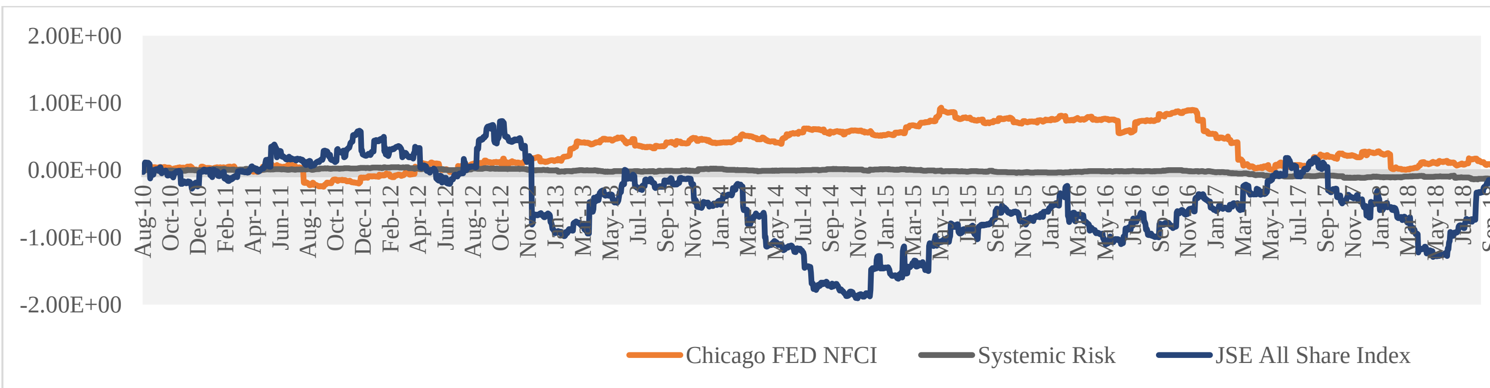
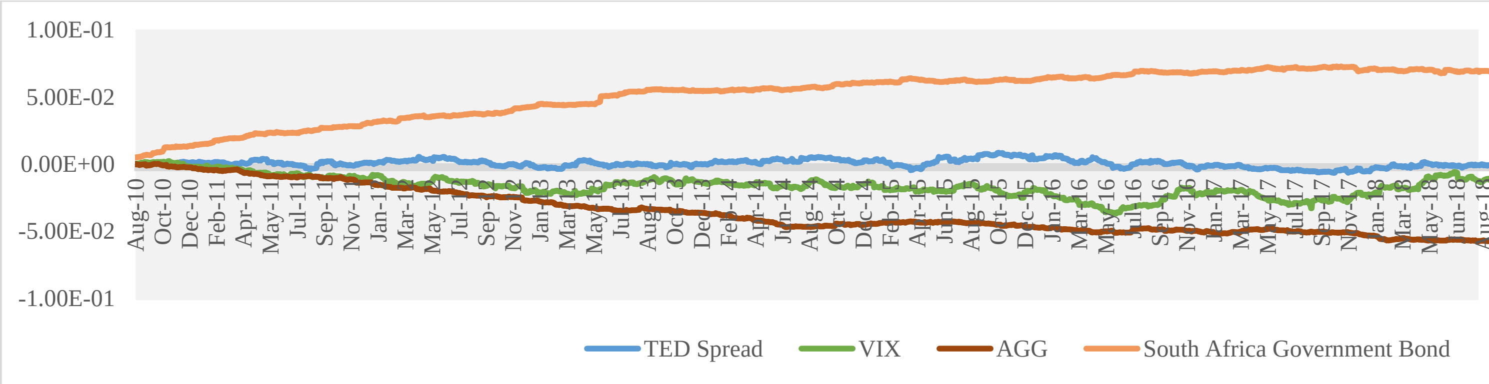


Figure 4: Time-varying Coefficients for Russia

Panel A



Panel B



Panel C

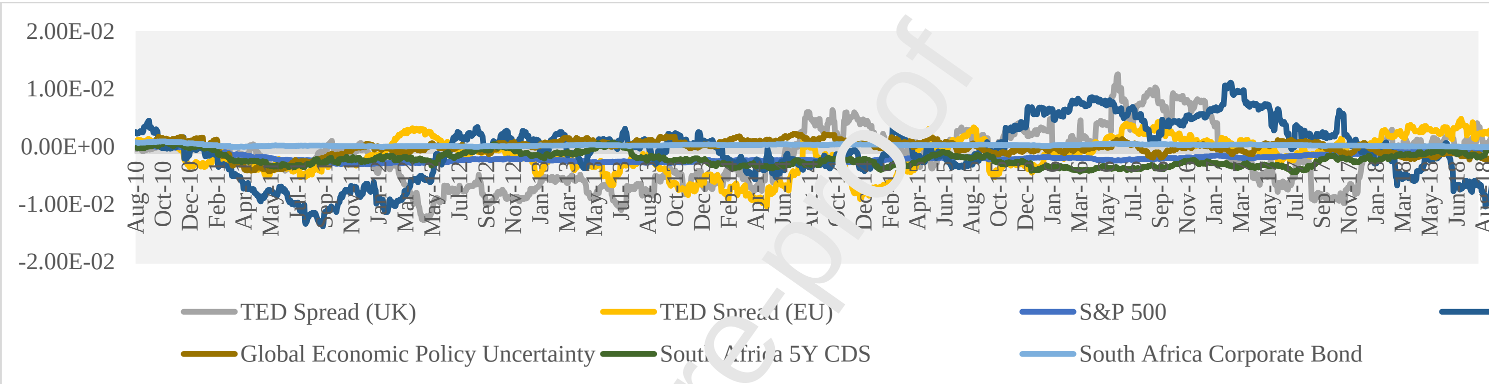
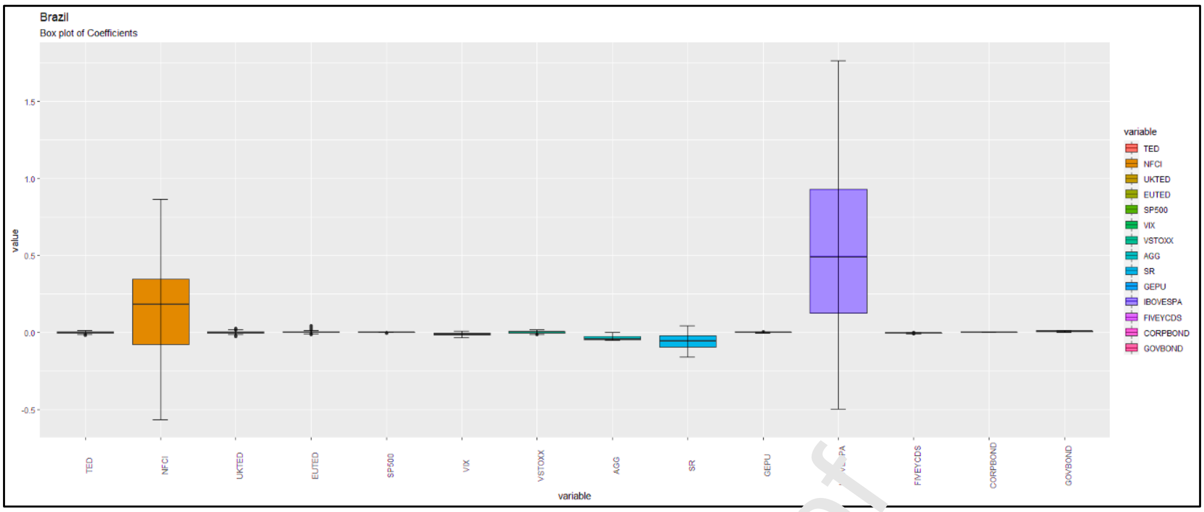
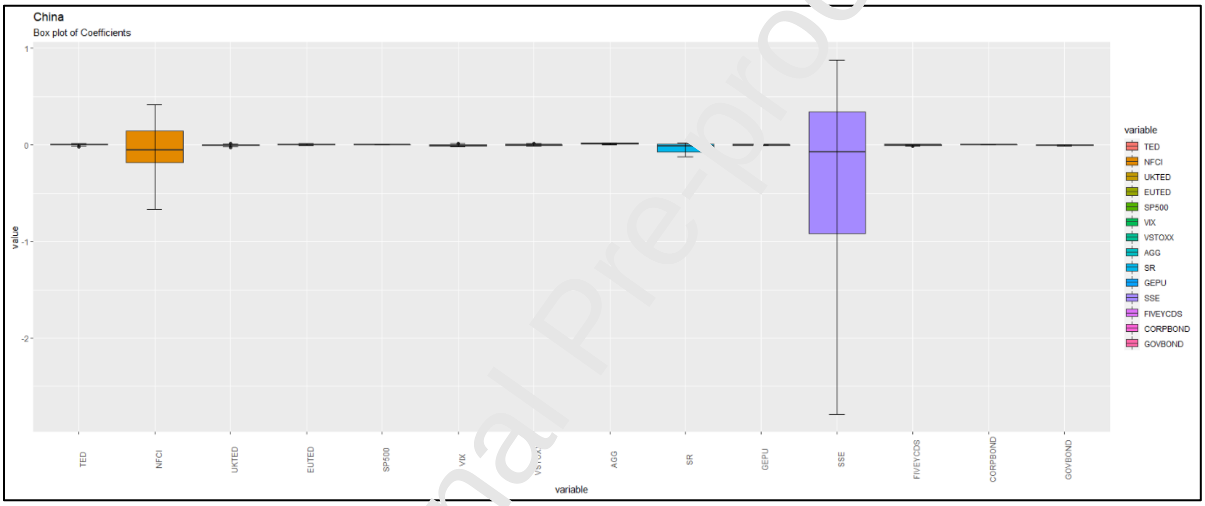


Figure 5: Time-varying Coefficients for South Africa

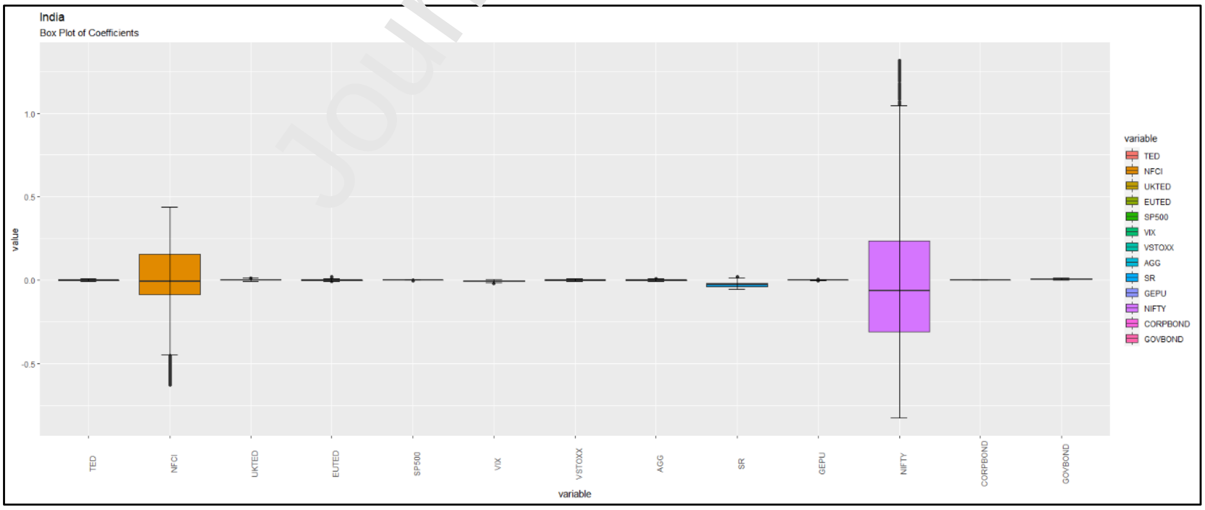
Panel A



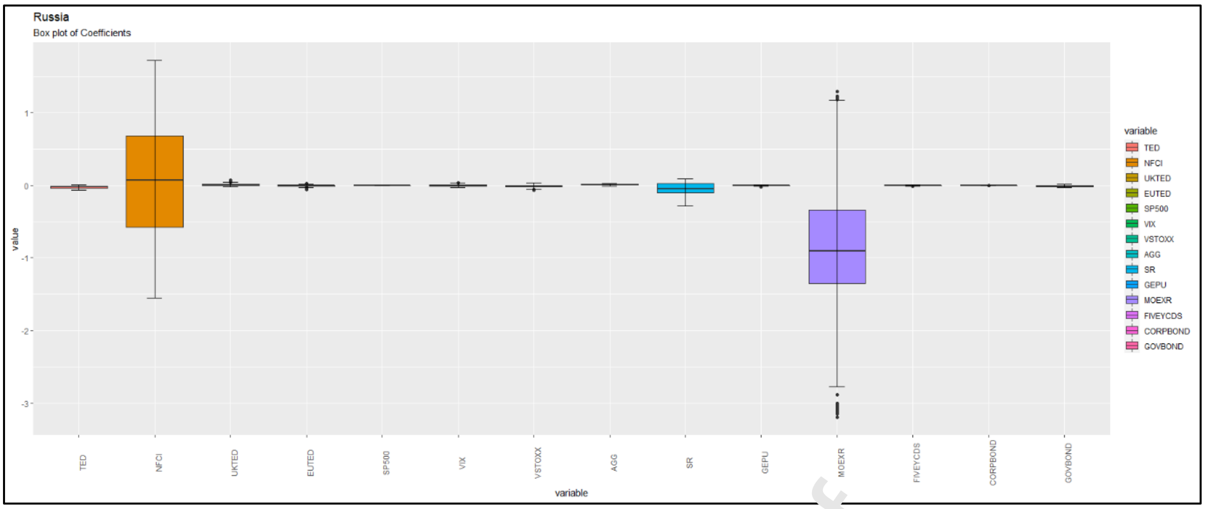
Panel B



Panel C



Panel D



Panel E

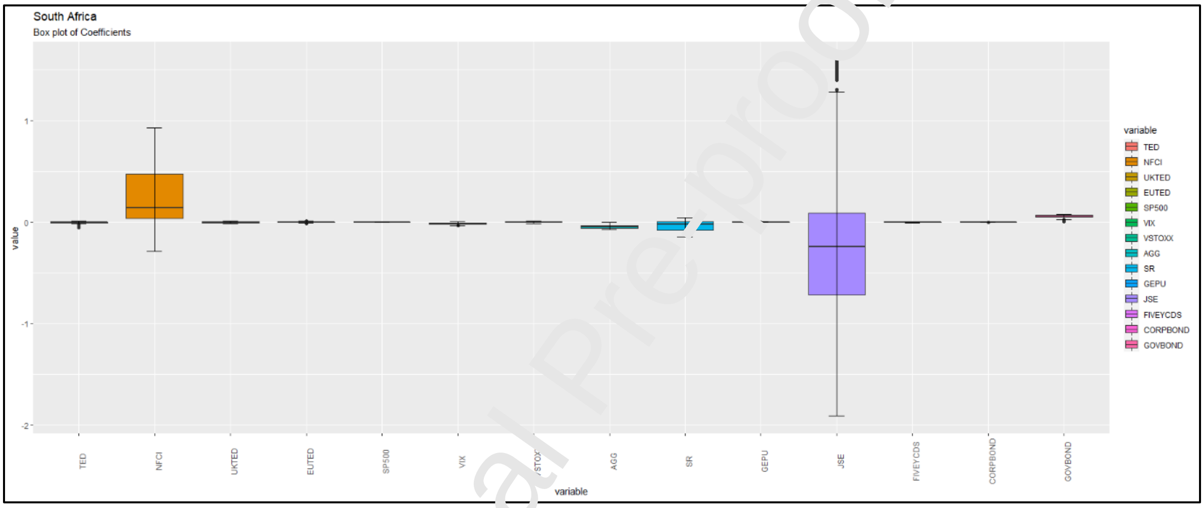
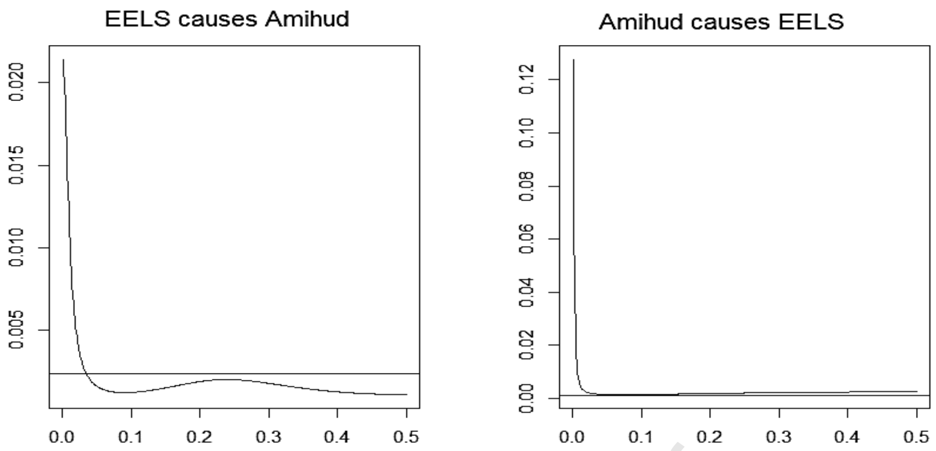
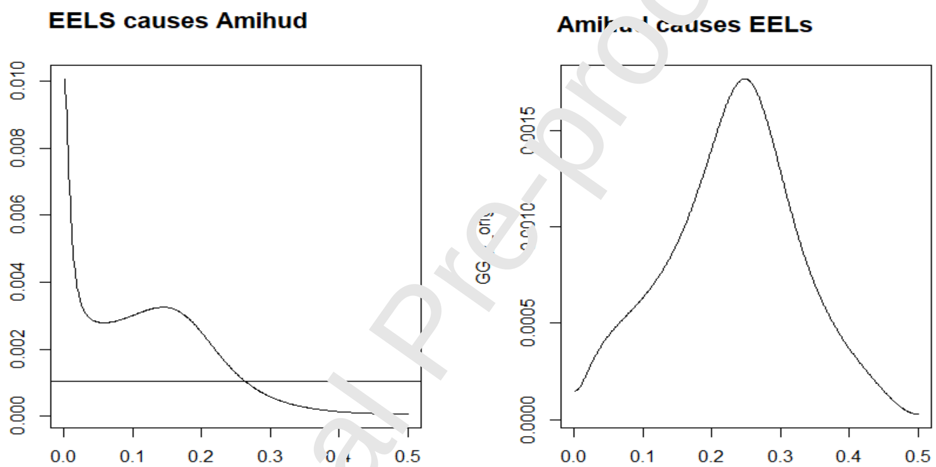


Figure 6: Box plot of Coefficients

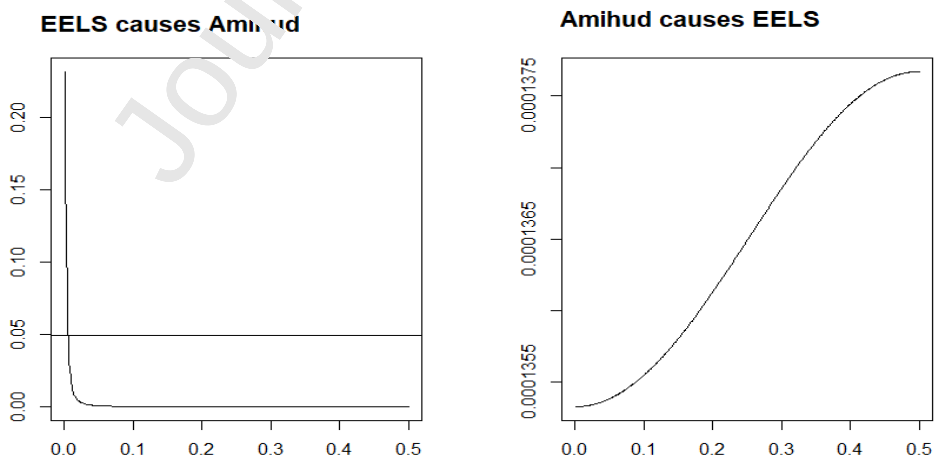
These figures illustrate the box plots of the obtained coefficients for different indicators on a country-level basis. The SSE denotes the Shanghai Stock Exchange, MOEXR represents the MOEX Russia index, JSE stands for the Johannesburg Stock Exchange, FIVEYCDS is the five-year CDS, and CORPBOND and GOVBOND are short forms for corporate and government bond indices, respectively. Other variables are as defined in the data section.



Brazil



China



India

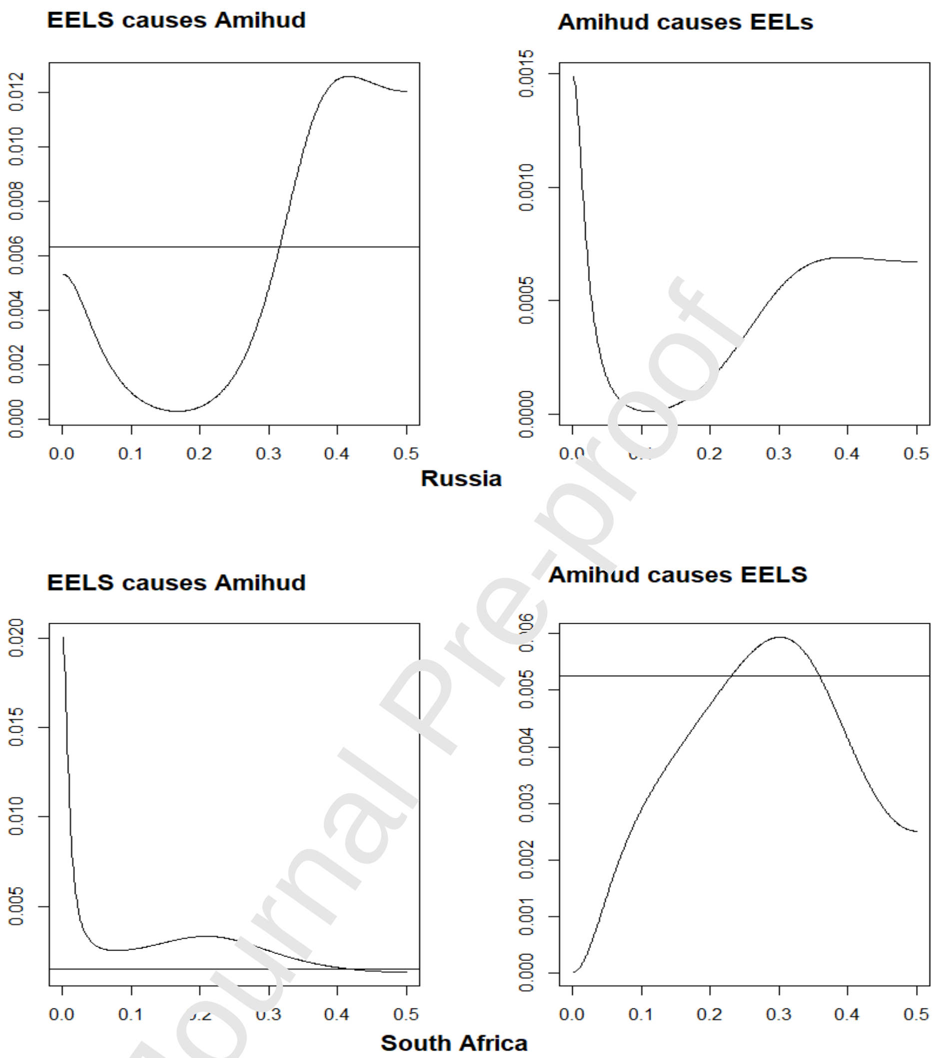
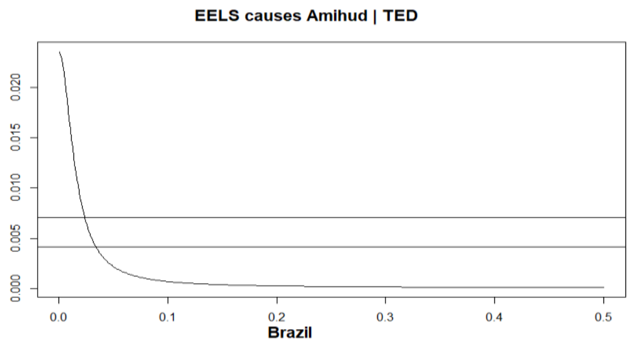
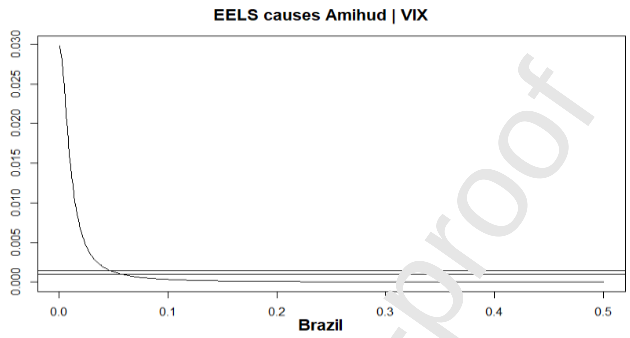
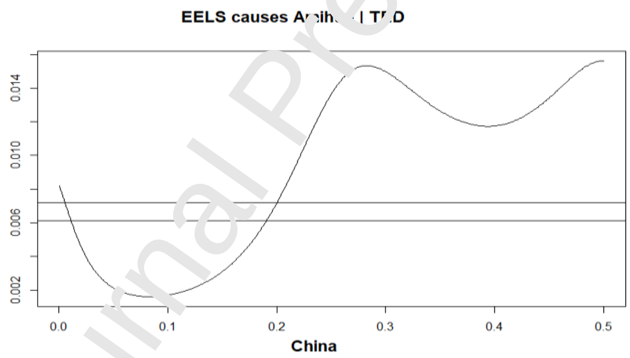


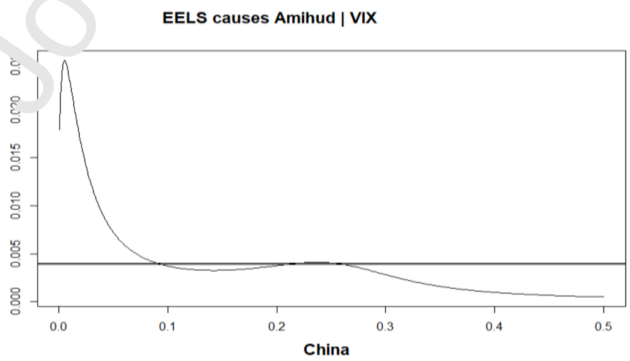
Figure 7: Granger Causality Results
(Funding Liquidity Risk to Market Liquidity Risk Hypothesis)

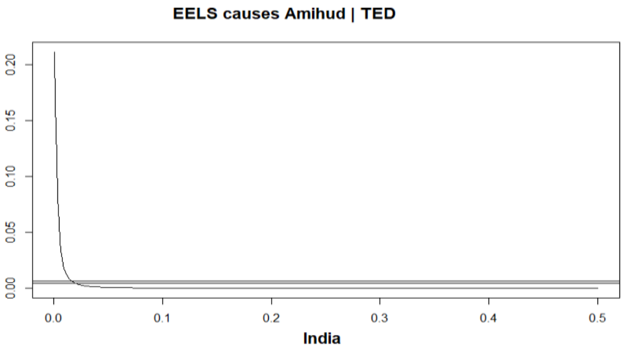
These figures depict the Granger causality in frequencies results associated with the hypothesis that interbank credit spread causes depression of liquidity in the corresponding country's financial markets. Bi-directional causality is also tested.

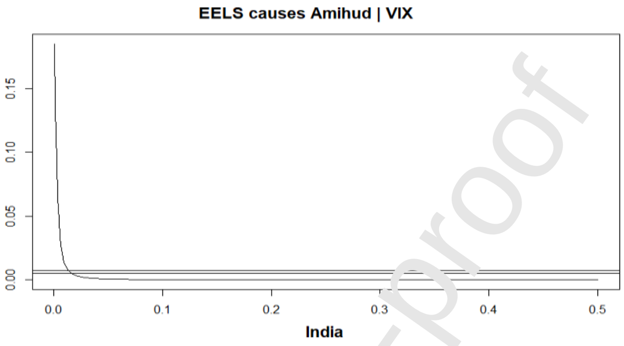

EELS causes Amihud | TED
0.000
0.005
0.010
0.015
0.020
0.0
0.1
0.2
0.3
0.4
0.5
Brazil

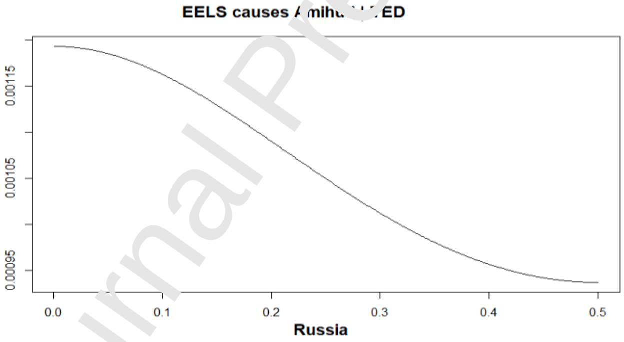

EELS causes Amihud | VIX
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.0
0.1
0.2
0.3
0.4
0.5
Brazil

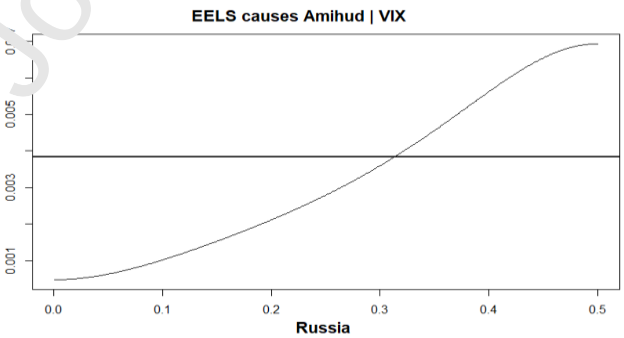

EELS causes
0.002
0.006
0.010
0.014
0.0
0.1
0.2
0.3
0.4
0.5
China


EELS causes Amihud | VIX
0.000
0.005
0.010
0.015
0.0
0.1
0.2
0.3
0.4
0.5
China


EELS causes Amihud | TED
0.00
0.05
0.10
0.15
0.20
0.0
0.1
0.2
0.3
0.4
0.5
India


EELS causes Amihud | VIX
0.00
0.05
0.10
0.15
0.0
0.1
0.2
0.3
0.4
0.5
India


0.00095
0.00105
0.00115
0.0
0.1
0.2
0.3
0.4
0.5
Russia


EELS causes Amihud | VIX
0.001
0.003
0.005
0.0
0.1
0.2
0.3
0.4
0.5
Russia

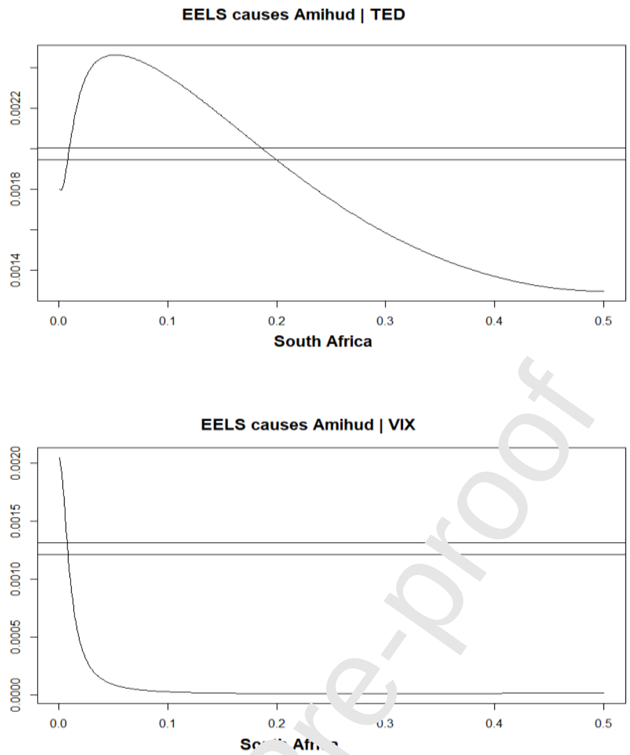


Figure 8: Granger Causality Results

(Funding Liquidity Risk to Market Liquidity Risk Hypothesis) conditional on TED spread and VIX

These figures depict the Granger causality in frequencies results associated with the hypothesis that interbank credit spread causes depression of liquidity in the corresponding country's financial markets, conditional on the TED spread and the VIX (these two measures are used as representatives of macroeconomic climate in the developed world (the US)).

Table 1: List of Variables

	Variable	**Proxy for**	**Empirical Precedence**
	US TED Spread	Credit risk	Boudt et al. (2017)
	UK TED Spread	Credit risk	Kellard et al. (2021) Benbouzid et al. (2018)
	EU TED Spread	Credit risk	Cerutti et al. (2017)
	S&P 500	The performance of the US stock market	Balcilar and Ozdemir (2013)
US/global variables	VIX, and VSTOXX	The forward-looking outlook of the global stock market uncertainty	Ben Amar and Carlotti (2021) Hammoudeh and McAleer (2015) Chiang et al. (2015)
	NFCI	The US financial condition	De Nicolò and Lucchetta (2017) Fink and Schüler (2015)
	Global Economic Policy Uncertainty	Global macroeconomic volatility	Li et al. (2020)
	Systemic risk	Markets' perception of the risk of widespread insolvency in the banking sector	The Federal Reserve Bank of Cleveland
	Amihud illiquidity	Market liquidity	Macchiavelli and Zhou (2021) Barardehi et al. (2021)
	AGG	Global investment-grade debt performance	Lin and Niu (2021)
	EELS Spread	Emerging economy market liquidity spread	Authors' contribution
Local variables - BRICS	CDS Spread	Corporate/sovereign credit risk	Nashikkar et al. (2011) Pelizzon et al. (2016)
	Stock market index	The performance of equities in the corresponding markets	Frankfurter (1976)
	Government bond index	The performance of government securities	Hill and Schneeweis (1983)
	Corporate bond index	The performance of corporate bond market	Hill and Schneeweis (1983)

Note**:** this table shows all the variables employed in this paper to verify the existence US-led influence in funding liquidity risk transmission to BRICS economies. The global variables listed are common in all estimations used for Equation (1). The data is sourced from Refinitiv EIKON and Bloomberg database. The starting and ending dates are as follows: For US or Global variables (07/10/2008 - 23/09/2021), Brazil (07/10/2008 - 23/09/2021), Russia (05/07/2010 -23/09/2021), India (10/07/2010 -23/09/2021), China (24/06/2016- 23/09/2021), and South Africa (10/08/2010-23/09/2021).

Table 2: Summary Statistics for BRICS Economies variables

		n	Mean	SD	Median	Min.	Max.	Skewness	Kurtosis	S.E.
Brazil	EELS spread	2,992	-0.02%	21.37%	0.01%	-240.27%	341.07%	2.01	69.32	0.39%
	IBOVESPA index	2,992	0.05%	1.74%	0.05%	-14.78%	14.66%	-0.11	10.96	0.03%
	CDS spread	2,992	-0.01%	3.58%	-0.16%	-37.26%	40.48%	0.79	21.10	0.07%
	Government Bond index	2,992	0.01%	2.31%	0.08%	-19.53%	15.94%	-0.68	10.54	0.04%
	Corporate Bond index	2,992	0.08%	9.48%	0.06%	-230.34%	230.57%	4.82	577.86	0.17%
	Amihud Illiquidity	4,566	58.42%	121.86%	22.28%	0.01%	2150.03%	7.45	85.69	1.80%
Russia	EELS spread	2,624	-9.33%	362.25%	-2.55%	-8500.00%	8700.00%	-1.53	273.69	7.07%
	MICEX Russia index	2,624	0.05%	1.19%	0.05%	-[illegible].34%	7.72%	-0.50	5.60	0.02%
	CDS spread	2,624	0.12%	3.99%	0.01%	-65.02%	95.50%	3.68	152.36	0.08%
	Government Bond index	2,624	-0.01%	1.87%	-0.04%	-12.34%	16.09%	0.80	9.11	0.04%
	Corporate Bond index	2,624	0.01%	0.84%	0.00%	-14.55%	16.85%	1.77	107.59	0.02%
	Amihud Illiquidity	4,282	4.56%	14.41%	0.18%	0.01%	187.62%	5.09	33.20	0.22%
India	EELS spread	3,289	0.11%	34.12%	0.01%	-438.20%	355.53%	-0.27	38.91	0.59%
	NIFTY index	3,289	0.05%	1.40%	0.07%	-12.98%	17.74%	0.08	15.26	0.02%
	Corporate Bond index	3,289	0.04%	1.74%	0.04%	-15.04%	13.57%	-0.03	7.41	0.03%
	Government Bond index	3,289	0.01%	0.59%	0.01%	-13.22%	12.86%	0.09	162.82	0.01%
	Amihud Illiquidity	4,562	0.03%	0.26%	0.01%	0.01%	17.40%	64.47	4285.51	0.01%
China	EELS spread	1,215	-24.81%	590.67%	-1.07%	-13400.00%	8200.00%	-11.29	312.77	16.95%
	Shanghai Composite index	1,215	0.02%	1.05%	0.06%	-7.72%	5.71%	-0.55	5.89	0.03%
	CDS spread	1,215	0.18%	3.86%	0.35%	-33.63%	33.86%	0.46	19.04	0.11%
	Government Bond index	1,215	0.00%	0.33%	0.01%	-5.50%	3.22%	-5.34	113.09	0.01%

	Corporate Bond index	1,215	-0.06%	1.35%	-0.11%	-8.08%	16.59%	2.34	25.89	0.04%
	Amihud Illiquidity	4,566	1.28%	2.88%	0.23%	0.01%	29.14%	4.04	20.70	0.04%
S. Africa	EELS spread	2,903	0.07%	5.05%	-0.04%	-78.81%	106.53%	4.85	157.34	0.09%
	JSE All Share index	2,903	-0.50%	30.71%	-0.98%	-427.97%	1271.50%	24.51	1057.09	0.57%
	CDS spread	2,903	0.05%	1.96%	0.11%	-12.67%	17.73%	0.08	6.27	0.04%
	Government Bond index	2,903	0.05%	3.65%	0.01%	-21.49%	82.00%	4.54	93.93	0.07%
	Corporate Bond index	2,903	0.24%	74.49%	1.06%	-1661.28%	19[illegible].64%	2.22	258.66	1.38%
	Amihud Illiquidity	4,565	1.80%	2.73%	0.76%	0.01%	30.60%	3.34	15.65	0.04%

Note: this table details the descriptive statistics of all BRICS country-specific variables. n denotes the number of daily observations. SD stands for standard deviation. All values sans *n*, skewness, and kurtosis are in percentage terms. SD, MAD, and SE stand for standard deviation, mean absolute deviation, and standard error, respectively. CDS represents credit default swap and EELS denotes emerging economy liquidity spread. The specification of the time-varying-parameter model relies on first-differences. As such, the variables described in this table are in changes form, with the exception of Amihud illiquidity, which is used in Granger causality exercises. Since Amihud's illiquidity ratio (we use the Barardehi et al.'s (2021) modified version in this paper) is very small in value, we multiply it by 10,000 for ease of interpretation, in line with empirical precedents.

Table 3: Summary Statistics for Global Variables

	n	Mean	SD	Median	Min.	Max.	Skewness	Kurtosis	S.E.
TED spread (US)	2,992	0.02%	0.63%	0.11%	-1.69%	1.28%	-0.6767	0.2113	0.01%
TED Spread (UK)	2,992	0.06%	0.77%	0.00%	-2.53%	2.47%	0.0832	1.0836	0.01%
TED Spread (EU)	2,992	0.29%	0.67%	0.18%	-1.46%	4.46%	1.7419	6.2026	0.01%
S&P 500	2,992	-0.13%	0.05%	-0.13%	-0.25%	0.05%	0.7384	1.1256	0.00%
VIX	2,992	-1.25%	1.01%	-1.46%	-3.45%	1.05%	0.2852	-0.8223	0.02%
VSTOXX	2,992	0.21%	0.57%	0.24%	-1.50%	1.59%	0.1603	-0.4448	0.01%
NCFI	2,992	15.14%	28.94%	17.99%	-56.69%	86.44%	0.0079	-0.4283	0.53%
Global Economic Policy Uncertainty	2,292	0.05%	0.17%	0.05%	-0.33%	0.58%	0.3908	-0.1959	0.00%
Systemic Risk	2,992	-5.99%	4.85%	-5.55%	-15.94%	4.48%	-0.0721	-0.7316	0.09%
AGG	2,992	-3.67%	1.49%	-4.42%	-5.42%	0.04%	1.1641	-0.0749	0.03%

Note: this table details the descriptive statistics of all global variables. *n* denotes the number of daily observations. SD and SE stand for standard deviation and standard error, respectively. The specification of the time-varying-parameter model relies on first-differences. As such, the variables described in this table are in changes form.

Imtiaz Sifat: Formal analysis; Methodology; Roles/Writing - original draft. Alireza Zarei: Formal analysis; Investigation; Methodology; Roles/Writing - original draft. Seyed Mehdi Hosseini: Data curation; Investigation; Roles/Writing - original draft. Elie Bouri: Supervision; Visualization; Roles/Writing - original draft.

Highlights

- Study interbank liquidity risk transmission to BRICS in crisis periods
- Find weak links between interbank credit market and US monetary policy and market conditions.
- Federal Reserve's National Financial Conditions Index (NFCI) —matters more.
- Interbank credit crunch shapes market liquidity risk in BRICS
- US uncertainty and credit market conditions exert some influence.