# Analysing the Role of Central Bank's Communication and Asset Markets in Flow of Information

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## Abstract

This paper studies the structure of the flow of macroeconomic information between policymakers and market participants in different countries in a globalised world. The paper identifies three main subsystems in the integrated economic system that facilitate information transmission: the stock market, the foreign exchange market, and the central bank's communication. It examines the mean and volatility information spillover between various entities (stock markets, foreign exchange markets, and CBs) and different countries through connectedness techniques and multilayer network analysis. The main findings suggest that the stock markets act as an amplifier of information, followed by the foreign exchange markets, while the central bank's communication actively influences information flow during uncertain times. Additionally, spillover between the mean and volatility information intensifies during crises, suggesting that they are conditioned on each other during systemic and unprecedented events. Moreover, it is observed that central banks' mean communication sentiment is conditioned on the standard deviation of their communication sentiment. This paper highlights the role of distinct subsystems and countries in the global information flow structure.

**Keywords:** Multilayer Networks, Information Spillover, Textual Analysis, Central Bank's Communication, Connectedness Analysis

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## 1. Introduction

An economic structure sustains itself through the interaction and coordination of diverse sets of economic agents (including policymakers and economic decision-makers), which gives rise to an interdependent economic system. The coordination between these agents is facilitated by the exchange of domestic and external information through several subsystems, such as markets and institutions like the central bank (hereafter, CB). In this context, the paper delineates the structure of the flow of macroeconomic information between policymakers and market participants across countries. In particular, the paper uses connectedness techniques and multilayer network analysis to look at the role of the stock market, the forex market (henceforth, the forex market), and the CB's communication in receiving and sending information signals in a global structure that is interconnected.

The spillover between individual markets and institutions has been explored in the literature, including: spillover across the equity markets (Diebold and Yilmaz, 2009; Akhtaruzzaman et al., 2021); spillover across the forex markets (Bubák et al., 2011; Kočenda et al., 2019); monetary policy spillover (Antonakakis et al., 2019); and CB's communication spillover (Armelius et al., 2020). However, these markets and institutions are connected in a broader economic system and are affected by each other. Recently, a strand of literature has focused on examining the spillover between equity and forex markets across countries (see Warshaw, 2020; Tian et al., 2022; Wang et al., 2023). This paper extends this scant literature by studying the spillover between the stock market, the forex market, and CB's communication across the world through its entity-level analysis, where each type of market or institution in a country is treated as an entity. This paper has a novel contribution in the country-level analysis. The current literature is more focused on individual markets and institution spillover (entity-level analysis) and doesn't look at them as a subsystem of the economic structure of a country. This paper addresses this gap by disentangling the information spillover between countries (and not entities themselves) through three crucial subsystems: the stock market, the forex market, and the CB. Thus, in a nutshell, the paper highlights and compares the roles of different subsystems (markets and institutions) through entity-level analysis and different countries through country-level analysis in information transmission.

In an intertwined economic system, the coordination between economic agents is essentially based on an information transmission network. This network builds on diverse signals[1] that impart information regarding agents' perceptions of the economic state and their subsequent choices. Agents exchange signals through multiple subsystems of the economic structure, like stock markets, forex markets, and CBs' communication. A detailed discussion of how signals flow between agents in an open economy is followed in section 2. Briefly, it can be understood as follows: Heterogeneous economic agents enter the market with a set of subjective beliefs, expectations, and preferences to make demand and supply decisions. In aggregate, these individual stakeholders play a vital role in guiding the economy's path. Thus, CBs closely monitor their expectations while setting monetary policy (Powell, 2021). On the other hand, CBs relay signals, through policy announcements and statements, about their assessment of the state of the economy and its near-term policy stance (Woodford, 2005; Blinder et al., 2008). The market participants incorporate these signals into their information set and further condition their actions (reactions) on the updated information set. Precisely, individuals and CBs are affected by each other's actions. Thus, they act as receivers and senders of signals and update their actions (reactions) based on the latest information exchanged.

This paper infers the aggregate beliefs of market participants through the behaviour of the stock market and the forex market, whereas it uses the sentiment of CB's speeches to capture signals from CB. The choice of these aspects of the flow of information is contingent on the following

[1] Signals can be anything through which agents convey information. For example, CB's communication, market participants' stock market reactions through prices, etc.

observations: First, the asset markets are structured in such a way that they combine the beliefs and expectations of different participants and manifest them in a composite outcome, mostly in the form of prices (Easley and Kleinberg, 2010). Thus, we use the stock and forex markets as instruments for aggregating and representing average beliefs among individuals about the economy. Second, financial markets are considered a decent predictor of an economy, and at the same time, they also drive macroeconomic fundamentals (Diebold and Yilmaz, 2015; Cieslak and Vissing-Jorgensen, 2021). These two characteristics make these markets critical parts of the structure of the flow of information. Lastly, communication has been found to be an effective instrument in managing expectations recently (Blinder et al., 2008; Hubert & Labondance, 2021). In this context, the notion of Keynesian coordination failure poses the possibility of multiple equilibria for the economy. It presents an intervention opportunity for the policymakers to guide the economy from one (say bad) equilibrium to another (say good) equilibrium by managing the expectations of the agents (Williamson, 2014). Thus, we incorporate CB's communication aspect while inspecting the flow of information as well.

The paper focuses on information spillovers across disparate entities like CBs, stock markets, and forex markets in a global economic system. Thus, information spillover indices, developed by Diebold and Yilmaz (2012, 2014), appear to be a natural choice of measurement here. It gives pairwise spillover between entities and a system-wide spillover index. However, these measures capture the extreme ends of spillover, from spillover between individual entities to system-wide spillover. What if we need to check spillover across groups of variables? To adjust the granularity of the analysis and draw meaningful inferences, the paper augments the information spillover indices with a block aggregation technique (see Greenwood-Nimmo et al., 2021). This uncovers spillover across groups of variables, like cross-subsystem spillover (say, spillover from the group of CBs to the group of stock markets). Moreover, the paper undertakes a time-varying analysis using the rolling window technique to understand the dynamics of spillover indices.

At this juncture, it is imperative to emphasise that information spillover can be of different types, say, first-moment (mean) and second-moment (volatility) information spillover[2]. This paper studies mean (mean model) and volatility (volatility model) spillover individually as well as in a single connectedness model (mean-volatility model). Studying the mean-volatility model brings out the conditionality between first- and second-moment information spillover over time.

This paper undertakes to study the information spillover network between countries through various subsystems like the stock market, the forex market, and the CB's communication. The use of a single-layer information network is not apt to represent such a structure as it is incapable of capturing the heterogeneity in channels of information spillover between countries. A single-layer network can depict information spillover between individual entities but can't treat it as part of the larger economic system of a country. Multilayer networks are capable of modelling such structures. Thus, we use them to understand information flow between countries, where the stock market, forex market, and CB are identified as layers of information transmission from one country to another. Further, a multilayer structure is imposed on the mean-volatility model with layers of mean and volatility information. This enables us to study the spillover between different entities by incorporating both mean and volatility information effects in the same structure. Moreover, defining a system in network structure gives access to its toolkit, which helps observe the dynamics embedded in that system. Network descriptors like strength, PageRank centrality, and PageRank versatility measures are

[2] Here, first-moment implies returns for the stock and forex markets, and average sentiment of CB's communication. The second moment captures volatility of the stock and forex market returns and CB's sentiment.

used to comprehend the role of each dimension of the flow of information and to determine important countries in the information transmission network.

The results of the paper suggest that information spillover in the economic system has a time-varying dimension, whereby it is more prominent during global events that raise uncertainty. The highest spillover is found among the stock markets and a few of the forex markets. Further, the analysis reveals a passive role of CBs in this structure. CBs actively contribute to the system only during systemic and unprecedented events. Additionally, CBs majorly mediate information spillover between first- and second-moment information, which aggravates conditionality between them during times of crisis. Further, advanced economies have more influence and sensitivity to information spillovers and are ranked higher in centrality measures. From the results, it is observed that the multilayer representation brings out different dynamics than the single-layer representation of the information flow, which are critical in their own ways.

This paper contributes to the existing literature in three ways. First, this is the first study examining the integrated macroeconomic information flow by examining the financial markets and the CB's communication in one structure. Second, this paper uses a novel multilayer network along with traditional networks to explain the structure of information flow through subsystems and identify important countries and entities within this structure. To the best of our knowledge, this is the first paper to look at spillover between countries through different subsystems and not entities themselves. Third, this paper adds the dimension of mean-volatility spillover, which reveals critical institutions mediating spillover between first- and second-moment information.

The rest of the paper is structured as follows: section 2 describes the flow of signals and information within and across countries. Section 3 outlines the data and methodology implemented. In section 4, results are presented, followed by a discussion. Finally, section 5 concludes.

## 2. Flow of signals and information

The perceptions of policymakers and market participants are central to directing economic transmission. These agents interact in an economic environment and exchange signals regarding their beliefs and expectations, which affect overall macroeconomic activity and give rise to a closely knit network structure. This section outlines the flow of signals and information between agents and the subsystems through which they interact[3].

Figure 1 depicts the flow of information with a special focus on three entities: CB, heterogenous agents, and external entities, among whom signals are exchanged. Here, "signal" refers to any means by which senders and receivers transact information. In the narrow context of this paper, this information relates to the beliefs of various agents (say, the general public, sophisticated investors, or policymakers) about the state of the domestic and global economies and their actions. In a system, signals can take several forms, say, price, communications, policy rates, etc. It does not have any intrinsic value of its own. Indeed, the information embedded in those signals is valuable (Skyrms, 2010).

In Figure 1, the solid arrows represent signals, where the pointed side indicates the receiver and the base shows the sender. In this diagram, there is also an information intermediary stratum. This contains two fundamental components: financial markets and media. This stratum mediates the transmission of information; however, in the act, it processes the available

[3] The flowchart depicted here excludes some other aspects like government, real activity markets, etc. to keep the focus aligned with that of the study.

information and manifests it accordingly[4]. The dotted line depicts the manifestation of information through intermediaries.

In an economic system, data on economic activities and signals emitted by various agents become part of the information set of the other agents and guide their actions. The CB of a country takes input about the state of the economy by observing present and forward-looking data on macroeconomic indicators like business cycle features, inflation, etc. In addition, CB monitors the financial market to gauge the aggregate expectations of market makers. It also tracks the cycle of pessimism and optimism amongst market participants by tracking, deducing, and influencing their sentiment through various aggregate platforms like Twitter (Angelico et al., 2022; Masciandaro et al., 2023). All these observations are collected in the information set of the CB and dictate their actions. The information set of the CB is reflected in the policy signals sent out by them. In particular, among others, CBs use four primary channels for policy signaling: policy rate setting, policy announcements and statements, reports, and speeches[5]. All these signals contain information about the CB's assessment of the state of the economy and its own policy action path in the present and near future.

These public signals are received by market participants. Additionally, market participants also draw inferences about the state of the economy and policymakers' actions from the data available in the public domain on macroeconomic indicators. They also assimilate information from the media. The heterogeneous agents interact in the market based on their information set and exhibit their aggregate beliefs in the form of prices in the financial markets. Additionally, they also reveal their views and course of action through social media. The aggregate signals of the heterogenous agents manifested in the financial market and media are captured by the

[4] A detailed discussion on signals and information processing can be found in Skyrms (2010).
[5] Minutes of the monetary policy committee meetings are also published in some countries. Apart from this, there are some occasional press releases and circulations available as well.

CB. Besides the domestic signals, the CB and heterogeneous agents' information sets also include knowledge embedded in the signals from agents in other countries. Furthermore, external signals directly manifest in the financial market and media due to globalisation.

In our design, we pick three aspects of the flow of information: the stock market, the forex market, and CB's communication (speeches) sentiment, for each country, and represent them as a multilayer network. A two-country example of such a multilayer network is displayed in Figure 2. In this setup, suppose information about a country, say $C_1$, is signalled through a subsystem, say, movement in its stock market. This signal is received by the other two subsystems (forex market and CB) of the country $C_1$ and by the subsystems (stock market, forex market, and CB) of another country $C_2$. In this paper, the subsystems are identified as layers, and countries are identified as nodes, as depicted in Figure 2. In each layer, both countries interact. The links within the layer represent spillover between countries through the same subsystem (say spillover from the stock market of $C_1$ to the stock market of $C_2$), and links across the layers depict spillover between or within countries from one subsystem to another (say spillover from the stock market of $C_1$ to the forex market and CB of $C_1$ and $C_2$). The former is known as intra-layer links, and the latter is called inter-layer links, displayed as solid arrows and dashed arrows, respectively, in Figure 2. Thus, this multilayer network represents the information flow described in Figure 1.

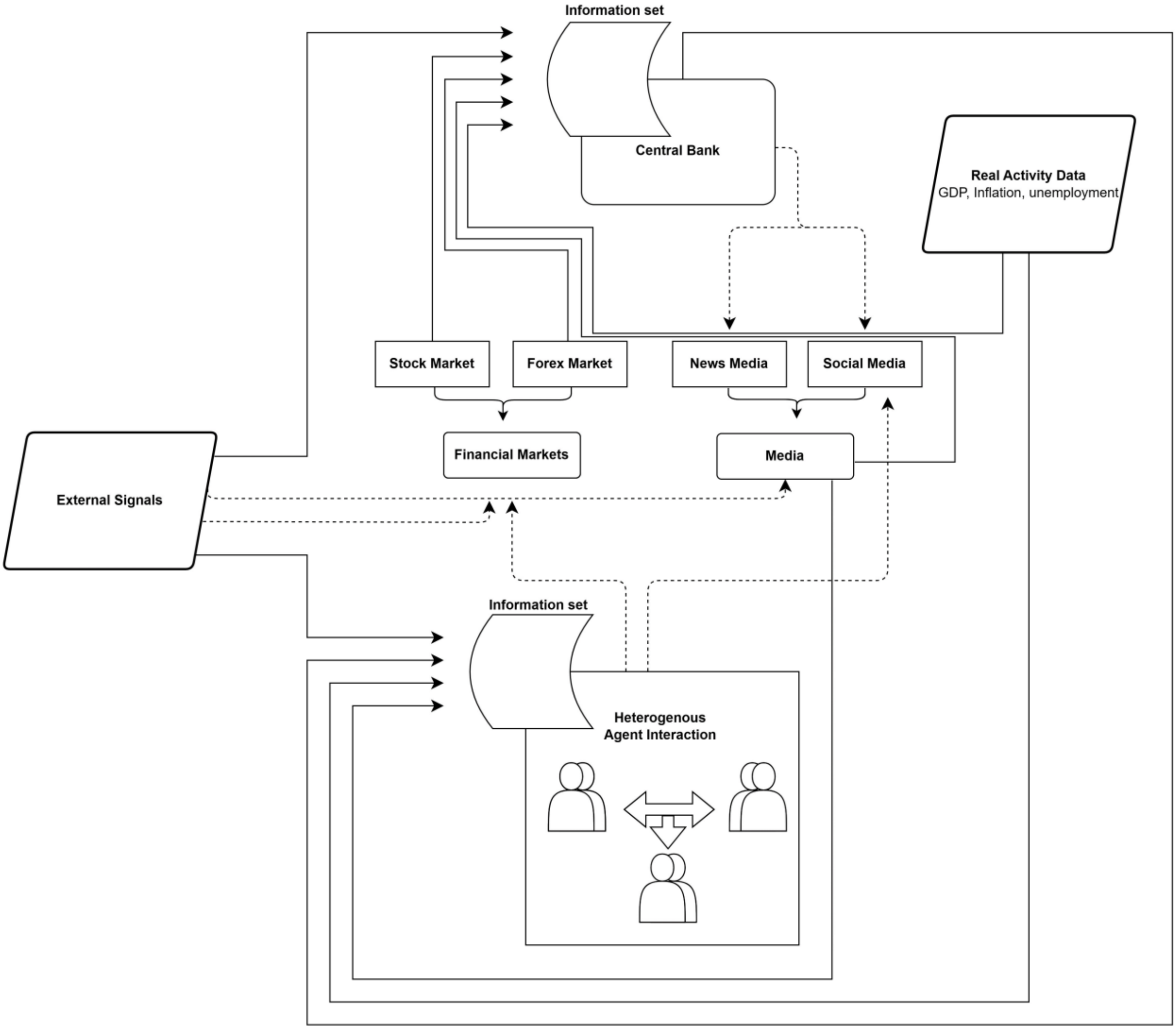



**Figure 1: Flow of signals and information between the stakeholders in an economy.**
This figure outlines the structure of the flow of signals between agents. There are two broad types of signals: domestic and external, and there are two types of decisionmakers: policymakers and heterogeneous agents.

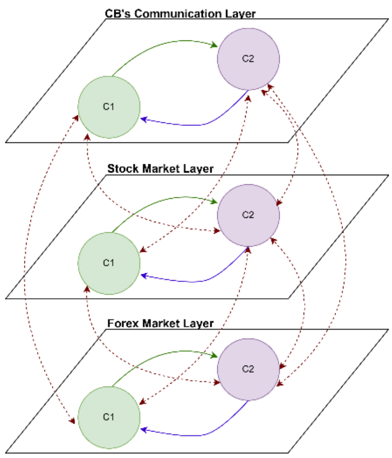



**Figure 2. Multilayer Network Structure Example**
The figure shows a multilayer network with two countries: $C_1$and $C_2$, and three layers: CB's communication layer, stock market layer, and forex market layer. There are two types of links: inert-layer (solid lines) and intra-layer (dotted lines).

## 3. Data and Methodology

This section contains details on the data and methods used in this paper. The underlying data, sample, and models used in this paper are described in sub-section 3.1. The estimation of CB's communication sentiment signal is outlined in sub-section 3.2. The information spillover indices computation for the system comprising the stock market, forex market, and CB's communication of each country is detailed in sub-section 3.3. The multilayer network structure and network descriptors are formally defined in sub-section 3.4.

### *3.1 Data, Selection of Sample, and Models*

The paper revolves around the interaction of the stock market, the forex market, and the CB's communication. We use CB's speeches to measure CB's communication as they are a comparatively more stable mode of communication (Armelius et al., 2020). Moreover, they are also available in large numbers across many countries, rendering them useful for this paper's research design. We scrapped the speeches for 118 CBs from the Bank of International Settlement (BIS) archive database from January 1997 to January 2023. Among 118 countries, only those countries were selected that had at least 200 speeches during the sample period, giving a sample of 15 countries[6]. Since the European Central Bank (ECB) was established in June 1998, the sample spans from July 1998 to January 2023. Thus, we received a total of 10,006 speeches for all the sample countries over the sample period. We further sourced data for each country's leading stock market index and real effective exchange rate (REER) from CEIC. The details of the data are given in Table 1.

This paper constructs three models: the mean model, the volatility model, and the mean-volatility model. The paper uses the average sentiment of CB's speeches and the log returns of

[6] If a country is a member of the Eurosystem, it is dropped even if it has at least 200 speeches. The ECB's speeches are taken as representative of them.

the stock and forex markets as mean measures. On the other hand, the paper uses the standard deviation of sentiment in CB's speeches and the GARCH (1,1) volatility of the stock and forex markets for volatility measures.

**Table 1. Details on sample countries and variable codes**

This table provides details on sample countries and the various codes used to represent their stock market, forex market, and CB variables. Here, countries are divided into three types: major advanced economies (MAE), advanced economies (AE), and emerging market economies (EME). The category is indicated in the Country Type column.

| Country | Country Code | Stock Market | Stock market Code | Central Bank | Central Bank Code | Currency | Currency Code | Country Type |
|---|---|---|---|---|---|---|---|---|
| Australia | AUS | S&P/ ASX | AU | Reserve Bank of Australia | RBA | Australian Dollar | AUD | AE |
| Canada | CAN | S&P/ TSX | CA | Bank of Canada | BoC | Canadian Dollar | CAD | MAE |
| Euro Area | EZ | Euro Stoxx | EA | European Central Bank | ECB | Euro | EUR | MAE |
| Hong Kong | HKG | HIS | HK | Hong Kong Monetary Authority | HKMA | Hong Kong Dollar | HKD | AE |
| India | IND | BSE 30 | IN | Reserve Bank of India | RBI | Indian Rupee | INR | EME |
| Japan | JPN | Nikkei | JP | Bank of Japan | BoJ | Japanese Yen | YEN | MAE |
| Malaysia | MYS | FTSE Bursa | MY | Central Bank of Malaysia | BNM | Malaysian Ringgit | MYR | EME |
| Norway | NOR | OSE | NO | Central Bank of Norway | CBN | Norwegia n Krone | NOK | AE |
| Singapore | SGP | FTSE Strait Times | SG | Monetary Authority of Singapore | MAS | Singapore Dollar | SGD | AE |
| South Africa | ZAF | JSE | ZA | South African Reserve Bank | SARB | South African Rand | ZAR | EME |
| Sweden | SWE | OMX | SE | Sveriges Riksbank | SCB | Swedish Krona | SEK | AE |
| Switzerland | CHE | SMI | CH | Swiss National Bank | SNB | Swiss Frank | CHE | AE |
| Thailand | THA | SET | TH | Bank of Thailand | BoT | Thai Bhat | THB | EME |
| United Kingdom | GBP | FTSE | GB | Bank of England | BoE | Pound Sterling | GBP | MAE |
| United States | USA | NYSE | US | Federal Reserve System | Fed | United States Dollar | USD | MAE |

### *3.2 CB's Communication Measure*

At this juncture, the first concern is to quantify the CB's communication, which has a qualitative dimension. To this end, we adopt textual analysis techniques to convert a large corpus of CB's speeches into meaningful facts, which can be further used in our connectedness model. We measure the inherent average sentiment in the speeches using a dictionary-based method. Following Tetlock (2007), Armelius et al. (2020), and Hubert and Labondance (2021), we adopt the finance field-specific dictionary proposed in Loughran and McDonald (2011) (hereafter, the LM dictionary). The LM dictionary contains lists of positive, negative, uncertain, litigious, strong modal, and weak modal words. We adopt a comprehensive approach by Rinker (2019) to locate the meaning of the words in context. In this approach, we account for valence-shifting words along with positive and negative sentiment words. Valence-shifting words can alter the weight or sign of sentiment polarity of the word.

We estimate sentiment at sentence level, $\delta_s$. The detailed process of obtaining $\delta_s$ is described in the appendix section A.1. Furthermore, we sum the sentiment value of all sentences and divide it by the number of sentences to obtain each country's monthly average sentiment value[7].

$$CBAvgSent = \left(\frac{\sum \delta_s}{N_s}\right) * 100$$

Here, $N_s$ is the number of sentences. The benefit of analysing sentiment at the sentence level is that we can easily derive the monthly standard deviation of sentiment for each country using the following formula,

$$CBStdDevSent = \left(\sqrt{\frac{\sum(\delta_s - CBAvgSent)^2}{N_s - 1}}\right)$$

[7] Here, an important point to note is that all sentences refer to sentences of all the speeches in a month.

We use $CBAvgSent$ and $CBStdDevSent$ variables as input for CB's communication in return and volatility connectedness models, respectively.

***3.3 Measuring connectedness***

### 3.3.1 Information spillover indices

Conventionally, the information spillover indices are computed via the variance decomposition matrix obtained from the vector autoregression (VAR) model (see Diebold and Yilmaz, 2012, 2014). In the present endeavour, we have 45 variables comprising the stock market, forex market, and CB of 15 countries. If these variables are taken with a minimum lag length of 1, a total of 2,026 parameters need to be estimated, which is much larger than the sample size ($2{,}026 \gg 295$). To overcome this constraint, LASSO VAR, as discussed in Dermirer et al. (2018) and Gabauer et al. (2020), is employed to compute spillover indices. The regularisation techniques in LASSO VAR aid shrinkage and the selection of parameters. The LASSO VAR with a lag-length of one[8] has been estimated using the penalized maximum likelihood approach.

The connectedness matrix, based on the normalised H-step ahead forecast error variance of the estimated LASSO VAR (details are discussed in appendix section A.2), is given as

$$C^H = \begin{bmatrix} \tilde{\tau}^g_{11} & \tilde{\tau}^g_{12} & \cdots & \tilde{\tau}^g_{1m} \\ \tilde{\tau}^g_{21} & \tilde{\tau}^g_{22} & & \tilde{\tau}^g_{2m} \\ \vdots & & \ddots & \vdots \\ \tilde{\tau}^g_{m1} & \tilde{\tau}^g_{m2} & \cdots & \tilde{\tau}^g_{mm} \end{bmatrix}$$

$\tilde{\tau}^g_{ij}(H)$ can be inferred as pairwise directional spillover from $j$ to $i$, where $j \neq i$. The total pairwise directional spillover from all other variables to $i$ is given as, $C^H_{i\leftarrow\bullet} = \sum_{j=1,j\neq i}^{m} \tilde{\tau}^g_{ij}(H)$. The total pairwise directional spillover from $i$ to all other variables is given as, $C^H_{\bullet\leftarrow i} =$

[8] Obtained by conventional lag-selection criteria

$\sum_{i=1,j\neq i}^{m} \tilde{\tau}_{ji}^{g}(H)$. In addition to these, system-wide connectedness can be measured using the Total Connectedness Index (TCI), given as,

$$TCI \ = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1,j\,\neq\,i}^{m} \tilde{\tau}_{ij}^{g}(H)$$

### 3.3.2 Block aggregation of information spillover indices

Block aggregation facilitates spillover analysis across groups of variables by expanding the connectedness measures (Greenwood-Nimmo et al., 2021). In the block aggregation scheme, the connectedness matrix ($C^H$ ) is reorganised in such a way that $N$ sub-groups containing $M$ variables each are formed. The $C^H$ matrix can be represented in the form of a matrix of sub-groups or blocks ($\mathcal{B}_{ij}$),

$$C^H = \begin{bmatrix} \mathcal{B}_{1\leftarrow 1} & \mathcal{B}_{1\leftarrow 2} & \cdots & \mathcal{B}_{1\leftarrow N} \\ \mathcal{B}_{2\leftarrow 1} & \mathcal{B}_{2\leftarrow 2} & & \mathcal{B}_{2\leftarrow N} \\ \vdots & & \ddots & \vdots \\ \mathcal{B}_{N\leftarrow 1} & \mathcal{B}_{N\leftarrow 2} & \cdots & \mathcal{B}_{N\leftarrow N} \end{bmatrix}$$

The within-group (in our case, within-layer when we define the category of institution as a layer in sections 3.4.1 and 4.2.2) spillover of $i$ is given as,

$$W_{i\leftarrow i}^{H} = \frac{1}{M} e_M' \mathcal{B}_{i\leftarrow i} e_M$$

Where, $e_M$ is a vector containing values 1. $W_{i\leftarrow i}^{H}$ shows the proportion of the H-step-ahead forecast error variance of variables of group $i$ explained by the variables of group $i$ itself. This can be further disintegrated into $O_{i\leftarrow i}^{H}$, aggregating the own-variable information spillover within the group, and, $C_{i\leftarrow i}^{H}$, aggregating the cross-variable information spillover between the variables belonging to the same group. They are given as,

$$O_{i\leftarrow i}^{H} = \frac{1}{m} trace(\mathcal{B}_{i\leftarrow i}) \text{ and } C_{i\leftarrow i}^{H} = W_{i\leftarrow i}^{H} - O_{i\leftarrow i}^{H}$$

The across-group (in our case, inter-layer) spillover of $j$ to $i$ group is given as,

$$\mathcal{F}_{i\leftarrow j}^{H} = \frac{1}{M} e_M' \mathcal{B}_{i\leftarrow j} e_M$$

### *3.4 Multilayer Network Analysis*

### 3.4.1 Definition and Structure

The spillover indices obtained in section 3.3.1 are used to define a multilayer network. This network describes systems in which nodes are connected through multiple subsystems (relationships), defined as layers (in the present case, the stock market, the forex market, and CB's communication). Recently, there has been a huge amount of literature focused on defining the concepts of multilayer networks (refer to Kivelä et al. (2014) and Boccaletti et al. (2014) for a formal review). We adopt the definition of multilayer network from Boccaletti et al. (2014), which defines multilayer network as $\mathrm{M} = (\boldsymbol{G},\ \boldsymbol{C})$. Here, $\boldsymbol{G} = \{\boldsymbol{\mathcal{G}_1}, \boldsymbol{\mathcal{G}_2}, \dots, \boldsymbol{\mathcal{G}_\alpha};\ \alpha \in \{1, 2, \dots, P\}\}$ is a set of graphs which is defined as, $\boldsymbol{\mathcal{G}_\alpha} = (\mathcal{V}_\alpha, \mathcal{E}_\alpha)$. $\boldsymbol{\mathcal{G}_\alpha}$ represents layer of $M$, which consists of a set of nodes, $\mathcal{V}_\alpha = \{v_1^\alpha, v_2^\alpha, \dots, v_q^\alpha\}$; and set of within-layer connections $\mathcal{E}_\alpha \subseteq \mathcal{V}_\alpha \times \mathcal{V}_\alpha$. These edges are called *intralayer linkages*. In contrast, $\boldsymbol{C} = \{\mathcal{E}_{\alpha,\beta} \subseteq \mathcal{V}_\alpha \times \mathcal{V}_\beta;\ \alpha, \beta \in \{1, 2, \dots, P\}, \alpha \neq \beta\ \}$. Thus, $C$ contains linkages between nodes of distinct layers, say $\mathcal{V}_\alpha$ and $\mathcal{V}_\beta$, called *interlayer linkages*. Furthermore, the graph $proj(M) = (\mathcal{V}_M, \mathcal{E}_M)$ is the projection network of $M$, where $\mathcal{V}_M = \ \bigcup_{\alpha=1}^{P} \mathcal{V}_\alpha$ and $\mathcal{E}_M = (\bigcup_{\alpha=1}^{P} \mathcal{E}_\alpha) \cup \left(\bigcup_{\alpha,\beta=1;\alpha\neq\beta}^{P} \mathcal{E}_{\alpha,\beta}\right)$.

An example multilayer network is shown in Figure 2 with three layers: CB's sentiment (CB), the stock market (SK), and the forex market (FX). The structure of Figure 2 can be formally defined as follows: set of graph is $\boldsymbol{G} = \{\boldsymbol{\mathcal{G}_{CB}}, \boldsymbol{\mathcal{G}_{SK}}, \boldsymbol{\mathcal{G}_{FX}}\}$. The sets of nodes are defined as $\mathcal{V}_{CB} = \{C_1^{CB}, C_2^{CB}\}$; $\mathcal{V}_{SK} = \{C_1^{SK}, C_2^{SK}\}$; and $\mathcal{V}_{FX} = \{C_1^{FX}, C_2^{FX}\}$, where $C_1^\alpha$ and $C_2^\alpha$ are countries, where $\alpha$ is the dimension or subsystem in which countries interact. The sets of intralayer edges are defined as $\mathcal{E}_{CB} = \{(C_1^{CB}, C_2^{CB}), (C_2^{CB}, C_1^{CB})\}$; $\mathcal{E}_{SK} = \{(C_1^{SK}, C_2^{SK}), (C_2^{SK}, C_1^{SK})\}$; and $\mathcal{E}_{FX} =$

$\{(C_1^{FX}, C_2^{FX}), (C_2^{FX}, C_1^{FX})\}$. The sets of interlayer edges (dashed line in figure 2) are defined as $\boldsymbol{C} = \{\mathcal{E}_{CB,SX}, \mathcal{E}_{CB,FX}, \mathcal{E}_{SX,FX}, \mathcal{E}_{SX,CB}\ \mathcal{E}_{FX,CB}, \mathcal{E}_{FX,SX}\}$. The intralayer edges show information spillover with entities of the same type, and the interlayer edges show information from one type of institution to another.

### 3.4.2 PageRank centrality and versatility

The greatest advantage of representing a complex system in a network structure is that it enables the identification of prominent nodes and their role in facilitating information transmission in the system. The PageRank centrality measure has received extensive application to identify such nodes. This measure accounts for both the direction and weight of the edges. A simplified version of ranking, $\mathcal{R}_j^i$, for monoplex structure as given in Page et al. (1999) is,

$$\mathcal{R}_j^i = \zeta \sum_{j \in \mathcal{B}_i} \frac{\mathcal{R}^j}{N_j}$$

Here, $\mathcal{B}_i$ is the set of all nodes pointing towards $i$, $N_j$ is the total edges from $j$, and $\mathcal{R}_j^i$ is the PageRank centrality measure for node $i$. This centrality method has been extended to examine nodes in multilayer structures. De Domenico (2015) incorporates layer information while measuring PageRank centrality with the ease of a tensorial representation of a multilayer network. Intuitively, it can be understood using the concept of random walks on graphs. In a monoplex, a random walker starts traversing the nodes one by one, jumping to neighbouring nodes at a rate of $\zeta$ and teleporting to another node in the complete network structure at a rate $\zeta'$. This is represented by a transition tensor (rank-2), $\mathcal{R}_j^i$. For multilayer networks, the walker can teleport to a node in the same or any other layer. Thus, the $\mathcal{R}_{j\beta}^{i\alpha}$ becomes a rank-4 transition tensor containing details on the node and layer traversing from and node and layer traversing to. It is defined as follows,

$$\mathcal{R}^{i\alpha}_{j\beta} = \zeta \mathcal{T}^{i\alpha}_{j\beta} + \frac{\zeta'}{NL} \mu^{\ i\alpha}_{\ j\beta}$$

Here, the adjacency tensor of a multilayer network is embodied in $\mathcal{T}^{i\alpha}_{j\beta}$ and $\mu^{\ i\alpha}_{\ j\beta}$ is a 4-dimensional tensor with elements equal to 1. Additionally, $\zeta' = 1 - \zeta$ and the value of $\zeta$ is set to the convention of 0.85. This PageRank centrality exploration in multilayer structure reveals versatile nodes (De Domenico, 2015; Wang et al., 2023), which puts weight on inter-layer spillovers. Thus, in this paper, we measure two levels of PageRank centrality or versatility: first, at the aggregate network (neglecting the layer information), and second, at the multilayer network.

## 4. Results and Discussion

This section compiles the results obtained on the information spillover between a set of 15 countries via distinct subsystems of information flow, primarily CB's communication sentiment, the stock market, and the forex market. Additionally, it also focuses on the type of information spillover: mean (return) spillover, volatility (risk or uncertainty) spillover, and mean-volatility spillover. The obtained spillover indices also become the basis for network analysis through single-layer and multilayer structures.

### *4.1 Connectedness Analysis*

The focus of this section is on the connectedness of three models: the mean model, the volatility model, and the mean-volatility model. In the mean model, the monthly log returns of the stock market and forex markets and the monthly average sentiment of speeches delivered by a CB are considered. In the volatility model, the GARCH (1,1) volatility estimate of the stock market and forex market is studied along with the dispersion of sentiment. The mean-volatility model combines variables from the above two models into a single model. The model estimating strategy behind the mean connectedness, volatility connectedness, and mean-volatility connectedness is the same; only the input variables change. First, we estimate a time-varying LASSO-VAR model at the first lag order (i.e., $p$ = 1)[9] with a rolling window of 72 months (6 years). Subsequently, we obtain a connectedness table for each time period from the forecast error variance decomposition of this model at the horizon of 12 months (i.e., $H$ = 12). Furthermore, we obtain an aggregate connectedness table by aggregating the connectedness table across time.

#### 4.1.1 Pairwise Connectedness

Connectedness at the individual variable level is measured via pairwise TO and FROM measures. The top 10 pairwise spillovers in all three specifications are presented in Table 2. In the mean information spillover model, the highest transmission is observed between USD and HKD, both TO and FROM, as reported in Table 2, Panel (a). This spillover in exchange rate can be attributed to the fact that the Hong Kong currency is linked to the currency of the US and thus follows its trail (Wang et al., 2023). Additionally, EA is highly informative for SE, CH, and GB. Sweden, Switzerland, and the United Kingdom have long economic and diplomatic associations with the Euro Area and, thus, their stock markets are interconnected (Feng et al., 2015). Overall, from mean spillover, it can be observed that the forex market and stock market of the US and Euro Area are general information emitters, and other advanced economies are receivers.

A similar pattern is observed for the volatility model except for the fact that all the top 10 information transmission positions are carried between stock markets, as depicted in Table 2,

[9] Obtained p = 1 after performing the conventional lag-selection criteria.

Panel (b). Thus, preliminary, it can be inferred that the stock markets substantially channel second-moment information conveying risk and uncertainty between countries. Volatility information spillover is more common in regional clusters like the Euro Area, Sweden, the United Kingdom, Switzerland, and the core economy of the US.

Moreover, in the mean-volatility model, except for spillover between HKD and USD, feedback is observed between the average sentiment of varied CBs and its dispersion of sentiment reflecting uncertainty. Such spillover is observed in BNM, CBM, SCB, and BOE, as shown in Table 2, panel (c). This result aligns with Hubert and Labondance's (2021) argument that the views of policymakers follow distributions for which mean and variance are related, i.e., they are reflected in each other. This study confirms this argument by observing a large spillover between the first- and second-moment information from CBs' communication.

**Table 2. Top 10 pairwise spillover**

This table contains the top 10 pairwise directional spillovers for the mean model, volatility model, and mean-volatility model. The "Mean" and "Vol" suffixes represent the mean and volatility estimates of the base variable in the mean-volatility model results.

| **(a) Mean Model** | | | **(b) Volatility Model** | | | **(c) Mean-Volatility Model** | | |
|---|---|---|---|---|---|---|---|---|
| From node $i$ | To node $j$ | weight | From node $i$ | To node $j$ | weight | From node $i$ | To node $j$ | weight |
| USD | HKD | 15.28 | EA | SE | 10.32 | Mean_USD | Mean_HKD | 12.5 |
| HKD | USD | 11.2 | SE | EA | 9.64 | Mean_BNM | Vol_BNM | 11.8 |
| EA | SE | 9.23 | EA | GB | 9.24 | Mean_CBN | Vol_CBN | 11.54 |
| EA | CH | 9.12 | EA | US | 8.76 | Mean_SCB | Vol_SCB | 11.53 |
| USD | EUR | 8.78 | EA | CH | 8.42 | Vol_SCB | Mean_SCB | 11.38 |
| HKD | EUR | 8.7 | GB | EA | 8.37 | Vol_BNM | Mean_BNM | 10.7 |
| SE | EA | 8.41 | US | GB | 8.14 | Vol_CBN | Mean_CBN | 10.22 |
| EA | GB | 8.37 | US | EA | 7.92 | Mean_HKD | Mean_USD | 9.76 |
| US | CA | 8.08 | GB | US | 7.89 | Mean_BoE | Vol_BoE | 9.07 |
| US | CH | 7.87 | SE | GB | 7.7 | Mean_EA | Mean_SE | 8.51 |

### 4.1.2 Dynamic Total Connectedness

Another measure of connectedness is system-wide spillover, which is embodied in the total connectedness index (TCI). The time-varying TCI ranges from 59.81 to 73.53, 55.37 to 72.40, and 69.10 to 81.13 for the mean model, volatility model, and mean-volatility model, respectively. Figure 3 plots the time-varying TCI for all three models. We notice that information spillover between entities is increasing sharply during the crisis period, regardless of the type of information shared (first- or second-moment). Evident high peaks are marked at the Global Financial Crisis (GFC) and COVID-19. However, we notice that volatility connectedness is decreasing less steadily than mean connectedness after the GFC. This can be associated with the Eurozone debt crisis, which began during the GFC and peaked in 2010 and 2012.

Another upsurge was found during the 2014 oil price crash due to increased supply and decreased demand pertaining to the economic slowdown. The peak is higher in the volatility model as it induces uncertainty and financial risk as many financial investors use crude oil as a hedge against inflation. In the timeline, one more event is registered as Brexit. On July 23, 2016, the Brexit referendum was held, and the outcome was in favour of Britain exiting the European Union. In March 2017, a request to exist was submitted. The Brexit conversation created uncertainty in the financial markets across the world, especially in the forex market. Additionally, the spike in volatility information spillover after COVID-19 episodes is much higher than return information spillover. The TCI in the mean-volatility model is similar to the TCI of the volatility model. First- and second-moment information is more connected during uncertain times.


Panel (a): TCI for Mean Model


Panel (b): TCI for Volatility Model


Panel (c): TCI for Mean-Volatility Model

**Figure 3: Total Connectedness Index**
The figure depicts the total connectedness index for the mean model, the volatility model, and the mean-volatility model. The dotted line marks global systemic and unprecedented events.

### 4.1.3 Block Aggregation - Intermediate Information Spillover

In order to understand the information spillover between groups of variables, we use the block aggregation technique (see Greenwood-Nimmo et al., 2016; Greenwood-Nimmo et al., 2021). We compute static (using the aggregate connectedness table) and time-varying information spillover between groups of variables. In this study, three distinct types of grouping are done.

First, we have grouped on the basis of institution type: CB group, stock market (SX) group, and forex market (FX) group. In this clubbing scheme, groups are created by aggregating 15 countries' similar-type entities for each group. This provides insight on how much total information spillover occurs within similar-type entities and between distinct types of entities, say within SX and between SX and FX or between SX and CB. Second, we have grouped on the basis of the moment of information: mean information and volatility information. This facilitates the characterization of the total spillover between mean and volatility information. In this scheme, aggregation is done over 45 (45 = 15×3, 15 for different countries, and 3 for types of institutions) variables in each group. Third, we group variables based on the country type: major advanced economy (MAE), advanced economy (AE), and emerging market economy (EME). The results for this grouping are reported in appendix A3.

The results for block aggregation of aggregate connectedness over time are reported in Table 3. Section A of the table reports spillover within and across groups. The diagonal elements of the block representation of the connectedness matrix show within-group spillover, and the off-diagonal elements show across-group spillover. While interpreting the results, it should be noted that the sum of information spillover from other groups and within groups is 100, i.e., the row sum is 100. The majority of spillover is within similar types of institutes (say, within stock markets, within forex markets, and within CBs' communication), ranging between 65 and 83 percent as observed from diagonal elements of section A of panels (a) and (b). Thus, results highlight that entities receive major information from similar entities in other countries. Nonetheless, cross-institution spillover is also substantial, ranging between 3 and 30 percent, as deduced from off-diagonal elements of the block representation of the connectedness matrix. The spillover from mean information to volatility information and vice versa is around 24 to 25 percent. Thus, no clear dominance appears.

Section B records the result of the disintegration of within-group spillover ($W^{H}_{i \leftarrow i}$) into its own-variable spillover ($O^{H}_{i \leftarrow i}$) and cross-variable spillover ($C^{H}_{i \leftarrow i}$). The own-variable effect shows the proportion of within-group spillover coming from variables themselves, and the cross-variable spillover explains the proportion of within-group spillover explained by other variables belonging to that group. It is observed that the SX group has the highest cross-variable spillover and the CB group has the lowest. This indicates that the stock markets of all the countries are highly connected.

**Table 3. Block Aggregation: Information spillover within and across varied groups**
This table contains the block aggregation results for mean, volatility, and mean-volatility models. Here, section A contains spillover between different groups, and section B presents the dissected results of within-group spillover effects into own-variable effects and cross-variable effects.

| **Panel (a): Mean Information Spillover** | | | | | | |
|---|---|---|---|---|---|---|
| **Section A** | | | | **Section B** | | |
| | CB | SX | FX | | Own | Cross |
| CB | 74.55 | 13.01 | 12.44 | CB | 56.97 | 17.58 |
| SX | 3.46 | 82.32 | 14.22 | SX | 14.21 | 68.11 |
| FX | 7.64 | 26.98 | 65.38 | FX | 33.56 | 31.83 |
| **Panel (b): Volatility Information Spillover** | | | | | | |
| **Section A** | | | | **Section B** | | |
| | CB | SX | FX | | Own | Cross |
| CB | 71.13 | 14.32 | 14.56 | CB | 55.2 | 15.93 |
| SX | 4.89 | 77.76 | 17.35 | SX | 17.67 | 60.09 |
| FX | 9.4 | 29.38 | 61.22 | FX | 35.36 | 25.86 |
| **Panel (c): Mean-Volatility Information Spillover** | | | | | | |
| **Section A** | | | | **Section B** | | |
| | Vol | Ret | | | Own | Cross |
| Vol | 75.47 | 24.53 | | Vol | 26.16 | 49.31 |
| Ret | 22.89 | 77.11 | | Ret | 24.75 | 52.36 |

The static analysis gives an overall picture. However, the time-varying block aggregation results in Figure 4 can be used to figure out how the spillover between groups changes over time. The results reveal interesting dynamics during systemic events like the GFC. It is observed that spillover increases across groups in uncertain times. The details and event mapping are reported below.

In the mean model, after the collapse of Lehman Brothers in September 2008, a sharp hike is marked in across-group spillovers (and a parallel drop is observed in within-group spillovers as the measures are in proportion), as evident from Figure 4, Panels a – c. However, in the volatility model, cross group spillover was high before the collapse of Lehman Brothers' (Figure 4, d – f). It is also observed that volatility information spillover between (to and from) CB and SX increased when the sub-prime crisis in the US became a global issue in August 2007 with BNP Paribus' announcement of no liquidity in its three major hedge funds (Figure 4, Panel e). Whereas, an increase in volatility information spillover from CB to FX was observed after the collapse of Lehman Brothers (Figure 4, Panel f).

Moreover, from Figure 4 (Panels g & h), we note an upsurge in across mean and volatility information spillover after the collapse of Lehman Brothers. Here, the spillover from volatility to mean group signals increased risk sensitivity of the market participants, and the spillover from mean to volatility signals that latent risk information is conditioned on the realised mean information (Greenwood et al., 2016). Thus, the beliefs of market participants about present conditions and risks are manifested in each other.

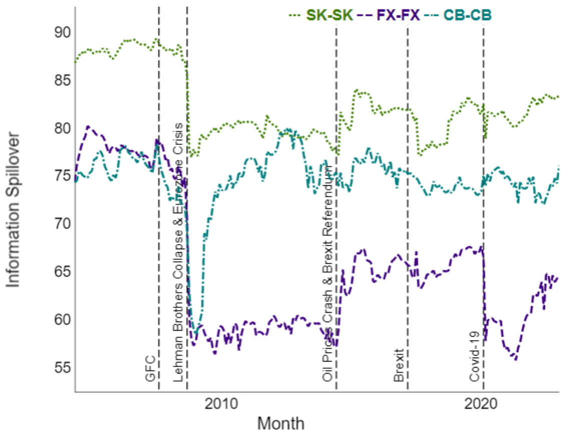
The 2014 oil price crash left forex markets in turmoil. Hence, across entity groups spillover decreased with a simultaneous increase within forex markets spillover (Figure 4, Panels a and d). We also notice that after the oil price crash of 2014, the spillover of information from FX and SX to CB in volatility model (Figure 4, Panel e) is increasing steadily. Thus, indicating that the CB is more observant of risks in these markets.

The advent of COVID-19 surged spillover across the stock and forex markets (Figure 4, Panels c and f). The volatility information spillover from CB to SX and FX groups increased (Figure 4, Panel e) during this time. The mean spillover from and to CB is maintained (Figure 4, Panel b). The spillover from volatility information to mean information also increases at the start of COVID-19 (Figure 4, Panel h).

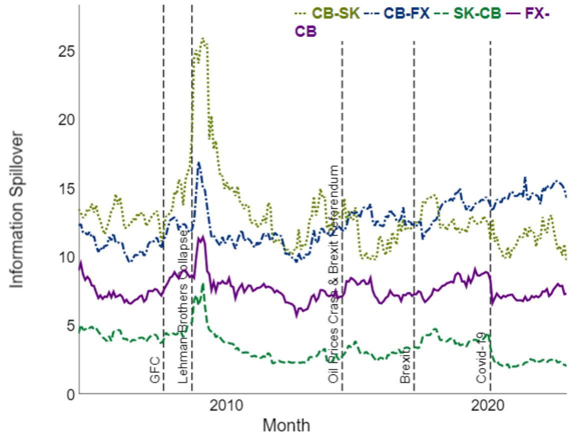
Altogether, the results indicate that the stock market has high information spillover both within- and across-groups. The results give evidence of increasing cross-institution volatility information spillover ahead of mean information spillover in systemic events like the GFC. It is observed that CBs became informative for the stock markets and vice versa during the GFC and the 2014 oil price crisis. The results also highlight the conditional relationship between mean and volatility information.

#### 4.1.4 Sensitivity Analysis

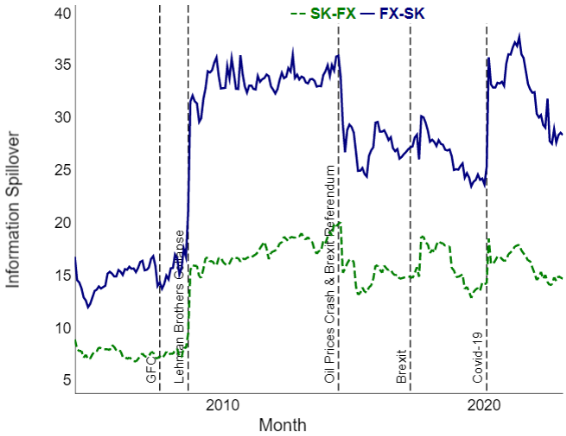
The sensitivity to the choice of parameters like rolling window and forecast horizon is also tested. We plot the TCI index for all three models with a forecast horizon of 6, 12, and 18 months and a rolling window of 60, 72, and 84 months. The results are reported in Figure A2 in the appendix. We observe similar patterns in the TCI of all three models across different parameter combinations. Thus, the results of this study are not sensitive to the choice of forecast horizon and the rolling window.



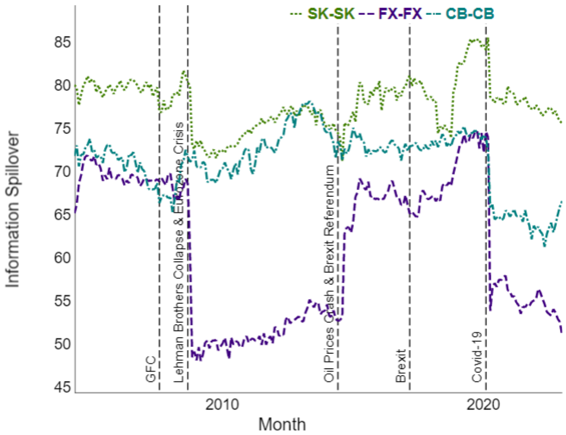

Panel a: Mean Model (within group spillover)



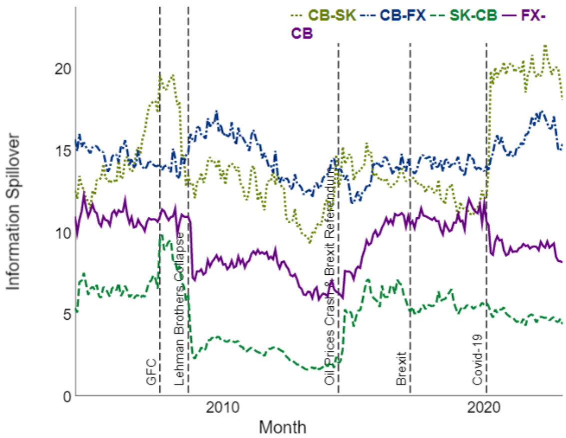

Panel b: Mean Model (across group spillover Part A)



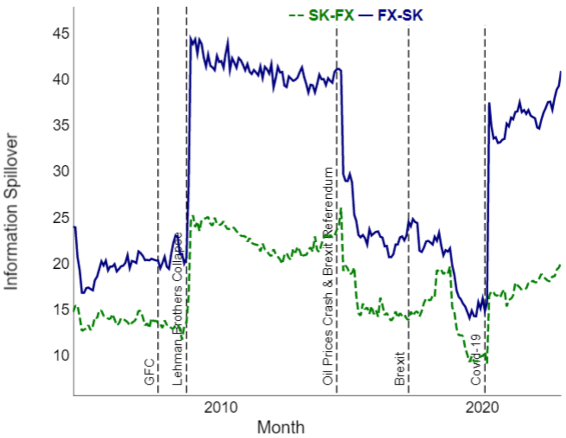

Panel c: Mean Model (across group spillover Part B)




Panel d: Volatility Model (within group spillover)



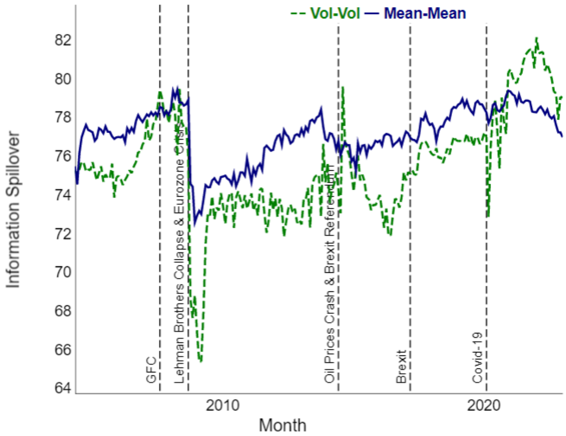

Panel e: Volatility Model (across group spillover Part A)



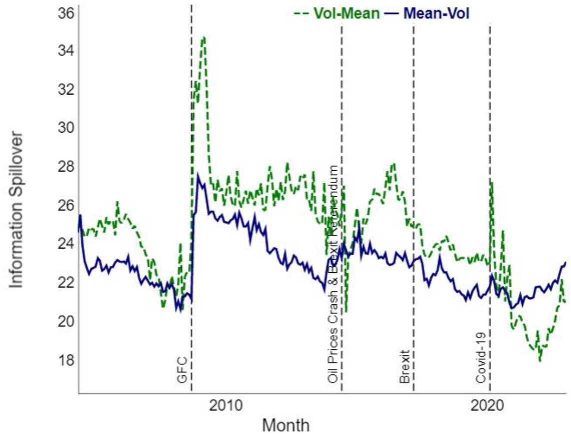

Panel f: Volatility Model (across group spillover Part B)

**Figure 4A: Block Aggregation**

The figure shows block aggregation results for the mean model and the volatility model. Here entities are grouped as stock market (SX), forex market (FX), and CB.




Panel g: Mean - Volatility Model (within group spillover)




Panel h: Mean -Volatility Model (across group spillover)

**Figure 4B: Block Aggregation**

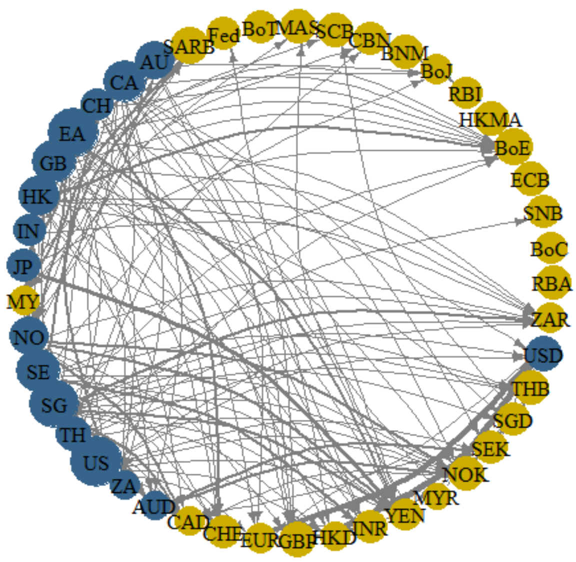
The figure shows block aggregation results for the mean-volatility model. Here entities are grouped into mean (Mean) and volatility (Vol) information groups.

### *4.2 Network Analysis*

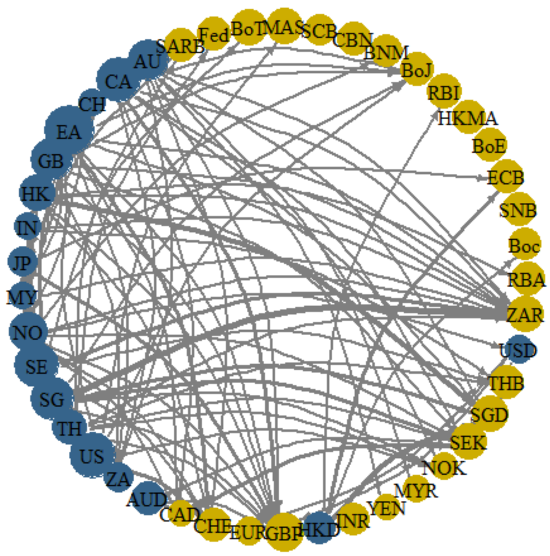
The connectedness table obtained in section 4.1 becomes the basis for network analysis as it gives weighted directional spillover between the entities, which can be defined as edges in network analysis. In this section, interactions are modelled as monoplex (single-layer) and multilayer networks. In a monoplex network, interactions are modelled at the financial markets and CB level of a country. However, as outlined in section 2, signals flow within and between countries through three types of institutions that reflect the beliefs of individuals and policymakers. Thus, in a multilayer network, we categorise the type of institution into layers and analyse spillover between countries through three subsystems. Thus, in a nutshell, this structure shows the role of a country in information transmission and not the financial market and CB themselves. In addition, the mean-volatility connectedness model also gives a basis for studying the interaction of financial markets and CB across the first and second moments of information. To accommodate this, a multilayer network is defined, where layers represent mean information and volatility information, and in each layer, all types of entities (markets and CB) interact. After delineating the structure, we study the comparative properties of nodes through strength measures, PageRank centrality measures, and PageRank versatility measures.

#### 4.2.1 Monoplex Network

Figure 5, panels a and b, depict the mean and volatility information spillover graphically using networks, respectively. The networks are trimmed for better representation. The node size is based on the out strength of the nodes. The direction of edge and weight is based on net pairwise dirctional connectedness index. It is observed that the stock and forex market are more active in influencing the overall system.




Panel (a): Mean information spillover




Panel (b): Volatility information spillover

**Figure 5: Monoplex Network Structure**

This figure is a pictorial representation of the spillover between various entities.

#### 4.2.1.1 Strength Measures

Further insights on the comparative features of nodes can be gained by analysing the in-strength and out-strength of each node. In-strength shows the sum of the weights of the incoming edges, and out-strength shows the sum of the weights of the outgoing edges. The former indicates the sensitivity of a node to other nodes, and the latter indicates the influence of a node on other nodes in a network. Following Long et al. (2021), the nodes in a network can be divided into leader, follower, communicator, and independent categories based on their in-strength and out-strength. In Figure 6, panels a and b, in-strength and out-strength are measured on the X- and Y-axes, respectively. Dashed vertical and horizontal lines indicate the mean value of the respective axes, which divide the plane into four quadrants. Nodes lying in the quadrant I have high influence over and high sensitivity to other nodes. Thus, they are communicators, the nodes spreading signals in the system. Quadrant II nodes are leaders with high influence on and low sensitivity to others, thereby becoming leading information emitters. Nodes falling in quadrant III are independent with low influence and low sensitivity. Lastly, quadrant IV nodes are portrayed as followers as they are more sensitive to other nodes with low influence in the system.

From Figure 6, no clear leader or follower is observed in the information spillover network. Interestingly, we observe that stock markets of all countries act as communicators of information, along with some forex markets like USD, AUD, CAD, and HKD. However, all the CBs have independent characteristics, along with some forex markets. Figure 7 shows the in- and out-strength of nodes over a period of time, depicting the time-varying sensitivity and influence of each node. An apparent time variation is observed in the in- and out-strengths in the figure. It is observed that stock markets have a clear influence and are sensitive to other nodes throughout time, with higher intensity during crises for both the mean and volatility models. Among the forex markets, the USD is sensitive to mean and volatility information as compared to other nodes throughout the sample period. Episodic spillover variation is also observed in other currencies. It increases during crises like the GFC and COVID-19. Alongside, as visible from Figure 7, CBs depict increased sensitivity during the GFC in the whole period, evidently more so for risk information. These results  of this subsection again accentuate the active role of the stock markets and a few forex markets in the flow of information and the passive role of the CBs.

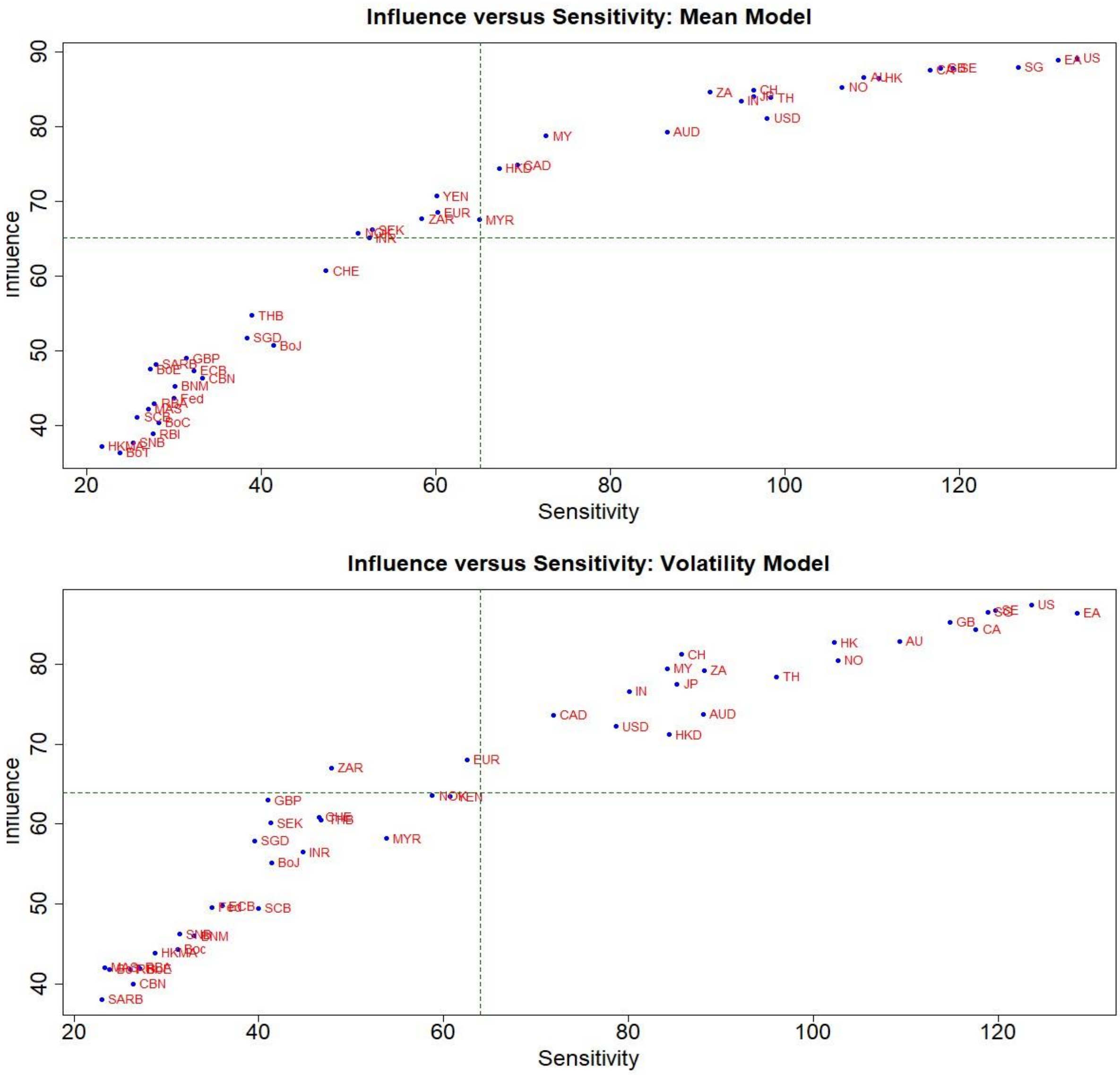



**Figure 6: Monoplex – Influence versus Sensitivity**
The figure compares the in-strength and out-strength of a node. The vertical and horizontal green dashed line represent the mean in strength and out-strength, respectively. This characterises the node into communicator, leader, follower, and independent categories.

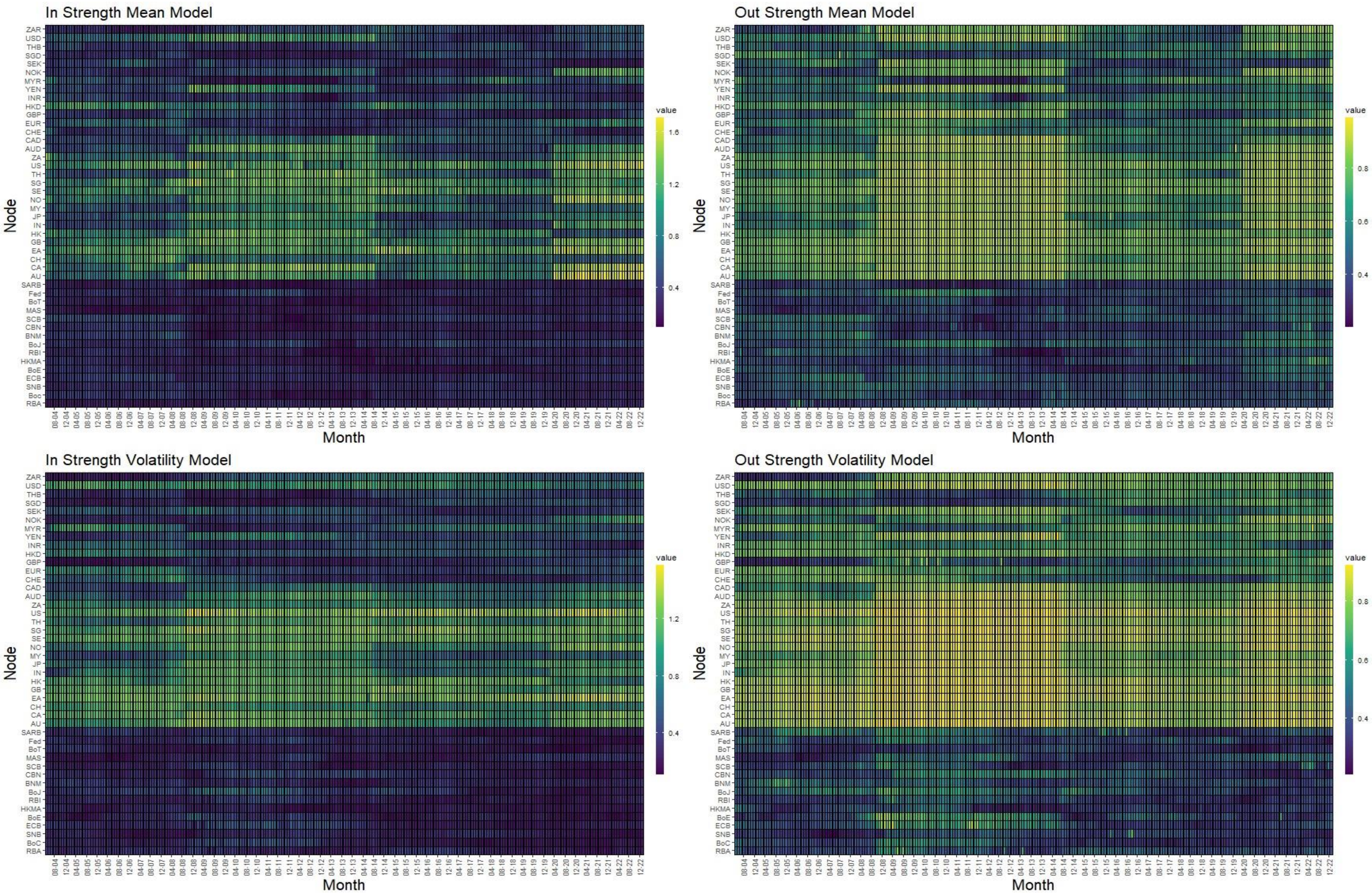



**Figure 7: Dynamic In-strength and Out-strength**

This figure plots the time-varying in-strength and out-strength measures for the mean network and the volatility network. Here, lighter shade indicates higher spillover.

#### 4.2.1.2 PageRank Centrality Measure

The paper employs PageRank centrality to rank financial markets and CBs in the information flow system. A higher rank of a node indicates higher influence in the information flow network. Table 3, panel a, lists the top 15 out of the total 45 nodes for the mean and volatility information monoplex network. It is observed that US and EA hold the top two positions in both models, coming out to be the central nodes in the system. This is in line with existing literature (see Feng et al., 2023). The US stock market has a higher influence in the mean information network, whereas the euro area stock market accumulates a higher volatility information network. The Euro area is more strongly interconnected regionally (Feng et al., 2023), thus playing a crucial role in risk information transmission, followed by the US. Singapore's stock market stands in the third and sixth positions in the mean and volatility models, respectively. Singapore has a high influence in Asian countries and is also highly connected to world markets (Vo and Tran, 2020), thus having a higher PageRank centrality. Thus, the ranking places the stock markets of MAE and AE higher than the stock markets of EMEs in the top 15. It is observed that top ranks are reserved by all the stock markets except for USD and AUD in the mean and volatility models, respectively. USD and AUD are among the most influential nodes in the forex market groups and, thus, have an effect on information networks as well.

### 4.2.2 Multilayer Network

This paper models agents' interactions consistent with section 2, whereby each country interacts with other countries to transact information through three subsystem (stock market, forex market, and CB) levels. Figures 8 and 9 show a multilayer network where each country sends and receives mean and volatility information, respectively, through CB's communication layer, stock market layer, and forex market layer. In the figures, solid lines depict intra-layer edges, whereas dashed lines depict inter-layer edges. The intra- and inter-layers are trimmed at the 80th and 95th percentiles, respectively. The top five intra- and inter-layer linkages for each layer have been reported in Table A1 of the appendix.

Further, interaction between nodes is also divided based on the type of information it is sharing, i.e., mean (return) and risk (volatility) information. Thus, we have two layers in this network: the mean interaction layer and the volatility interaction layer, which contain all the entities. Table A2 of the appendix presents the top five intra- and inter-layer linkages for each layer of this network. Figure 10 plots the multilayer interaction between entities including mean and volatility information. From the figure, we can note strong coupling edges. These are the edges that show spillover between the same nodes across different layers. Thus, depicting conditionality between first- and second-moment information.

**Table 4: Pagerank Centrality – Monoplex**

This table list down the top 15 entities in the PageRank centrality ranking for the mean network and the volatility network.

| | **Panel a:** PageRank Centrality - Monoplex | |
|---|---|---|
| Rank | Mean | Volatility |
| 1 | US | EA |
| 2 | EA | US |
| 3 | SG | SE |
| 4 | GB | GB |
| 5 | SE | CA |
| 6 | CA | SG |
| 7 | HK | AU |
| 8 | AU | NO |
| 9 | NO | HK |
| 10 | CH | TH |
| 11 | TH | ZA |
| 12 | JP | AUD |
| 13 | ZA | JP |
| 14 | IN | CH |
| 15 | USD | MY |

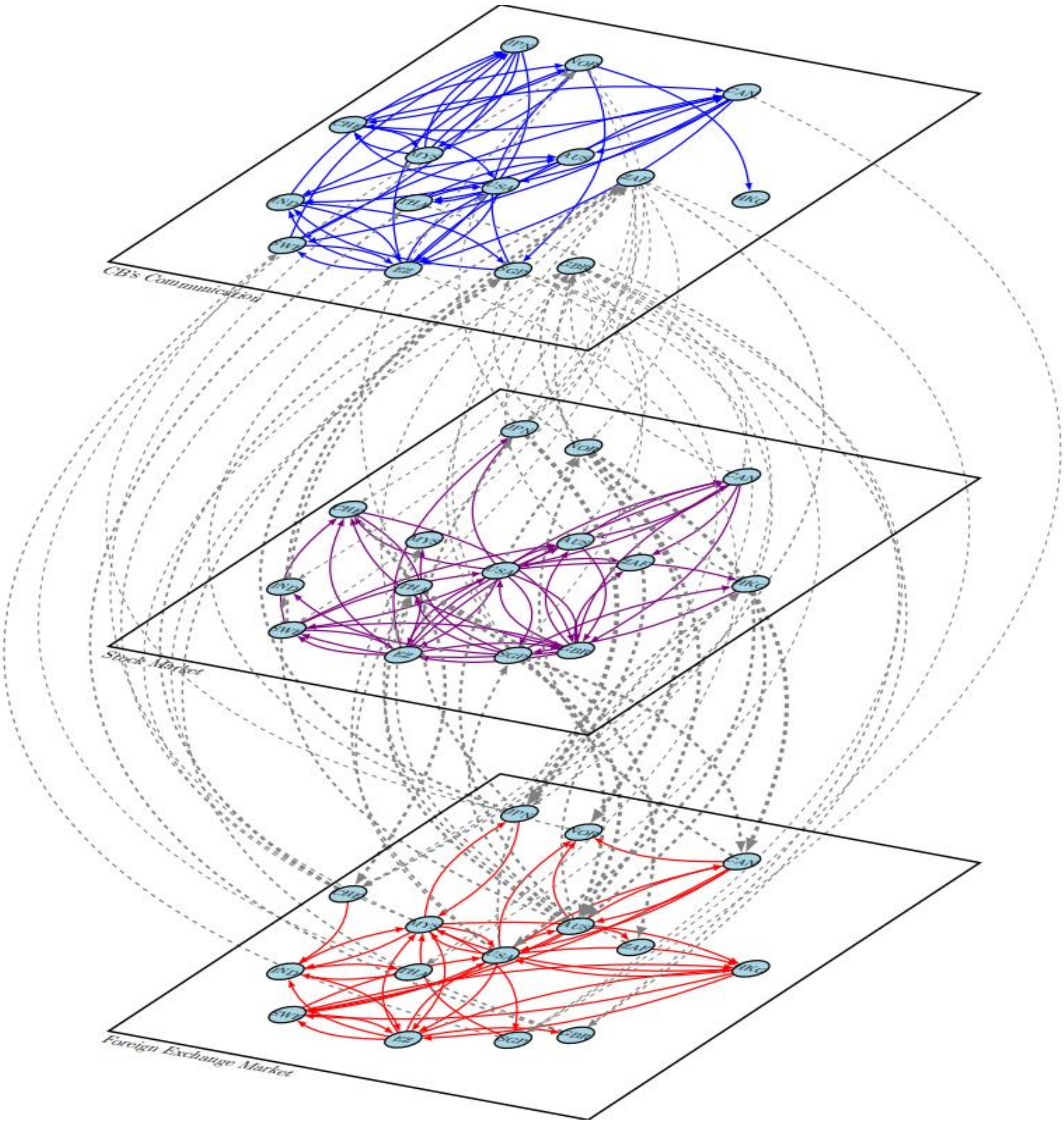



**Figure 8: Multilayer Mean Information Spillover Network**

In this figure, countries interact through three layers (subsystem): CB's communication, the stock market, and the forex market. The solid arrow shows intra-layer spillover, i.e., spillover from subsystem x of a country to subsystem x of another country. The dashed arrow shows inter-layer spillover from subsystem x of a country to subsystem y of that same country or another country.

### 4.2.2.1 Strength Measures

Moving forward, strength analysis for the multilayer structure is carried out. Based on the in-strength and out-strength, nodes of the network are again characterised into communicator, leader, follower, and independent categories, as in section 4.2.1.1. In the multilayer structure, strength analysis is based on the country level, where strength from three institutional layers (accounting both inter and intra spillovers) is accounted for and represented as the strength of a country. Figure 11 shows the distribution of countries across the stated categories. It is observed that all MAEs, except for GB and JP, plot farthest in the communicator category in both the mean and volatility multilayer networks. Other communicators include AEs like SE, AU, and HK. However, we notice that EMEs mostly fall into the independent category, with ZA located in the follower quadrant in the mean model. Thus, it can be said that information spillover between MAE and AE is higher.

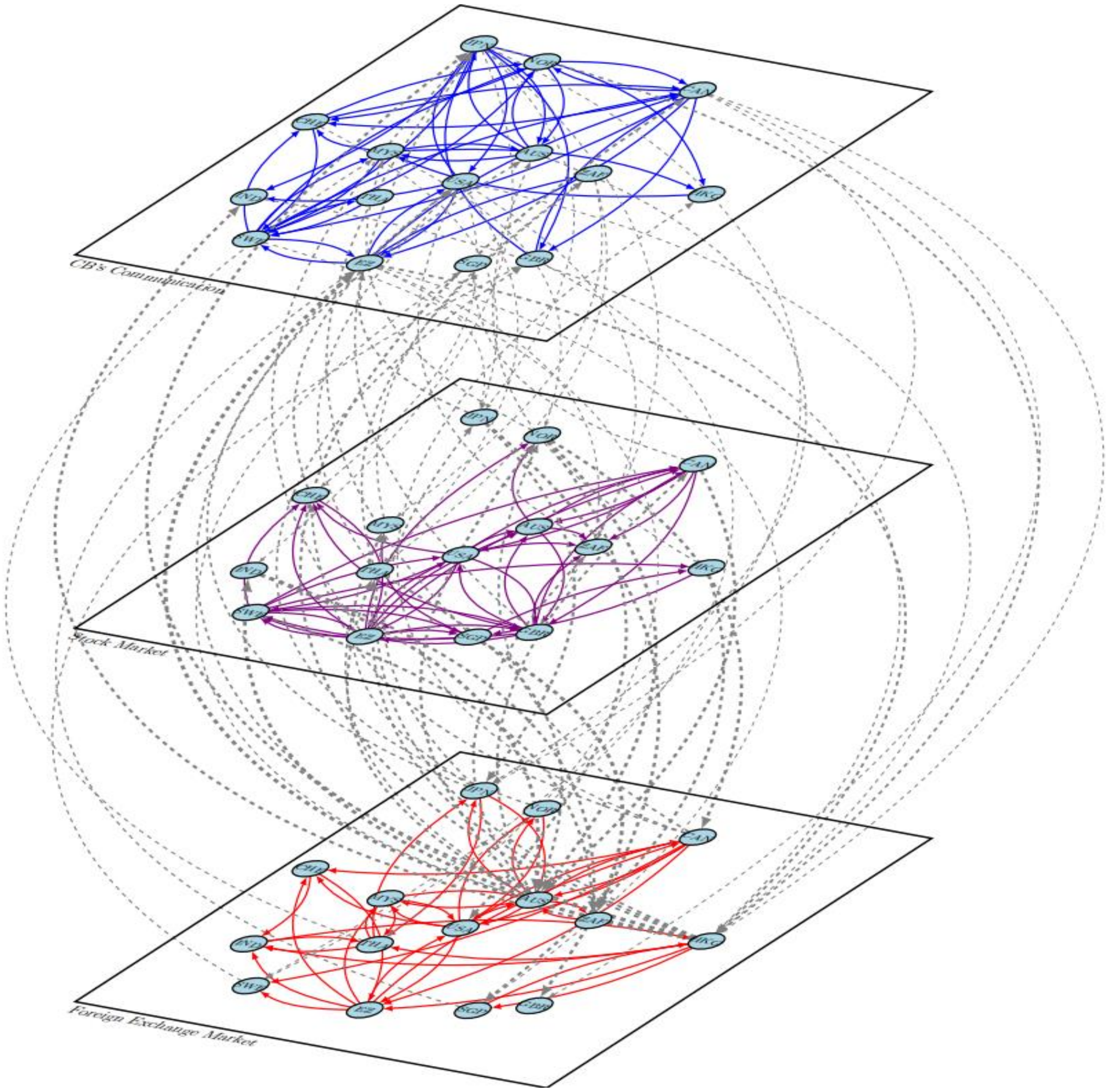



**Figure 9: Multilayer Volatility Information Spillover Network**
In this figure, countries interact through three layers (subsystem): CB's communication, the stock market, and the forex market. The solid arrow shows intra-layer spillover, i.e., spillover from subsystem x of a country to subsystem x of another country. The dashed arrow shows inter-layer spillover from subsystem x of a country to subsystem y of that same country or another country.

Figure 11, panel C shows that the distribution of entities is different in the mean-volatility multilayer network, where both first- and second-moment information are taken into account, than in Figure 6, where mean and volatility information spillovers are studied separately. CBs also appear as communicators. This is mainly due to spillover between first- and second-moment information. Combining these results with block aggregation results, our argument for the greater role of CB's communication during crises is intensified. The second-moment information aids the first-moment information and vice versa, aggravating spillover from CBs during crises.

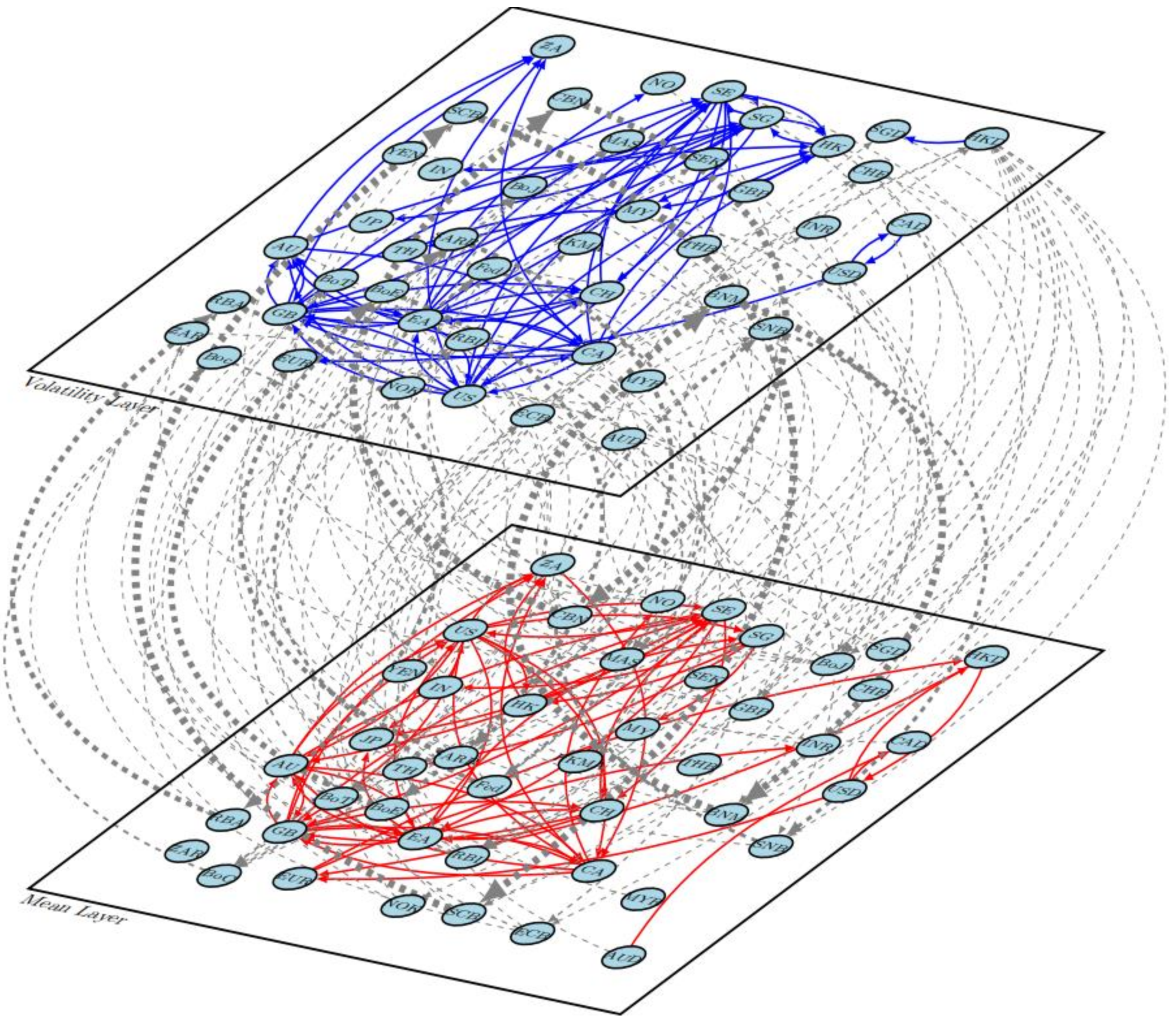



**Figure 10: Multilayer Mean-Volatility Spillover Network**

In this figure, entities interact through two layers (subsystem): mean information layer and volatility information layer. The solid arrow shows intra-layer spillover, i.e., spillover from mean (or volatility) information of an entity to mean (or volatility) information of another entity. The dashed arrow shows inter-layer spillover from mean (or volatility) information of an entity to volatility (or mean) information of the same or another entity.

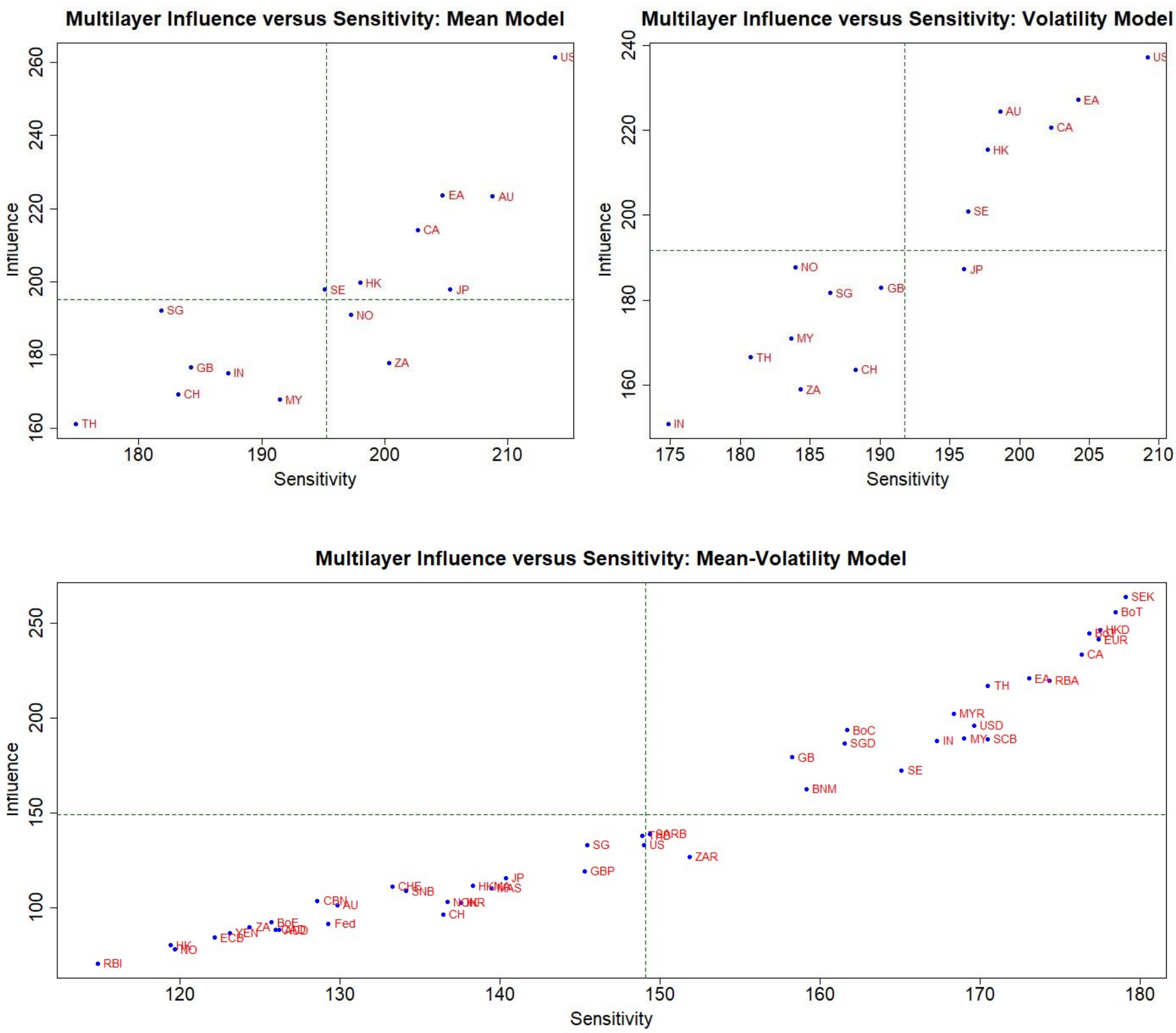



**Figure 12: Multilayer networks – Influence versus Sensitivity**
The figure compares the in-strength and out-strength of a node. The vertical and horizontal green dashed line represent the mean in strength and out-strength, respectively. This characterises the node into communicator, leader, follower, and independent categories.

### 4.2.2.2 PageRank Versatility

PageRank centrality in a multilayer structure uncovers versatile nodes. Panel a of Table 5 reveals a different story in comparison to Panel b of Table 5. In Panel b of Table 5, the PageRank centrality is calculated by projecting the multilayer network as a monoplex[12]. It ranks the USA and the EZ as dominant nodes. However, mean and volatility multilayer networks reveal JPN, EZ, and USA, and HKG, EZ, and CAN, as leading nodes, respectively. These nodes are ranked

[12] This is different from the results reported in section 4.2.1.2 for monoplex networks. Here, the nodes are countries and not entities themselves.

higher despite the fact that the United States and Euro Area have stronger connections because, in a multilayer network, special attention is paid to inter-layer spillover. These nodes bridge information transmission across layers and are well connected to hubs, thus being versatile. Table 5, panel a, also presents PageRank versatile nodes for the mean-volatility model. The three leading positions are taken by HKD, SCB, and CBN, which suggests that spillover between risk and mean information is highly mediated by these nodes. Hong Kong's forex market mediates mean and volatility information spillover. It is also noticed that CBs rank higher in this network structure as compared to any other. As evident from Figure 10 as well, the spillover between mean and volatility information is primarily mediated by CBs; thus, they rank higher in the mean-volatility multilayer network structure.

**Table 5. Multilayer PageRank Centrality and Versatility**

The table reports the top 15 nodes in the PageRank versatility ranking for multilayer networks. It also reports the top 15 nodes in the PageRank centrality ranking for aggregate networks (a multilayer network projected as a monoplex in which layer information is not accounted for).

| **Rank** | **Panel a:** PageRank Versatility - Multilayer Network | | | **Panel b:** PageRank Centrality – Aggregate Network | | |
|---|---|---|---|---|---|---|
| | Mean | Volatility | Mean-Volatility | Mean | Volatility | Mean-Volatility |
| 1 | JPN | HKG | HKD | USA | EZ | US |
| 2 | EZ | EZ | SCB | EZ | USA | EA |
| 3 | USA | CAN | CBN | CAN | AUS | SG |
| 4 | MYS | SWE | BNM | HKG | SWE | SE |
| 5 | NOR | USA | EUR | AUS | CAN | CA |
| 6 | IND | JPN | USD | SWE | GBP | GB |
| 7 | CAN | MYS | BoJ | JPN | HKG | HK |
| 8 | AUS | AUS | SNB | IND | SGP | AU |
| 9 | HKG | CHE | Fed | MYS | NOR | NO |
| 10 | SWE | NOR | RBA | CHE | MYS | TH |
| 11 | CHE | THA | ECB | SGP | CHE | CH |
| 12 | SGP | IND | CAD | NOR | JPN | ZA |
| 13 | THA | SGP | AUD | ZAF | ZAF | IN |
| 14 | ZAF | GBP | MYR | GBP | THA | JP |
| 15 | GBP | ZAF | NOK | THA | IND | USD |

## 5. Conclusion

The heterogeneous agents and policymakers receive and send signals about their perception of the economy and their actions. The paper attempts to delineate the structure of the flow of these signals and information between various agents both within and across 15 countries. The study recognises three subsystems: stock markets, forex markets, and CBs' communication, through which information flows between agents globally. Information transmission is studied at two levels: the mean (return or first moment) and the volatility (risk or second moment) levels. The analysis undertaken in this paper can be understood in three broad categories: entity-level analyses, country-level analyses, and information moment-level analyses. In entity-level analysis, insights are drawn about the role of the stock market, forex market, and CB of all the countries in the flow of information through mean and volatility connectedness and single-layer network analysis. On the other hand, country-level analyses reflect information flow between countries, whereby financial markets and CBs are treated as subsystems through which information is transacted. It is carried out using multilayer network analysis. The information moment-level undertakes the study of the conditionality between mean and risk information through mean-volatility connectedness and multilayer network analysis.

The results of entity-level analysis show that the stock markets of different countries and forex markets like USD, AUD, EUR, and HKD have an active role in the transmission of information. They amplify the signals in the system, whereas CBs are dormant and active only in times of crisis. Additionally, the block aggregation techniques show intermediate spillovers between the stock market group, the forex market group, and the CB group. It suggests that cross-group spillover increases during global events like the GFC, Brexit, and COVID-19 and decreases during the 2014 oil price crash, which majorly affected the forex market. This shows that during times of high global economic uncertainty, agents are interdependent in shaping their beliefs and are very sensitive to each other's actions. The monoplex network identifies the stock markets as communicators of information. Further, the stock markets of the US and Euro Area are central to the information flow structure.

The country-level analysis through a multilayer network structure reveals that the MAEs and AEs are the communicators of the information. It also identifies countries that have greater influence on information transmission across subsystems or layers (say, CB's communication layer to the stock market layer) through PageRank versatility. It is observed that countries like Japan and Hong Kong have a greater role in mediating inter-layer spillovers in the multilayer network. The information moment-level analysis reveals that the mean and volatility information are conditioned on each other. The mean and volatility information became more informative to each other during the GFC and COVID-19. It is also noticed that CBs' communication and the forex market play a pivotal role in spillover between first- and second-moment information.

Thus, this work contributes to the existing literature by delineating the structure of information flow at entity-level, country-level, and information moment-level. It also identifies central nodes and presents a comparative analysis of countries and entities. This work presents novel insights for policymakers and financial market participants on the connectedness of countries through three channels, moving closer to the representation of the complex structure. However, this work incorporates only financial markets and policymakers. The analysis can be extended further to include other integral parts of the complex economic system, such as real sectors and media intermediaries.

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# Appendix A

### A.1 Detailed process of measuring sentiment

To calculate the sentiment, we account for valence-shifting words along with positive and negative sentiment words. Valence-shifting words can alter the weight or sign of sentiment polarity of the word. They are broadly characterised into four categories: negators, amplifiers, de-amplifiers, and adversative conjunctions. Negators are the words that flip the sign of the polarity of polar words if they occur with them. For example, in the statement "It is not a good sign for the economy", the occurrence of "not" with "good" makes the statement negative. Whereas, amplifiers and de-amplifiers upweight and downweight the sentiment, respectively. For example, the use of amplifiers like "definitely" in the statement "It is definitely not a good sign for the economy" and de-amplifiers like "partly" in the statement "It is partly not a good sign for the economy" strengthen and diminish the negative statement, respectively. At last, an adversative conjunction reduces the polarity of the clause before it. For example, the use of an adversative conjunction like "but" in the statement "It is not a good sign for the economy, but it is a transitory disturbance", whereby the occurrence of “but” downtones the former negative clause.

The process adopted to compute the sentiment of speeches is summarised in the following steps:

1. We combine all the speeches in a month for a country and then break down the documents to the sentence level. The unit of measurement for sentiment is sentence level.
2. Then, we search for keywords from the positive and negative word lists of the LM dictionary. After pinpointing the polar word, we select five words before and two words after it to form a cluster.

3. Then, we look for the valence-shifting words in the cluster and assign weight according to their category. For negators, we multiply the polarity value (1 in the case of a positive word and -1 in the case of a negative word) with -1 to show a sign flip. Amplifiers and de-amplifiers upweight and downweight the sentiment by 0.8, respectively. In the case of an adversative conjunction, if the polar word occurs in the clause before the adversative conjunction, then it is de-amplified, and if it occurs in the clause after the adversative conjunction, then it is amplified by 0.25, respectively.
4. Further, all these aspects are combined to get the cluster's sentiment (refer to the appendix for more details). The sentiment of all the clusters in a sentence is summed up and divided by the square root of the number of words in that sentence.

### A.2 LASSO Estimation and Connectedness Matrix

The LASSO estimation for each variable $j, j = 1, \dots, k$ is given as follows:

$$\underset{\gamma}{argmin}\left(\left[T^{-1}\left\| y_{jt} - \gamma_{j0} - \sum_{i=1}^{p}\sum_{j=1}^{k}\gamma_{ji}y_{j(t-i)}\right\|_2\right] + \lambda P\right) ;$$

$$P = \left\|\gamma_{j0} + \sum_{i=1}^{p}\sum_{j=1}^{k}\gamma_{ji}\right\|_1$$

The first part is a mean squared error loss function. $\lambda P$ is the Lasso penalty. Here, $\lambda$ is the tuning parameter that dictates the total strength of the penalty. A 10-fold cross-validation is implemented to choose the value of $\lambda$.

The key feature of VAR-based models is that they ease comprehension of spillover relations through their impulse response and forecast error variance decomposition analyses. To get various connectedness indices, Diebold and Yilmaz (2012) first use the Wold decomposition theorem to convert the VAR(p) model in Vector Moving Average (VMA) form: $y_t = I + \sum_{i=1}^{\infty}\theta_i\, y_{t-i}$, where $I$ is the identity matrix and, $\theta_i$ is the $p * p$ matrix of coefficients for $i = 1, \dots, p$.

Following this, general variance decomposition, introduced in Koop et al. (1996) and Pesaran and Shin (1998), is carried out. This measure is order-invariant (Diebold and Yilmnaz, 2012). Through this decomposition, an H-step-ahead forecast error variance matrix is obtained. Thus, the H-step-ahead forecast error variance of $i$ is given as

$$\tau_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(\boldsymbol{u}_i'\boldsymbol{\theta}_i\boldsymbol{\Sigma}\boldsymbol{u}_i)^2}{\sum_{h=0}^{H-1}(\boldsymbol{u}_i'\boldsymbol{\theta}_i\boldsymbol{\Sigma}\boldsymbol{u}_i)}$$

Here, the selection vector, $\boldsymbol{u_i}$ is zero on all places except $i$, and $\boldsymbol{\Sigma}$ is the covariance matrix of $\boldsymbol{\mu_t}$ with $\sigma_{jj}$ as $j$th diagonal element. However, $\sum_{j=1}^{1} \tau_{ij}^{g}(H)$ is not equal to 1. Thus, we use the standardised measure for connectedness measures, which is normalised to have a percentage interpretation:

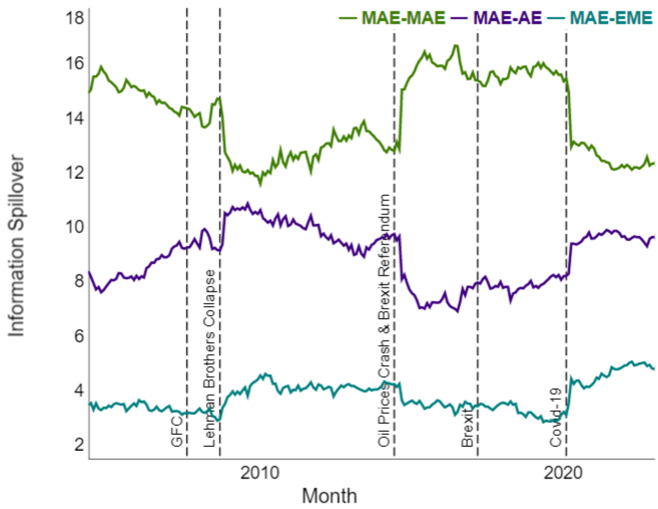
$$\tilde{\tau}_{ij}^{g}(H) = \frac{\tau_{ij}^{g}(H)}{\sum_{j=1}^{1} \tau_{ij}^{g}(H)} \times 100$$

Thus, the connectedness matrix is given as,

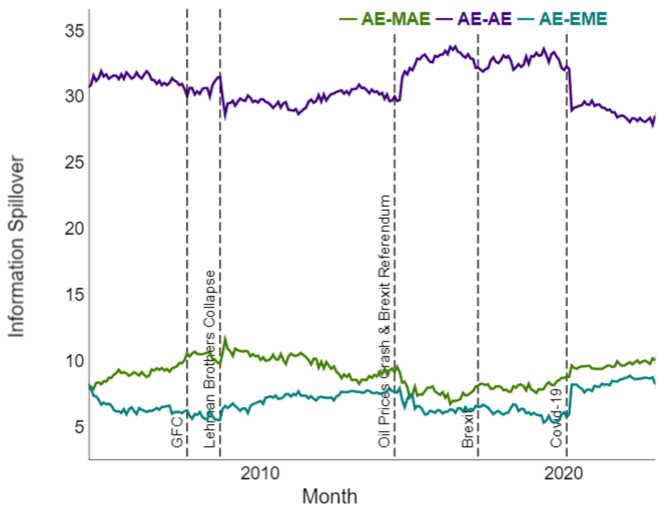
$$C^{H} = \begin{bmatrix} \tilde{\tau}_{11}^{g} & \tilde{\tau}_{12}^{g} & \cdots & \tilde{\tau}_{1m}^{g} \\ \tilde{\tau}_{21}^{g} & \tilde{\tau}_{22}^{g} & & \tilde{\tau}_{2m}^{g} \\ \vdots & & \ddots & \vdots \\ \tilde{\tau}_{m1}^{g} & \tilde{\tau}_{m2}^{g} & \cdots & \tilde{\tau}_{mm}^{g} \end{bmatrix}$$

### A.3 Block Aggregation – MAEs, AEs, and EMEs

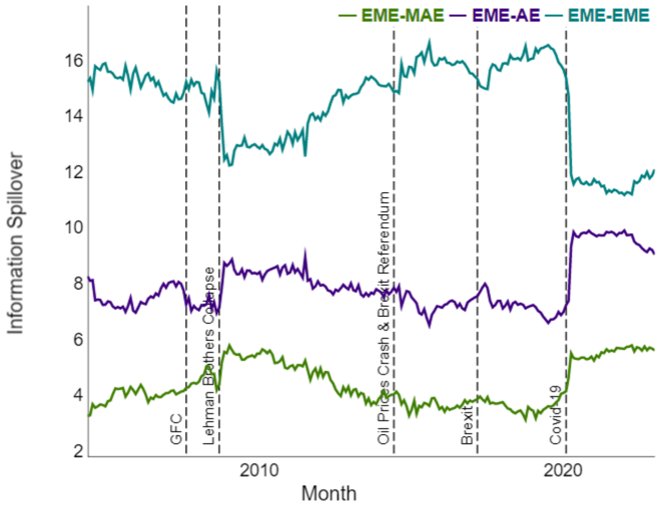
This identifies the nature of spillover at the economic maturity level. We have 5 MAEs, 6 AEs, and 4 EMEs in our sample. Thus, there are 15, 18, and 12 variables in each respective group.




Panel (a): MAEs to others



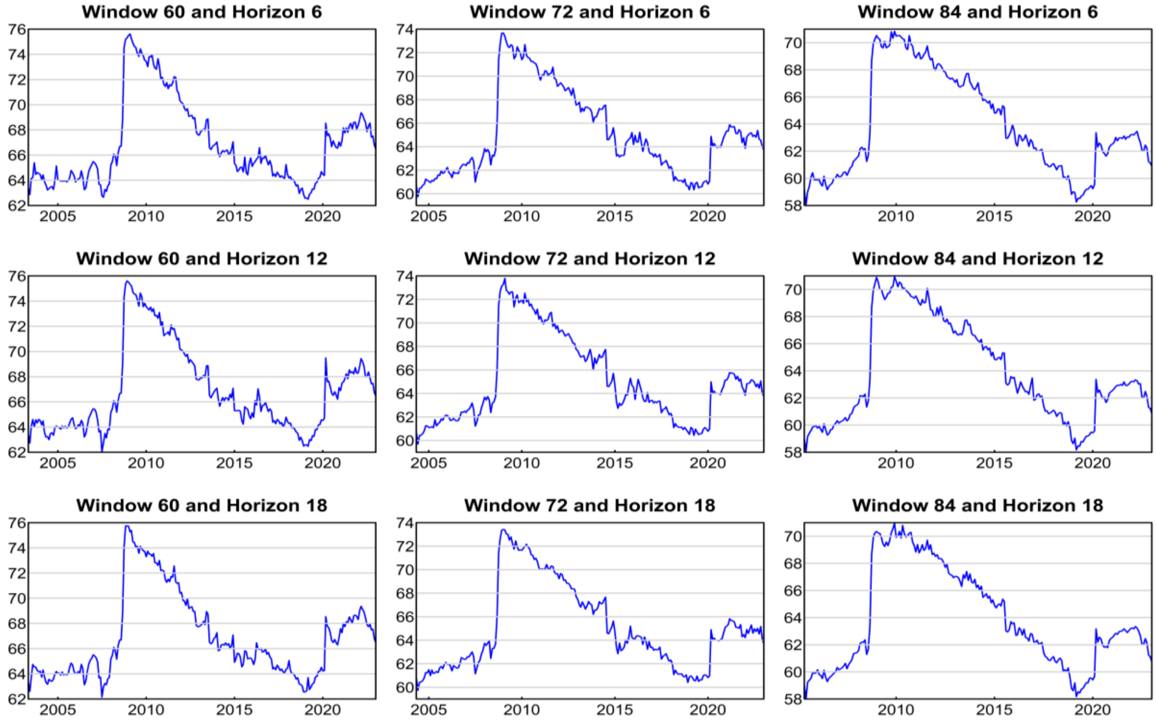

Panel (b): AEs to others



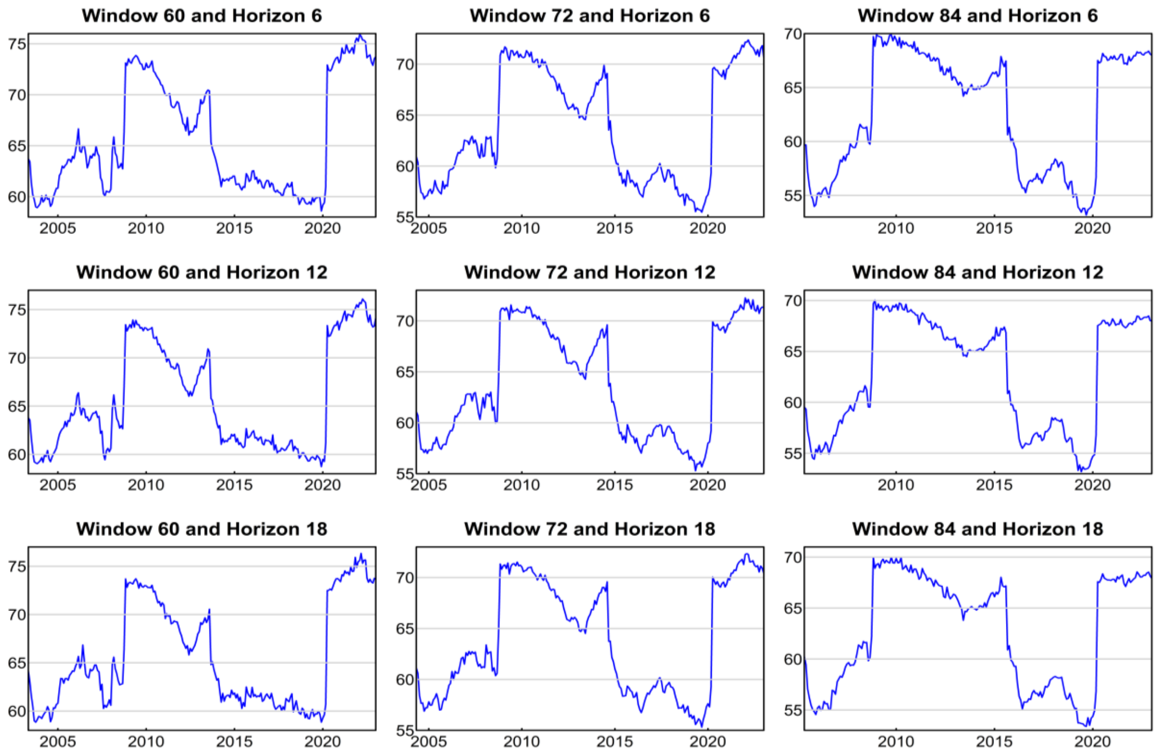

Panel (c): EMEs to others

**Figure A1: Block Aggregation – MAEs, AEs and EMEs**

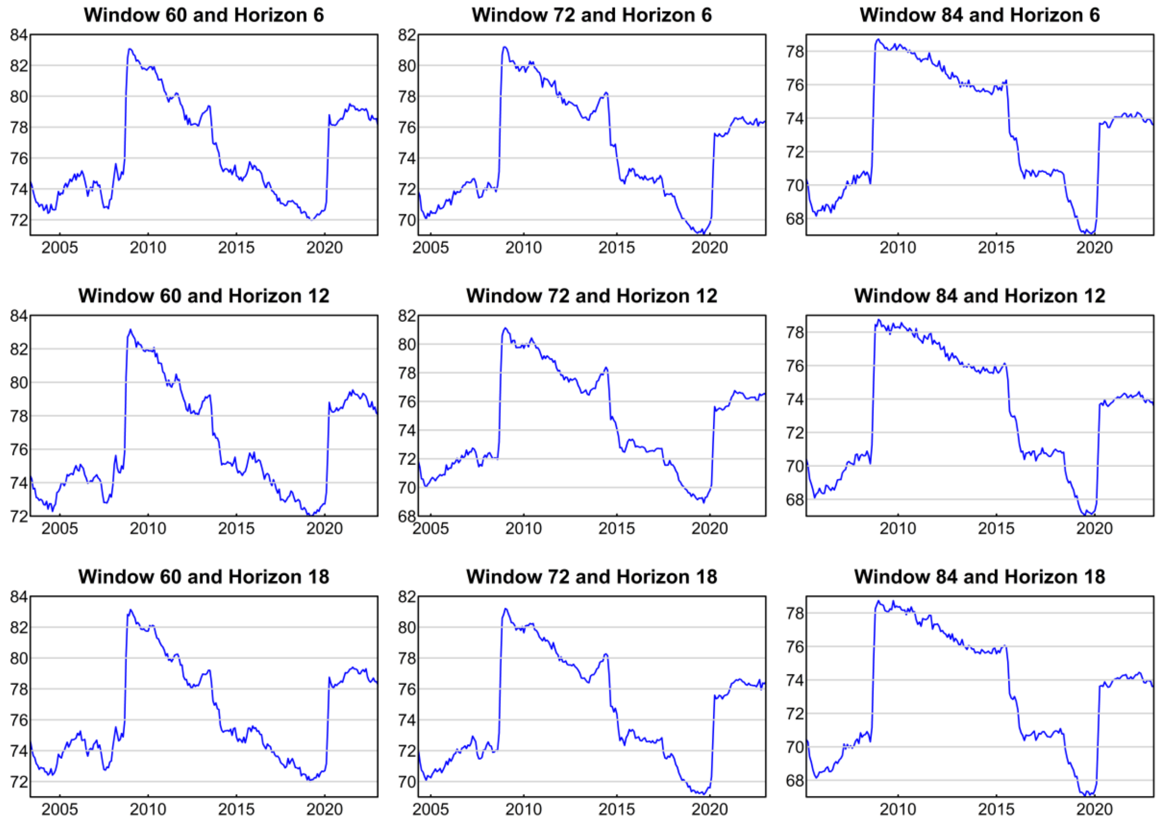
## A.4 Sensitivity Analysis




Panel A. Mean Model




Panel B. Volatility Model




Panel C. Mean-Volatility Model

**Figure A2. Sensitivity analysis**

### A.5 Top 5 inter and intra layer connection

**Table A1. Top 5 inter and intra layer connection: Mean and Volatility Models**

| | | Mean Model | | | Volatility Model | | |
|---|---|---|---|---|---|---|---|
| From layer α | To layer β | From node $i$ | To node $j$ | Weight | From node $i$ | To node $j$ | Weight |
| CB Communication | CB Communication | BoJ | RBI | 5.05 | SCB | SNB | 4.48 |
| | | CBN | SNB | 4.43 | SNB | SCB | 4.23 |
| | | BoJ | BNM | 4.15 | SCB | CBN | 3.88 |
| | | RBI | BoJ | 3.96 | SCB | BNM | 3.63 |
| | | SNB | CBN | 3.5 | SNB | CBN | 3.51 |
| | Stock Market | SARB | IN | 1.12 | ECB | HKD | 2.89 |
| | | SARB | SE | 0.79 | BoJ | HKD | 2.56 |
| | | SARB | NO | 0.75 | RBI | HKD | 1.88 |
| | | BoE | HK | 0.7 | RBA | YEN | 1.87 |
| | | BoE | AU | 0.64 | Fed | HKD | 1.67 |
| | Foreign Exchange Market | SARB | CHE | 2.15 | ECB | JP | 1.3 |
| | | BoT | GBP | 2.11 | Fed | ZA | 0.92 |
| | | MAS | GBP | 2 | Fed | TH | 0.9 |
| | | MAS | YEN | 1.79 | BNM | NO | 0.88 |
| | | BoE | SGD | 1.56 | Fed | CH | 0.87 |
| Foreign Exchange Market | CB Communication | YEN | MAS | 3.27 | HKD | ECB | 4.79 |
| | | GBP | BoT | 2.65 | HKD | BoJ | 3.61 |
| | | CHE | SARB | 2.52 | HKD | RBI | 3.48 |
| | | GBP | MAS | 2.33 | HKD | BoC | 3.15 |
| | | NOK | ECB | 2.04 | HKD | Fed | 2.4 |
| | Stock Market | AUD | TH | 3.47 | AUD | IN | 4.33 |
| | | AUD | NO | 3.41 | AUD | NO | 3.51 |
| | | CAD | NO | 3.25 | AUD | CA | 3.04 |
| | | YEN | JP | 3.16 | AUD | TH | 3 |
| | | AUD | SG | 2.93 | AUD | ZA | 2.93 |
| | Foreign Exchnage Market | USD | HKD | 15.28 | USD | CAD | 7.38 |
| | | HKD | USD | 11.2 | CAD | USD | 6.83 |
| | | USD | EUR | 8.78 | USD | EUR | 6.23 |
| | | HKD | EUR | 8.7 | HKD | SGD | 5.81 |
| | | USD | CAD | 7.5 | EUR | CHE | 5.33 |
| Stock Market | CB Communication | IN | SARB | 3.54 | JP | ECB | 2.52 |
| | | SE | SARB | 3.1 | CH | Fed | 2.46 |
| | | HK | BoE | 2.56 | TH | SARB | 2.37 |
| | | NO | SARB | 2.53 | SG | BoJ | 2.3 |
| | | AU | BoE | 2.21 | EA | BoJ | 2.25 |
| | Stock Market | EA | SE | 9.23 | EA | SE | 10.32 |
| | | EA | CH | 9.12 | SE | EA | 9.64 |
| | | SE | EA | 8.41 | EA | GB | 9.24 |
| | | EA | GB | 8.37 | EA | US | 8.76 |
| | | US | CA | 8.08 | EA | CH | 8.42 |
| | | JP | YEN | 5.72 | SG | ZAR | 4.57 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Foreign Exchange Market | NO | CAD | 4.93 | IN | AUD | 4.37 |
| | | NO | NOK | 4.86 | NO | AUD | 3.98 |
| | | SG | AUD | 4.59 | JP | GBP | 3.83 |
| | | TH | AUD | 4.26 | CA | AUD | 3.77 |

**Table A2. Top 5 inter and intra layer connection: Mean-Volatility Model**

| From layer α | To layer β | From node *i* | To node *j* | Weight |
|---|---|---|---|---|
| | | EA | SE | 8.47 |
| | | SE | EA | 8.07 |
| | | EA | GB | 7.32 |
| | | EA | US | 7.25 |
| Volatility Spillover | Volatility Spillover | EA | CH | 7.01 |
| | | SCB | SCB | 11.38 |
| | | BNM | BNM | 10.7 |
| | | CBN | CBN | 10.22 |
| | | SARB | SARB | 6.9 |
| Volatility Spillover | Mean Spillover | BoE | BoE | 6.83 |
| | | USD | HKD | 12.5 |
| | | HKD | USD | 9.76 |
| | | EA | SE | 8.51 |
| | | EA | CH | 8.25 |
| Mean Spillover | Mean Spillover | SE | EA | 7.82 |
| | | BNM | BNM | 11.8 |
| | | CBN | CBN | 11.54 |
| | | SCB | SCB | 11.53 |
| | | BoE | BoE | 9.07 |
| Mean Spillover | Volatility Spillover | RBA | RBA | 7.67 |