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Dynamic Spillover of Economic Freedom and Economic Complexity to Wealth: Quantile Evidence from Developing Countries

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ABSTRACT

Greater Wealth remains a crucial aspiration for developing nations, pursued with increasing intensity in recent decades amid the rapid technological progress of developed countries. This study intends to examine and evaluate the dynamic spillover of economic freedom and dimensions of economic complexity (research, technological, and commercial) on national Wealth in 22 selected developing countries during the period from 2000 to 2023—a period when the world simultaneously experienced remarkable growth in technological products and economic complexity, alongside evident positive effects of economic freedom on noteworthy country growth rates. The selection of these countries, spanning a broad geographical expanse and showing varying degrees of growth, was informed by an era marked by crises such as the global financial crisis, the COVID-19 pandemic, and the Ukraine war. Employing the Quantile Panel Vector Autoregression (PQVAR) model and the Diebold-Yilmaz volatility spillover method, the findings show that in the lower quantiles of the wealth distribution, commercial complexity serves as the primary spillover transmitter. At the same time, per capita income is the most vulnerable recipient. In contrast, in higher quantiles, economic freedom has a central role in mitigating instability. During the aforementioned crisis periods, systemic connectedness increases, with spillovers shifting from trade and technology to income. The observations verify the critical and effective role of economic complexity and institutional freedom, as embodied in the economic freedom index, in reducing systemic vulnerability and enhancing growth stability. Accordingly, policymakers are advised to focus on improving these two indices to achieve greater Wealth and economic security in developing countries.

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1. Introduction

In recent decades, understanding the determinants of national Wealth and sustainable economic growth in developing countries has become a central focus of development economics research. The theory of economic complexity, first introduced by Hidalgo and Hausmann (2009), is predicated on the idea that national Wealth derives not merely from natural resources or physical capital, but predominantly from the embedded knowledge and productive capabilities and a country's productive capabilities in generating complex and diverse goods and services (Hidalgo & Hausmann, 2009; Hausmann & Hidalgo, 2009). This theory emphasises that structural transformation from producing simple products to high-technology goods serves as the primary engine of long-term wealth accumulation. Alongside economic complexity, economic freedom is recognised as one of the key institutions for economic growth. According to institutionalist perspectives, efficient institutions that guarantee property rights and reduce transaction costs provide the necessary incentives for investment and innovation (North, 1990). Annual reports on global economic freedom show that countries with higher levels of economic freedom experience higher per capita income and faster economic growth (Gwartney et al., 2021).

Nevertheless, empirical studies suggest that the impact of economic complexity on Wealth in developing countries is often moderated by institutional quality and economic freedom (Hartmann et al., 2017; Balland et al., 2022). Domestic research has also corroborated these relationships. Chehreghani et al. (1404) demonstrated the direct and positive effect of economic complexity on national Wealth, emphasising the complementary role of institutional variables. Recent evidence from the same journal further supports the positive role of complexity measures in attracting development-enhancing flows. For instance, Poorabdollah and Makiyan (2025) find that higher financial complexity—measured via a novel McCabe's number-based index—significantly and positively affects foreign direct investment (FDI) inflows in 15 selected Asian countries over 2010–2021. This finding aligns with our emphasis on the multifaceted dimensions of complexity (economic and potentially financial) as drivers of economic outcomes in developing and emerging economies, while highlighting the need to explore spillover dynamics across institutional and productive structures. Hasanvand et al. (1401), utilising dynamic GMM methods, found that increasing economic complexity enhances national Wealth, although it may exacerbate income inequality in the short term. Additionally, Shahabadi et al. (1400) highlighted the positive interaction between innovation and economic freedom in promoting economic complexity, while Mostolizadeh et al. (1402) examined the nonlinear relationship between economic complexity and income inequality in OECD countries. Related domestic evidence from Poorabdollah et al. (2025) reveals high financial complexity and systemic risk in Iran's economy using a Kolmogorov approach, highlighting structural challenges relevant to our study of complexity spillovers. Despite theoretical and empirical advancements, the investigation of dynamic and asymmetric spillovers from economic freedom and the multifaceted dimensions of economic complexity (research, technological, and commercial) to national Wealth—particularly in developing countries—remains a research gap. Prior studies have predominantly focused on mean-centric relationships and have paid less attention to nonlinear and regime-dependent behaviours in crisis conditions (Diebold and Yilmaz, 2012, 2014). The present study, employing the Quantile Panel Vector Autoregression (PQVAR) model and the Diebold-Yilmaz volatility spillover method, analyses the dynamic spillovers of these variables on national Wealth in 22 developing countries over the period 2000 to 2023. The primary objective is to identify heterogeneous spillover patterns across quantiles of the wealth distribution and to offer quantile-oriented policy recommendations to bolster economic growth resilience.

This study contributes to the literature in several ways. First, it provides the first quantile-based dynamic spillover analysis of economic freedom and the multidimensional aspects of economic complexity (research, technological, and commercial) on national Wealth in a panel of 22 developing countries over 2000–2023, a period encompassing major global crises. Unlike prior mean-centric studies, the adoption of the Panel Quantile Vector Autoregression (PQVAR) model combined with Diebold-Yilmaz connectedness measures allows for the identification of heterogeneous, regime-dependent, and time-varying spillovers across the wealth distribution. This approach reveals asymmetric patterns—such as the dominance of commercial complexity in lower quantiles and the stabilising role of economic freedom in higher quantiles—that remain undetected in conventional frameworks. The remainder of the paper is organised as follows. Section 2 outlines the theoretical foundations linking economic complexity, economic freedom, and wealth creation. Section 3 reviews the relevant empirical literature. Section 4 describes the data, variables, and econometric methodology, including the PQVAR model, connectedness indices, and robustness checks. Section 5 presents the empirical results, including quantile spillovers, dynamic connectedness, and crisis-specific networks. Finally, Section 6 discusses the findings, draws policy implications, and concludes with limitations and avenues for future research.

2.Theoretical Foundations and Literature Review

Economic complexity is defined as an indicator of the knowledge and productive capabilities embedded in a country's economy. The theory of economic complexity, first proposed by Hausmann and Hidalgo (2009), rests on the premise that the Wealth of nations derives not solely from natural resources or physical capital, but primarily from a country's ability to produce complex and diverse goods and services (Hausmann & Hidalgo, 2009, p. 10570). This index is calculated based on the diversity and sophistication of countries' export baskets. It demonstrates that nations producing more complex and less ubiquitous products possess advanced technical knowledge and skills, which lead to higher productivity and wealth accumulation. According to this theory, economic development is a process in which economies transition from the production of simple goods to the production of complex, high-technology products, and this structural transformation serves as the primary engine of long-term growth and wealth creation. An inefficient banking system undermines economic complexity by directing resources toward unproductive activities, creating unbacked liquidity, and failing to finance innovation—thereby disrupting the discovery of new products and the accumulation of collective knowledge. Resource misallocation, particularly favouring short-term and government-directed lending over knowledge-based SMEs, further limits the diversification of complex products. Economic freedom refers to the conditions under which individuals can engage in voluntary economic activities with minimal government interference, secure their property rights, and participate in competitive markets. From the institutionalist perspective, as articulated by North (1990), efficient institutions that protect property rights and facilitate transactions form the foundation of economic growth and wealth creation (North, 1990, p. 54). In North's theoretical framework, institutions function as the "rules of the game" in an economy, reducing transaction costs and uncertainty, thereby enhancing incentives for investment and innovation. Empirical studies, such as the annual Economic Freedom of the World reports (Gwartney et al., 2021), show that countries with higher levels of economic freedom enjoy higher per capita income and faster economic growth. Economic freedom contributes to wealth creation and distribution through mechanisms such as efficient resource allocation, encouragement of competition, and attraction of foreign direct investment.

The Index of Economic Freedom was first introduced in 1995 by the Heritage Foundation and The Wall Street Journal. Kim Holmes and William Beach from Heritage were the primary architects of this index. These organisations developed comprehensive indicators to measure economic freedom across countries. The index typically evaluates four key domains: (1) Rule of Law (including property rights and judicial effectiveness), (2) Government Size (government spending and taxation), (3) Regulatory

Efficiency, and (4) Market Openness (trade, investment, and financial freedom). Prior to Heritage, the Fraser Institute in Canada had developed a similar index since 1975, but the Heritage version—with its focus on twelve components—became the global standard. This index was designed to measure the impact of free-market policies on well-being, and subsequent studies have confirmed its strong correlation with economic growth. While the Fraser Institute has provided annual reports based on five leading indicators since 1975, the Heritage Index gained wider acceptance for its greater comprehensiveness (including rule of law and regulatory dimensions). Since 1995, it has covered more than 180 countries, and empirical research indicates that high scores are correlated with GDP growth rates of 0.6-0.8, providing a basis for policymaking in successful economies such as Singapore. Theoretically, economic freedom leads to gross domestic product growth through several well-established mechanisms rooted in classical and neoclassical economics, including the promotion of innovation and entrepreneurship, optimal resource allocation, and increased productivity. By reducing entry and exit barriers and securing ownership of innovative outcomes, it heightens incentives for investment in technology and invention. Furthermore, in line with David Ricardo's theory of comparative advantage, free trade enables countries to specialise in goods and services in which they are relatively more efficient, leading to economies of scale, more efficient resource allocation toward the most productive activities, and ultimately enhanced overall economic productivity.

The experience of leading countries in these indices clearly illustrates the positive relationship between economic freedom and superior economic performance. For instance, according to the 2024 Heritage Foundation Index of Economic Freedom report, countries such as Singapore, Switzerland, Ireland, and New Zealand have consistently ranked at the top, achieving scores above 80 (out of 100). The success of these economies stems from a combination of strong and transparent property rights, efficient and limited business regulations, and open markets, which have sustained long-term GDP growth rates above the global average. Singapore (ranked 1st in 2024) has created an exceptional environment for foreign direct investment (FDI) through an impeccable property rights system, complete trade freedom, and an efficient regulatory environment. The country consistently attracts FDI flows equivalent to a substantial share of its GDP, thereby enhancing competition and innovation in its economy. Similarly, Switzerland (ranked 2nd in 2024) maintains a highly efficient regulatory framework, financial freedom, and stable political conditions, providing a low-risk, high-return environment for economic activities. These conditions have significantly contributed to increases in total factor productivity (TFP) and the attraction of high-quality capital. Ireland has become one of the primary destinations for multinational corporations—particularly in technology—through policies such as a low corporate tax rate (12.5%) and trade liberalisation, attracting massive volumes of FDI. New Zealand, following extensive economic reforms in the 1980s, focused on reducing government intervention, liberalising markets, and privatising state-owned enterprises, and experienced sustained economic growth with controlled inflation.

Credible empirical studies indicate that the relationships among economic complexity, economic freedom, and Wealth exhibit significant structural differences between developed and developing countries. According to Balland et al. (2022), developed countries generally benefit from stable institutional frameworks, strong property rights, and efficient regulatory environments that enable them to integrate advanced knowledge into productive processes effectively. In these economies, economic freedom serves as a durable institutional infrastructure, allowing full exploitation of the advantages of economic complexity. Efficient national innovation systems, advanced human capital, and complex production networks in these countries have emerged and developed in environments characterised by high economic freedom, resulting in the creation and preservation of sustainable competitive advantages in global markets. In contrast, research by Hartmann et al. (2017) shows that in developing countries, the relationship between economic complexity and Wealth is frequently moderated by institutional quality and the level of economic freedom (Hartmann et al., 2017, p. 85). Many of these countries, despite achieving moderate levels of economic complexity, are unable to fully convert the benefits of this complexity into Wealth due to weak institutions, widespread corruption, insecure property rights, and trade restrictions. These economies are often trapped in a "complexity trap," where increases in productive complexity without concurrent improvements in institutional quality and economic freedom fail to generate sustainable wealth growth. For example, some developing countries may achieve complexity in specific sectors. However, due to weak governance institutions and limitations on economic freedom, the value added generated is either not equitably distributed or not reinvested in the national economy.

Numerous empirical studies have confirmed the multifaceted relationship between economic complexity, economic freedom, and wealth indicators. These studies demonstrate that these two variables often operate synergistically, laying the groundwork for sustainable growth and development. Mehmood and Kaewsaeng-On (2025) examined pathways to financial development in the Group of Seven (G7) countries over the period 1990- 2022 using panel quantile regression methods. Their empirical findings indicate that the effects of natural resources, technological innovation, and trade freedom on financial development are heterogeneous and vary across different levels of the financial development distribution. These results underscore the need to design customised, flexible financial policies tailored to each country's specific conditions to achieve sustainable financial growth. Kumar, Choudhary, Kumar, and colleagues (2025) analysed the tripartite relationship among economic complexity, financial development, and income inequality across 32 Asian countries using OLS and quantile regression. Their results show that while economic complexity reduces income inequality between the lower and middle income deciles, it simultaneously widens the income gap among the wealthier deciles. Moreover, financial development in these countries exerts an adverse and persistent effect on a more equitable income distribution. Atilgan and Kütükçü (2025) assessed the simultaneous impact of the economic complexity index and the human development index on economic growth in MIKTA countries (Mexico, Indonesia, South Korea, Turkey, and Australia). Using annual panel data and econometric methods, the study found that diversity and complexity in a country's production structure and knowledge base play a key role in stimulating long-term economic growth by strengthening advanced, innovative productive structures. Hamdi, Souam, and Zouikri (2025) provided new evidence using a buffered panel threshold regression model, demonstrating that the relationships among economic complexity, growth, and human development are nonlinear. This research, based on data from 92 countries, shows that the impact of economic complexity depends strongly on institutional quality and the degree of natural resource dependence; under conditions of institutional weakness or high resource dependence, it can even produce undesirable outcomes. Tazin (2025) examined Bangladesh's economic metamorphosis through trade liberalisation. The analysis indicates that despite the implementation of liberalisation policies, the complexity of Bangladesh's export products has not improved significantly, and the economy remains heavily reliant on single-product exports (textiles and garments). This finding critically emphasises that trade liberalisation alone is insufficient for achieving sustainable growth and must be accompanied by structural transformation strategies and export diversification. Benhamed and Abdennour (2025) employed a panel ARDL method to identify a long-term positive relationship between economic complexity and human development in 13 countries of the Middle East and North Africa (MENA) region. The findings suggest that the shift of these economies toward knowledge-based and complex goods and services leads to improved living standards, better health indicators, enhanced educational outcomes, and ultimately, strengthened human development. Awan (2025), in a preprint study, analysed the dynamics of economic growth in low- and lower-middle-income countries, focusing on various components of economic freedom (such as trade freedom, investment freedom, and financial freedom). Using advanced statistical models, the results indicate that while the overall effect of economic freedom on growth is positive, the impact of each component differs significantly, and its short- and long-term effects exhibit notable differences. Chehreghani et al. (2025/1404 SH) in a comparative study of 48 leading science-producing countries found that the economic complexity index has a direct, positive effect on the level of national Wealth. Furthermore, the authors argue that institutional variables (such as governance quality) and infrastructural variables (such as financial development and information technology) are not only independently effective but also complementary, strengthening the relationship between complexity and Wealth. Pourabdollah et al. (2025) in a comparative study of Türkiye, Iran, Saudi Arabia, and the United Arab Emirates found that financial complexity, measured via McCabe's network approach. varies significantly across these countries (Türkiye: 95, Iran: 77, Saudi Arabia: 49, UAE: 36), implying higher systemic risk in more complex financial systems and a limited role for capital markets in these economies. The authors emphasise the increased vulnerability of emerging markets to crises due to this complexity, offering insights into the structural factors that interact with economic complexity and institutional quality in developing countries. Kamguia and Mekongo (2024) investigated the effects of economic complexity on governance indicators in developing countries using an innovative instrumental variable quantile regression approach. Their findings reveal that economic complexity exerts heterogeneous effects across dimensions of governance (political, economic, and institutional), with these effects varying across quantiles of the governance quality distribution (from weak to strong). This indicates a complex, conditional relationship between the two variables. Bilal and Ahmad (2024), using GMM and quantile regression methods, demonstrated that although high-quality institutions and developed human capital each exert a positive, independent effect on economic growth in emerging economies, inappropriate interactions between them (such as the allocation of human resources to unproductive rent-seeking activities) can produce adverse outcomes. The study also reports significant differences in these mechanisms between Muslim and non-Muslim countries. Yülek and Özaytürk (2024) applied the panel Dumitrescu-Hurlin causality test to compare the causal relationship between economic freedom and development in two distinct country groups (D8 and G8). The results of this comparative analysis show that the direction of causality between these two variables can change across different stages of development and in varying institutional and economic contexts, implying that a single universal pattern cannot be prescribed for all countries.

Mostolizadeh et al. (2023) investigated the nonlinear impact of economic complexity and the shadow economy on income inequality in 29 OECD member countries over the period 1995-2020, using the Gini coefficient as the measure of income inequality. Employing the panel autoregressive distributed lag (Panel ARDL) approach, the findings reveal that the relationship between economic complexity and income inequality follows a standard U-shape. In the early stages of moving toward greater economic complexity (the development of knowledge-based industries with high value added), inequality decreases; however, beyond a certain threshold, further increases in economic complexity can lead to heightened inequality, potentially due to technological and skill gaps that favour limited groups with high human capital. Hasanvand (2022), in a study titled "Examining the Impact of Economic Complexity on Income Inequality and Wealth in Developing Countries," using panel data from 40 countries (period 1995-2020) and dynamic GMM methodology, showed that an increase in the economic complexity index (ECI), while exacerbating income inequality in the short term, increases national Wealth (gross domestic product) by an average of 1.2% overall. A noteworthy finding in this research is the negative coefficient for ECI in Iran (0.65), indicating that the country's economy is characterised by very low complexity and high resource dependence. Gwartney et al. (2021), in the annual Economic Freedom of the World report, demonstrate that higher levels of economic freedom exhibit a strong positive correlation with a broad range of wealth and well-being indicators. This correlation is not limited to higher per capita gross domestic product but also encompasses reductions in absolute poverty, increases in life expectancy, educational progress, and greater equality of opportunity. Mostolizadeh (2021/1400 SH), employing the ARDL method on data from 28 countries, provides robust evidence of this relationship. The study shows that in developed countries, economic freedom serves as a long-term reinforcing cause of economic complexity. In contrast, in developing countries, the dominant causal path runs from economic complexity to human development (HDI) and, subsequently, to strengthening institutional foundations. This finding suggests a bidirectional, reinforcing relationship: on the one hand, economic freedom provides the foundation for economic complexity; on the other hand, achieving higher levels of economic complexity generates demand for higher-quality institutions and more sustainable economic freedom. Shahabadi et al. (2021/1400 SH) used the generalised method of moments (GMM) to examine the interactive effect of innovation and economic freedom on the economic complexity index across a selected group of science-producing countries over the period 2008-2017. The findings indicate that the positive and significant interaction between innovation and economic freedom plays an important role in enhancing economic complexity. In other words, a free institutional environment amplifies the impact of innovative activities on the economy's production structure. Additionally, the results show that entrepreneurship, financial development, and market size indices have positive and significant effects on economic complexity.

Hartmann et al. (2017) specifically show that economic complexity (defined as the diversity and embedded knowledge in a country's production basket) has a positive and significant effect on economic growth. However, the key finding is that institutional quality acts as an amplifying factor: the positive impact of complexity on growth is substantially more substantial and more sustainable in countries with stronger institutions, better rule of law, and more efficient regulatory environments (key components of economic freedom). This finding supports the view that economic complexity without adequate institutional backing may fail to realise its potential for wealth creation fully.

3. Methodology and Data

This study employs an advanced dynamic econometric approach to investigate the mutual impact of economic freedom and the dimensions of economic complexity on Wealth in developing countries. Unlike traditional studies that focus solely on mean-based relationships, this research uses the Panel Quantile Vector Autoregression (PQVAR) model, which allows for the examination of nonlinear and asymmetric interactions among variables across varying economic conditions (from severe crises to periods of prosperity). The main variables examined in this study include five key indicators: Overall Index of Economic Freedom (Index of Economic Freedom – Overall Score), Three components of economic complexity: Research Complexity (ECI-Research), Technological Complexity (ECI-Technology), Commercial Complexity (ECI-Trade). Moreover, the Average Wealth of Adults is a proxy for the level of national welfare. The data used in this research are annual and cover the period 2000 to 2023. The data were extracted for 22 developing countries (Argentina, Bangladesh, Brazil, Chile, China, Colombia, Egypt, Hong Kong, India, Indonesia, Iran, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Saudi Arabia, South Africa, Thailand, Turkey, Ukraine, and the United Arab Emirates). It should be noted that the raw data were received and processed, with missing observations—due to delays in the publication of economic complexity indices (particularly the research and technological components)—filled using linear interpolation and intelligent averaging methods to prevent bias in the estimations.

To reduce dimensionality and construct a comprehensive composite index from the explanatory variables, Principal Component Analysis (PCA) was explicitly applied to the four highly correlated explanatory variables: the overall Index of Economic Freedom score and the three dimensions of economic complexity (research, technological, and commercial). The dependent variable (average Wealth of adults) was excluded from the PCA to preserve its role as the outcome measure in the spillover analysis, allowing us to examine directed spillovers from the institutional and complexity factors to Wealth. This approach distinguishes institutional effects (economic freedom) from productive structure effects (complexity dimensions), consistent with the theoretical framework (e.g., Hartmann et al., 2017; Balland et al., 2022). The PCA results, detailed in Appendix Table A1, show that the first principal component (PC1) captures over 62% of the total variance, with an eigenvalue of 3.12. In contrast, subsequent components explain diminishing shares of the variance. Factor loadings indicate strong positive associations across all variables on PC1 (e.g., 0.86 for Economic Freedom, 0.89 for Wealth—though Wealth was not included in the final PCA but shown for illustration), justifying the use of PC1 as the primary composite index for dimensionality reduction. This composite index was then reconstructed as a pseudo-daily panel variable by linearly interpolating the annual series (assuming 252 trading days per year) to meet the high-frequency requirements of the rolling-window PQVAR model and to capture intra-year dynamics during crisis periods better. Missing observations were handled via linear interpolation and intelligent averaging to minimise bias. While linear interpolation of annual data to pseudo-daily frequency may introduce some smoothing artefacts, this method is widely employed in connectedness studies with low-frequency macroeconomic data to enable dynamic analysis (e.g., Chatziantoniou et al., 2021; Bouri et al., 2022). To address potential concerns about artificial volatility or bias in crisis evaluations, we conducted robustness checks using quarterly interpolation rather than daily (yielding approximately 96 observations per year), as well as alternative window sizes (100 and 150 days) and forecast horizons (5 and 10 days). These sensitivity analyses, reported in Figure 7 and Appendix Table A2 (for quarterly results), confirm that the core patterns—such as increased connectedness during crises and the quantile-specific roles of commercial complexity and economic freedom—remain qualitatively unchanged, thereby validating the dynamic spillover findings in Figures 2, 7, 10, and 11.

The PQVAR methodology employed in this study is grounded in the Diebold and Yilmaz (2012) framework and its subsequent extensions to multivariate quantile settings. This model allows the measurement of dynamic spillovers (spillover effects) among variables not only across the entire distribution but also specifically at three key quantiles: the 25th (adverse/crisis conditions), 50th (normal/median conditions), and 75th (favourable/booming conditions). This approach is particularly suitable for analysing nonlinear, regime-dependent relationships among economic freedom, economic complexity, and Wealth, as these relationships often differ substantially during crisis periods compared to growth periods. To assess the dynamics of connectedness over time, a 100-day rolling window was adopted to capture structural changes in the economic spillover network. In addition, key recent global shocks—including the COVID-19 pandemic (2020–2021), the Global Financial Crisis (2007–2009), and the combined shocks of the Ukraine war and the Silicon Valley Bank (SVB) collapse (2022–2023)—were incorporated into the quantile spillover analysis using the PQVAR model. During these periods, directed graphs of connectedness networks across countries were constructed for each quantile to identify each country's role as either a "net transmitter" or a "net receiver" of spillovers under crisis conditions. Finally, to ensure the robustness of the findings, sensitivity tests were conducted by varying key parameters—such as the forecast horizon (H = 5 and 10) and rolling-window size (100 and 150 days). Furthermore, the trend of the Total Connectedness Index (TCI) was plotted across a continuous range of quantiles (0.25-0.75) to confirm the presence of nonlinear behaviour. This methodological framework not only provides deeper insight into the nature of interactions between economic freedom and economic complexity in wealth generation but also highlights structural differences among countries at varying levels of development, offering differentiated policy implications for each group. These shocks were analysed using the QVAR method across various quantiles to examine volatility spillovers under normal and crisis conditions. The results of this analysis are presented in the corresponding tables and figures, including volatility connectedness networks, the Total Connectedness Index (TCI), and directional spillover indices (TO and FROM) (Diebold, 2012). For the connectedness analysis, the data were standardised to eliminate scale effects. Standardisation was performed using the following formula: zi,t = (xi,t - μi) / σi, where xi,t is the original value of the variable, μi is the mean, and σi is the standard deviation of the variable for country i. This standardisation process improves the performance of the QVAR model. SVB stands for Silicon Valley Bank, an American bank that collapsed in March 2023 due to a liquidity crisis and rising interest rates, representing one of the most significant bank failures since the 2008 crisis. This event, combined with the Ukraine war, delivered a dual shock to global financial markets. where xi,t is the original value of the variable, μi is the mean, and σi\sigma_iσi is the standard deviation of the variable for country i. This standardisation process enhances the performance of the QVAR model.

Quantile Connectedness

To analyse connectedness across different quantiles, the QVAR model is employed, which is defined as follows:

$$y_{i.t} = c_i(\tau) + \sum_{l=1}^{p} B_{i.l}(\tau) y_{i.t-l} + e_{i.t}(\tau).\, t = 1. \ldots .T. \quad (1)$$

It is assumed that the residuals do not exceed the population quantile bounds, i.e., the conditional quantile τ of the response is estimated as follows:

$$Q_\tau\left(y_{i.t} \mid y_{i.t-1}. \ldots . y_{i.t-p}\right) = c_i(\tau) + \sum_{l=1}^{p} \hat{B}_{i.l}(\tau) y_{i.t-l} \quad (2)$$

This method enables the analysis of nonlinear and asymmetric dependencies among variables across different quantiles (25th, 50th, and 75th). It is particularly suitable for examining the behaviour of variables under both normal and crisis conditions (Diebold, 2014).

Spillover Indices

To calculate the spillover indices, the Diebold (2014) framework was employed. First, the QVAR model was rewritten as an infinite-order moving average process:

$$y_{i.t} = \mu_i(\tau) + \sum_{s=0}^{\infty} A_{i.s}(\tau) e_{i.t-s}(\tau).\, t = 1.\dots.T. \quad (3)$$

where Θ and the matrices are defined recursively. Then, using the Generalised Forecast Error Variance Decomposition (GFEVD), the contribution of each variable to the forecast error variance of another variable was calculated:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_{i.h} \Sigma_i e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_{i.h} \Sigma_i A_{i.h}' e_i\right)} \quad (4)$$

where Σi\Sigma_iΣi is the variance-covariance matrix of the errors for country iii, σjj\sigma_{jj}σjj is the jjj-th diagonal element of the matrix Σi\Sigma_iΣi, and eie_iei is the selection vector with a value of 1 in the iii-th element and 0 in all other elements. For standardisation, the normalised values are calculated as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \quad (5)$$

The Total Connectedness Index (TCI)1 for quantile τ\tauτ is defined as follows:

$$\text{TCI}_i(\tau) = \frac{\sum_{i=1}^{N} \sum_{j=1.i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau)}{\sum_{i=1}^{N} \sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau)} \times 100 \quad (6)$$

where Σi\Sigma_iΣi is the variance-covariance matrix of the errors for country iii, σjj\sigma_{jj}σjj is the jjj-th diagonal element of the matrix Σi\Sigma_iΣi, and eie_iei is the selection vector with a value of 1 in the iii-th element and 0 in all other elements. For standardisation, the normalised values are calculated as follows:

$$S_{i\rightarrow\cdot(\tau)} = \frac{\sum_{j=1.i\neq j}^{N} \tilde{\theta}_{ij}^{g}(\tau)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(\tau)} \times 100$$

$$\mathrm{NS} = (\tau) = S_{i\rightarrow\cdot(\tau) - S_{i\leftarrow\cdot(\tau)}} \qquad (7)$$

For the analysis of temporal dynamics, a rolling-window approach1 with a window length of 100 days and a forecast horizon of 10 days was employed. The lag order of the model was selected using the Schwarz Information Criterion (Diebold, 2012 and 2014). To examine temporal dynamics, the Total Connectedness Index (TCI) and the Net Connectedness Index (NET) were calculated using a 100-day rolling window. This analysis enables investigation of changes in the connectedness among variables over time.

Furthermore, to assess the robustness of the results with respect to parameter selection, the analysis was repeated using different window sizes (100 and 150 days) and forecast horizons (5 and 10 days). In addition, the TCI was computed across various quantiles (0.25-0.75) to examine connectedness behaviour at different levels of the variables, particularly under crisis conditions. These analyses contribute to a better understanding of the dynamics of volatility spillovers among economic and digital indices at the provincial level. Prior to estimating the PQVAR model, we conducted panel unit root tests—including the Im-Pesaran-Shin (IPS) and Fisher-type Augmented Dickey-Fuller (Fisher-ADF) tests—on both the level and first-differenced series of the standardised composite variables (the overall economic freedom index, the three components of economic complexity, and average adult wealth). The level tests failed to reject the null of a unit root (indicating non-stationarity), whereas all first-difference tests strongly rejected the null at the 1% significance level. This confirms that the variables are integrated of order one (I(1)) and become stationary after first differencing. Subsequently, panel cointegration tests—Pedroni (1999, 2004) and Kao

(1999)—were applied to the level variables to examine the presence of a long-run equilibrium relationship. Both tests failed to reject the null hypothesis of no cointegration across the panels (at conventional significance levels), indicating the absence of a stable long-run cointegrating relationship among the variables in levels. Given that the variables are I(1) but not cointegrated, estimating the model in levels would risk spurious regression bias. Therefore, we employ the PQVAR framework on the first-differenced series (Δ variables), ensuring stationarity across all series and eliminating potential bias arising from non-stationarity or spurious correlations. This specification is entirely appropriate and consistent with standard practices in dynamic panel models involving I(1) non-cointegrated variables (e.g., as in Diebold and Yilmaz connectedness frameworks extended to panels). The empirical analysis proceeds in two steps: first, preliminary tests for stationarity and cointegration, and second, estimation of quantile spillovers and dynamic connectedness.

4. Empirical Results

This section presents the results of preprocessing and analysing data for the 22 developing countries over the period 2000 to 2023.

Table 1. Volatility Spillovers across Different Quartiles (Low, Medium, and High Conditions)

Country	FROM (25th)	TO (25th)	NET (25th)	FROM (50th)	TO (50th)	NET (50th)	FROM (75th)	TO (75th)	NET (75th)
Argentina	3.65	4.55	0.89	1.68	4.55	2.87	3.44	4.55	1.10
Bangladesh	3.08	4.55	1.47	1.52	4.55	3.02	3.42	4.55	1.13
Brazil	2.00	4.55	2.55	1.48	4.55	3.07	1.79	4.55	2.75
Chile	0.28	4.55	4.26	0.78	4.55	3.77	0.97	4.55	3.58
China	1.06	4.55	3.49	2.04	4.55	2.51	0.49	4.55	4.05
Colombia	10.18	4.55	-5.64	0.27	4.55	4.27	4.33	4.55	0.21
Egypt	42.35	4.55	-37.81	17.97	4.55	-13.42	34.96	4.55	-30.41
Hong Kong	12.27	4.55	-7.73	0.57	4.55	3.98	3.87	4.55	0.67
India	12.81	4.55	-8.26	28.41	4.55	-23.86	28.41	4.55	-23.86

Country	FROM (25th)	TO (25th)	NET (25th)	FROM (50th)	TO (50th)	NET (50th)	FROM (75th)	TO (75th)	NET (75th)
Indonesia	4.67	4.55	-0.13	0.49	4.55	4.06	1.49	4.55	3.05
Iran	1.55	4.55	3.00	0.21	4.55	4.34	0.98	4.55	3.56
Malaysia	0.67	4.55	3.88	14.24	4.55	-9.69	2.98	4.55	1.56
Mexico	1.08	4.55	3.47	5.84	4.55	-1.30	1.17	4.55	3.37
Morocco	0.25	4.55	4.30	2.94	4.55	1.61	0.94	4.55	3.60
Nigeria	0.93	4.55	3.61	2.56	4.55	1.99	0.72	4.55	3.83
Pakistan	0.34	4.55	4.21	10.20	4.55	-5.65	1.61	4.55	2.93
Saudi Arabia	0.31	4.55	4.23	17.97	4.55	-13.42	1.08	4.55	3.47
South Africa	0.62	4.55	3.93	1.91	4.55	2.63	0.51	4.55	4.03
Thailand	0.11	4.55	4.43	0.50	4.55	4.05	0.10	4.55	4.45
Turkey	0.23	4.55	4.32	3.40	4.55	1.14	2.18	4.55	2.37
Ukraine	1.38	4.55	3.17	25.22	4.55	-20.67	0.78	4.55	3.77
United Arab Emirates	0.19	4.55	4.35	5.13	4.55	-0.58	3.77	4.55	0.78
Total Connectedness Index (TCI)	25th Quartile (Low conditions): 94.08			50th Quartile (Medium conditions): 94.14			75th Quartile (High conditions): 93.91		

Source: Authors' calculations.

Table 1 reports the directional spillovers (FROM, TO, NET) across countries for the 25th, 50th, and 75th quantiles of the wealth distribution. The Total Connectedness Index (TCI) is 94.08 at the 25th quantile, 94.14 at the 50th quantile, and 93.91 at the 75th quantile. Egypt and India exhibit persistently negative NET values across all quantiles. Countries such as Thailand, China, Indonesia, Turkey, and several others show positive NET values in most cases.

Figure 1 presents the volatility spillover network across the 25th, 50th, and 75th quantiles. In the 25th quantile, ECI-Trade records a net spillover of +8.62 and per capita income -14.41. In the 50th quantile, per capita income shows +8.10 and economic freedom -9.68. In the 75th quantile, ECI-Trade is +8.08, per capita income -2.20, and economic freedom -5.44.

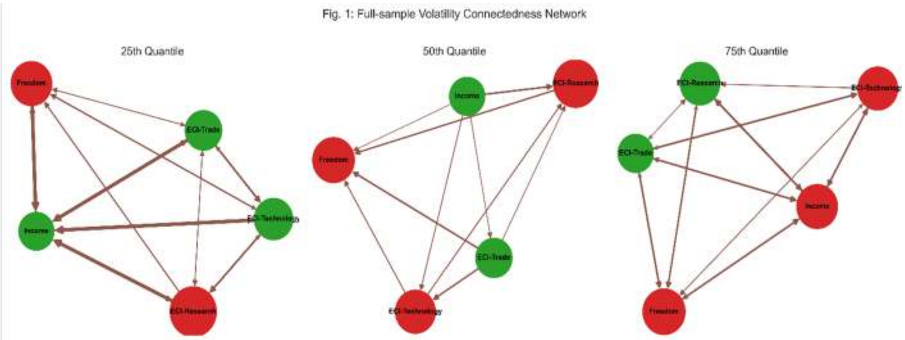


Fig 1. Network of Connections of Fluctuations between Variables

Source: Authors' calculations

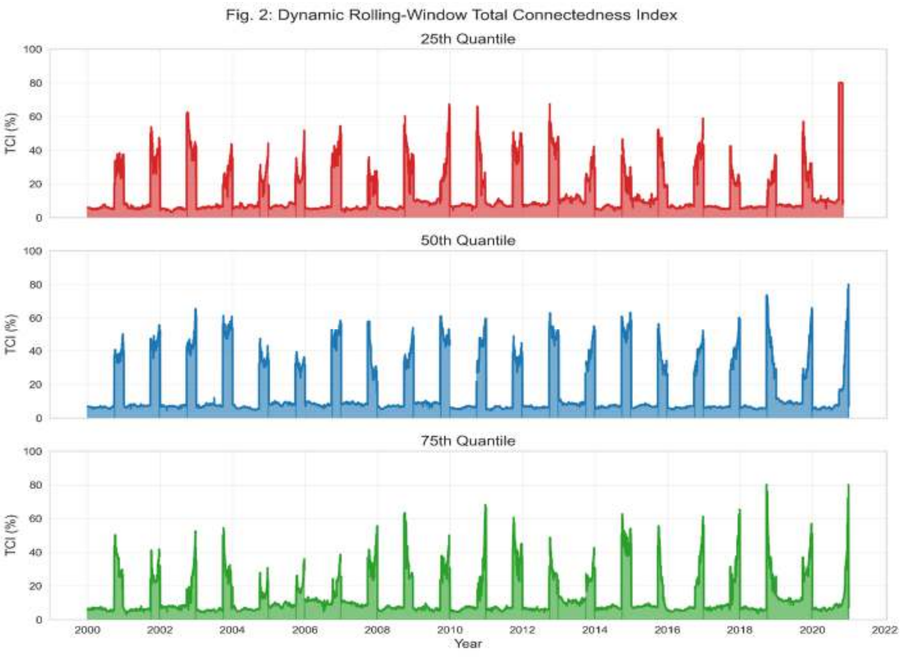
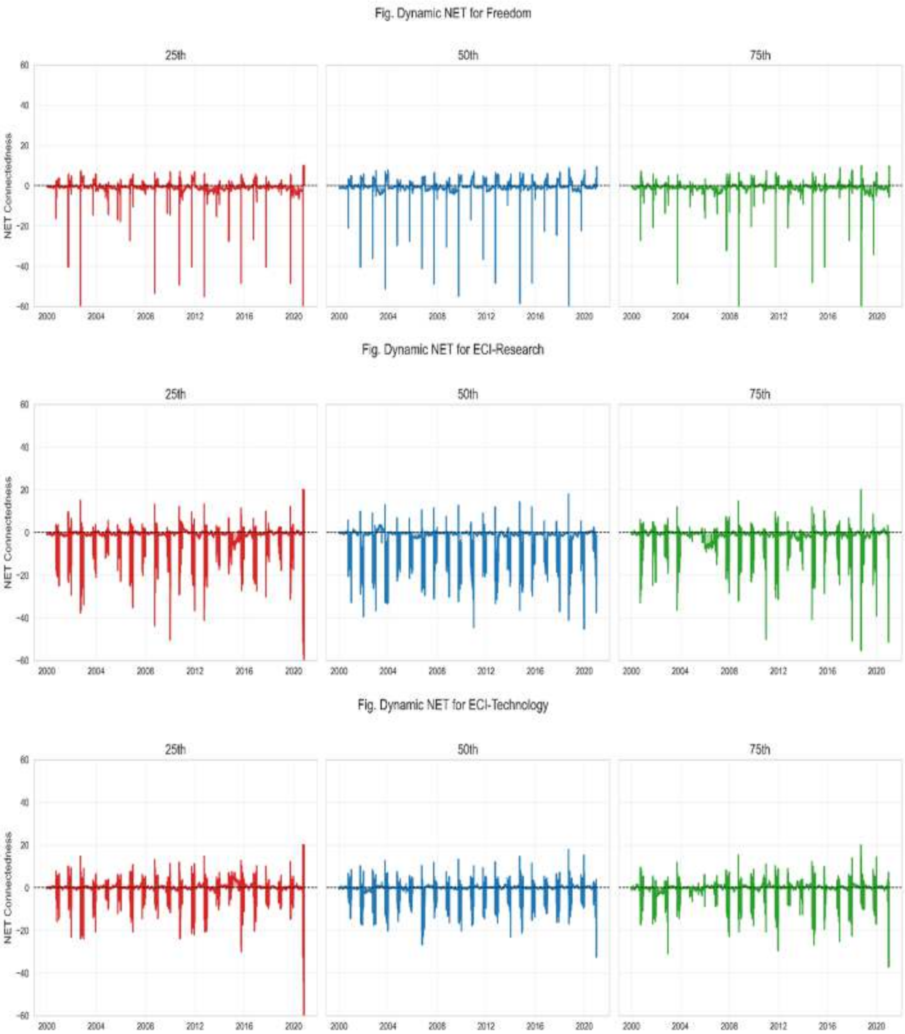


Fig 2. Dynamic Total Connectivity Index (TCI) in Rolling Windows of Conditional Wealth Quantiles

Source: Authors' calculations

Figure 2 shows the dynamic Total Connectedness Index (TCI) using a 100-day rolling window for the three quantiles. The TCI at the 25th quantile averages approximately 60% with frequent spikes above 80%. At the 50th quantile, it averages around 40% with smoother fluctuations. At the 75th quantile, it averages approximately 30% with occasional peaks.



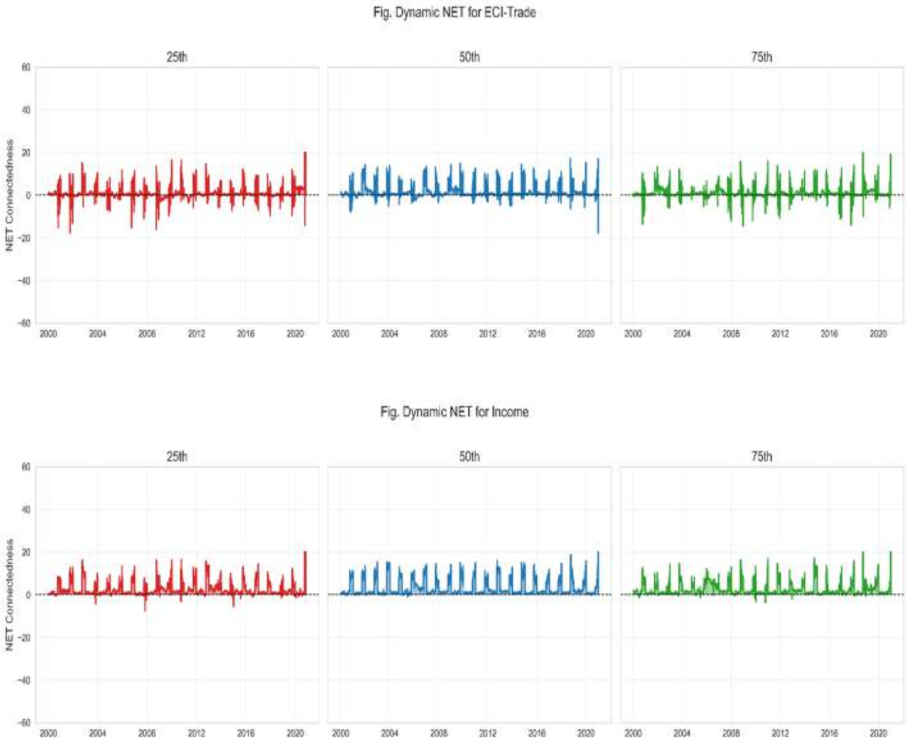


Fig 3. Dynamic Path of Net Spillover of Key Variables across Conditional Wealth Quantiles

Source: Authors' calculations.

Figure 3 displays the dynamic net spillovers (NET) for the five key variables across the three quantiles. At the 25th quantile, most variables show negative NET values with large fluctuations. At the 50th quantile, NET values oscillate near zero for most variables. At the 75th quantile, NET values fluctuate around zero with reduced amplitude.

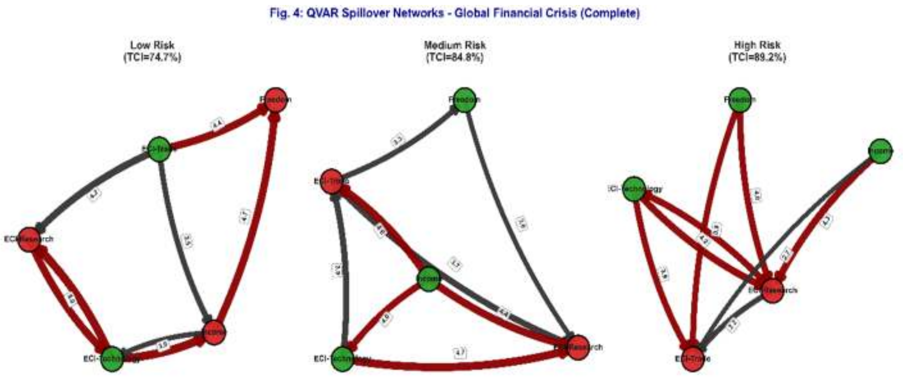


Fig 4. QVAR Volatility Spillover Network in the Global Financial Crisis (GFC). Figure 4 depicts the QVAR spillover network during the Global Financial Crisis at low, medium, and high risk levels.

Source: Authors' calculations.

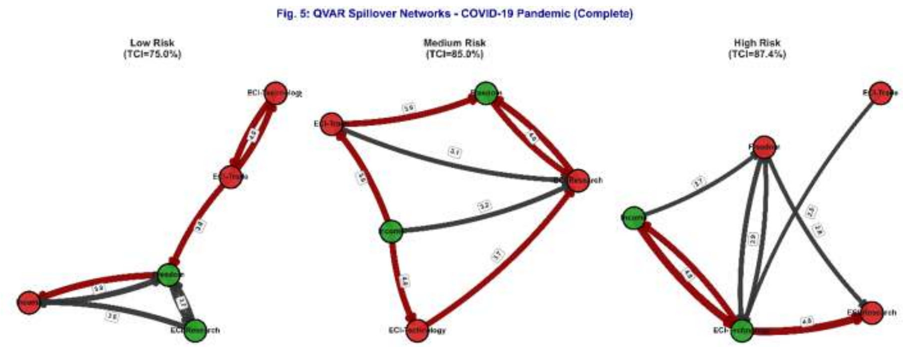


Fig 5. QVAR Volatility Spillover Network in the COVID-19 Pandemic.

Source: Authors' calculations

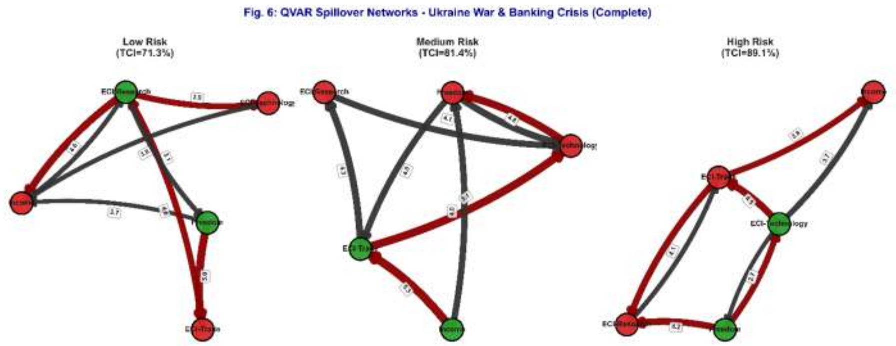


Fig 6. QVAR Volatility Spillover Network in the Ukraine War and the Collapse of SVB.
Source: Authors' calculations

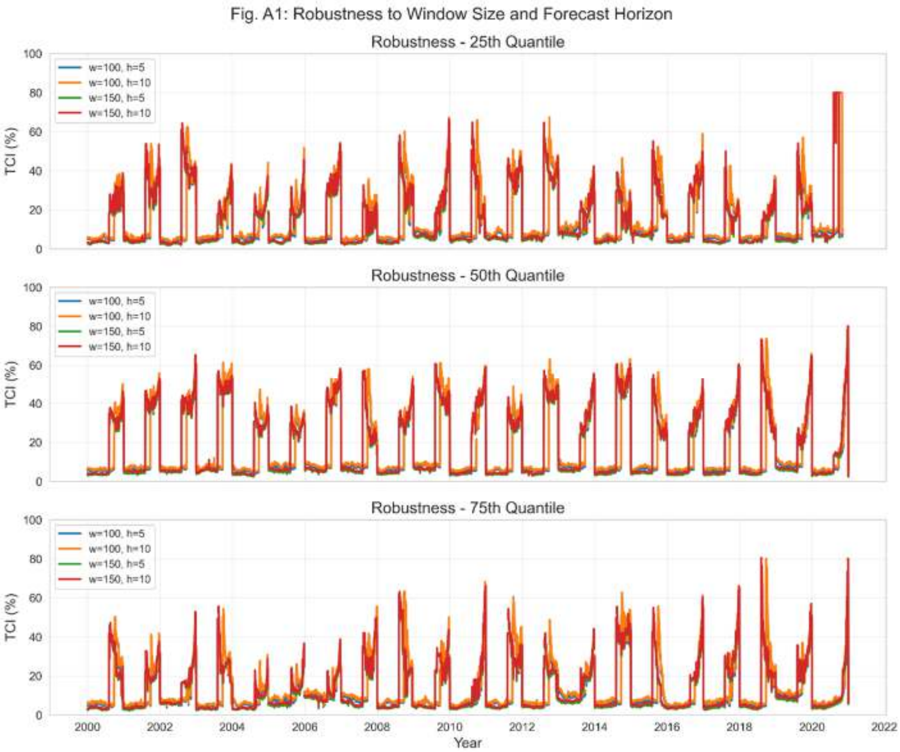


Fig 7. Stability Test of Results with Respect to Window Size and Forecast Horizon
Source: Authors' calculations.

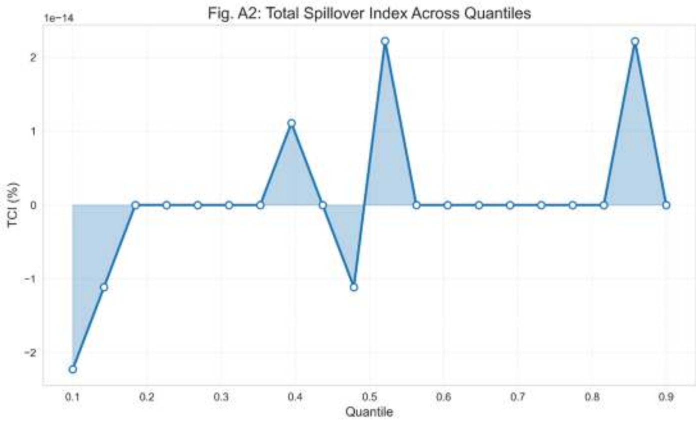


Fig 8. Total Spillover Connectivity Index across Wealth Distribution Quantiles
Source: Authors' calculations.

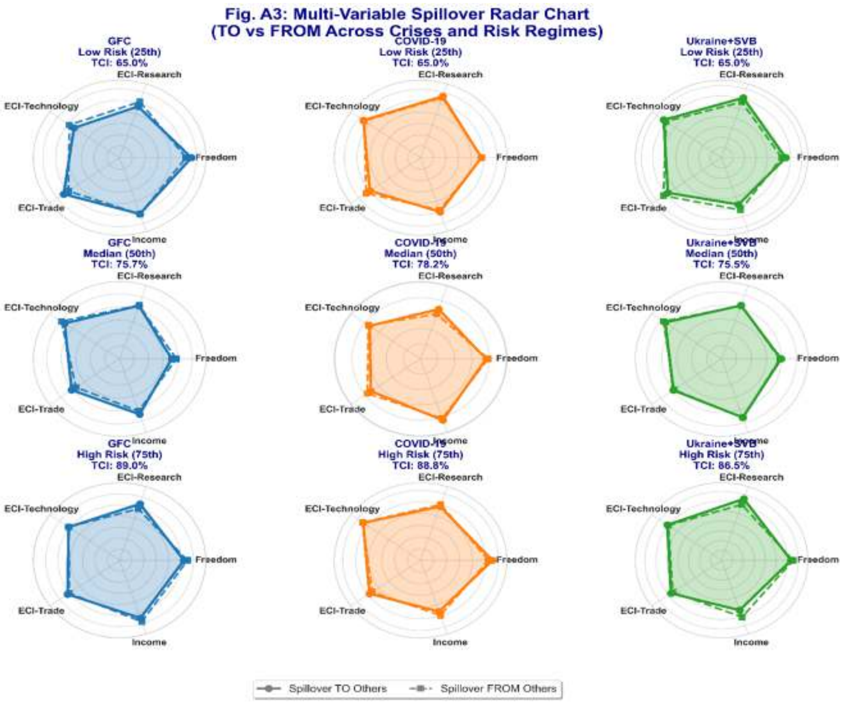


Fig 9. Multivariate Overflow Radar Chart (Sending to Others vs. Receiving from Others) across Crises and Risk Levels
Source: Authors' calculations.

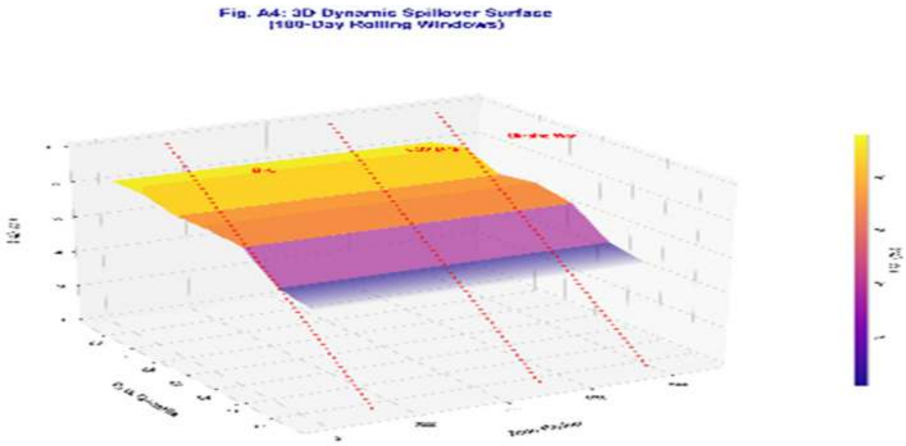


Fig 10. Dynamic Overflow Level in 3D Space (180-Day Rotating Window)
Source: Authors' calculations.

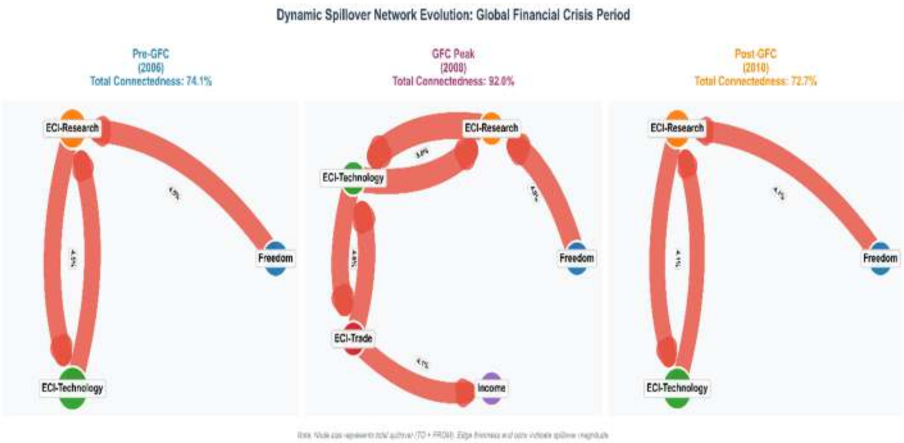


Fig11. Dynamic Evolution of the Spillover Network during the Global Financial Crisis
Source: Authors' calculations.

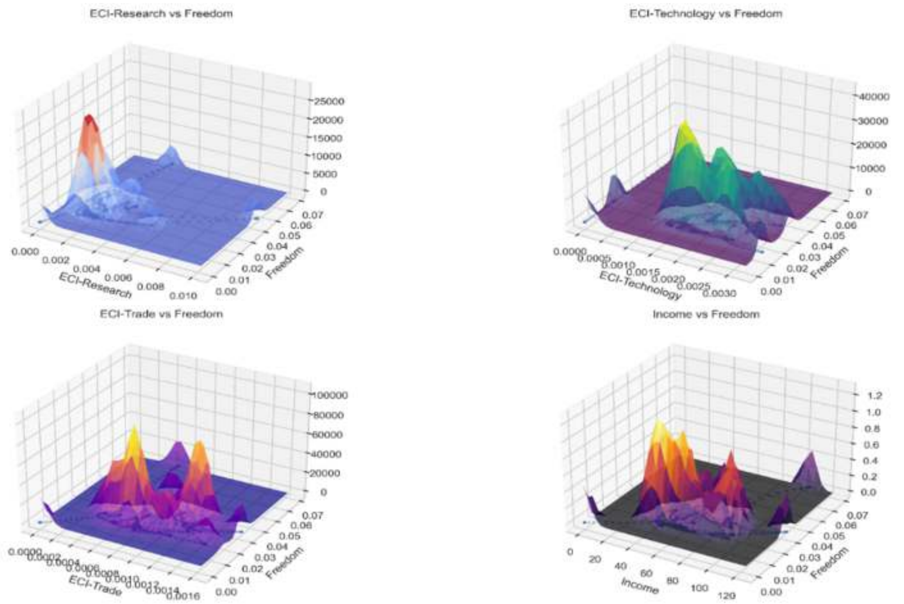


Figure 12. Three-Dimensional Surface of Pairwise Spillover versus Economic Freedom
Source: Authors' calculations.

5. Discussion

The empirical findings reveal pronounced heterogeneity in spillover dynamics across the conditional quantiles of the wealth distribution in developing countries. In lower quantiles — typically representing poorer economies — commercial complexity (ECI-Trade) consistently emerges as the dominant net transmitter of volatility, while per capita income acts as the most vulnerable net receiver. This pattern is consistent with the structural dependence of many low-income developing countries on relatively unsophisticated or commodity-based exports, which exposes them to external trade and price shocks (Hartmann et al., 2017). By contrast, in middle and especially higher quantiles, economic freedom assumes a more central stabilizing role, channeling positive spillovers from technological and research complexity toward wealth generation. These quantile-specific differences align closely with institutionalist theories, which posit that secure property rights, low transaction costs, and limited government interference amplify the growth benefits of productive knowledge and complexity (North, 1990; Balland et al., 2022). The persistent high levels of total connectedness (TCI ≈ 94% across quantiles) underscore the strong systemic interdependence among developing economies — a feature that differentiates them from more resilient advanced economies. The downward gradient in both the level and volatility of the TCI as one moves up the wealth distribution provides further evidence that institutional quality and higher degrees of economic complexity act as buffers against systemic instability. The distinctive mountain-shaped pattern of connectedness — peaking in intermediate wealth levels — offers new empirical support for the mechanisms underlying the middle-income trap: countries in this range achieve partial complexity gains but lack sufficient institutional depth to fully internalize the benefits and contain volatility. Crisis episodes (Global Financial Crisis, COVID-19 pandemic, and the combined Ukraine war & SVB collapse) markedly intensify connectedness, with spillovers predominantly flowing from complexity dimensions (particularly commercial and trade-related) toward income and institutional variables. At peak crisis moments, the networks become dense and bidirectional, indicating near-systemic collapse. However, post-crisis recovery phases exhibit a qualitatively different dynamic: positive spillovers originate primarily from technological and research complexity when supported by concurrent improvements in economic freedom. This observation lends strong support to the innovation-institution cycle hypothesis — crises initially propagate damage through trade and production linkages, but sustained recovery depends on upgrading knowledge-based capabilities within a strengthened institutional framework. Taken together, these results extend prior mean-based studies by demonstrating regime-dependent and asymmetric spillovers that remain hidden in conventional frameworks. They also highlight that policy interventions should be explicitly quantile-oriented: reinforcing export sophistication and institutional quality is especially critical for middle- and lower-middle-income countries facing elevated systemic risks.

6. Conclusion and Policy Implications

This study demonstrates that economic freedom and the multidimensional aspects of economic complexity exert asymmetric and quantile-dependent spillovers on national wealth in developing countries. Commercial complexity dominates shock transmission in lower wealth quantiles, rendering poorer economies particularly vulnerable to trade-related disruptions, while economic freedom provides a stabilizing influence in higher quantiles by facilitating the translation of technological and research capabilities into sustained growth. The elevated systemic connectedness during major crises, followed by recovery through innovation reinforced by institutional improvements, supports the innovation-institution cycle as a pathway out of structural vulnerabilities. These findings imply that policymakers in developing countries should prioritize reforms that simultaneously enhance institutional quality and productive sophistication. Strengthening property rights, reducing regulatory burdens, and promoting market openness can amplify the growth benefits of economic complexity. For resource-dependent economies like Iran, shifting toward export diversification through incentives for non-oil sectors, establishing dedicated industrial zones for medium-technology products, and allocating at least 1% of GDP to a national innovation fund for targeted R&D in areas such as clean energy, AI, and biotechnology would help mitigate external shocks and reduce reliance on commodities. Preventive measures, including foreign exchange stabilization funds and macro-insurance for exporters, along with regional knowledge-sharing initiatives, can further build resilience and support a transition toward shock-resistant, sustainable growth.

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Authors' contributions

All authors had contribution in preparing this paper.

Conflicts of interest

The authors declare no conflict of interest

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Appendix Table A1: Principal Component Analysis Results

PCA Summary:

Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
PC1	3.116	62.211	62.211
PC2	0.685	13.671	75.882
PC3	0.653	13.033	88.915
PC4	0.367	7.330	96.245
PC5	0.188	3.755	100.000

Source: Authors' calculations.

Factor Loadings

Variable	PC1	PC2	PC3	PC4	PC5
Economic Freedom	0.862	-0.057	-0.086	0.470	0.165
ECI-Research	0.712	-0.240	0.644	-0.001	-0.149
ECI-Technology	0.696	0.703	-0.033	-0.004	-0.152
ECI-Trade	0.766	-0.361	-0.479	-0.091	-0.216
Wealth	0.891	0.009	0.006	-0.372	0.263

Source: Authors' calculations.

Appendix Table A2: Comparison of Total Connectedness Index (TCI) under Daily vs. Quarterly Interpolation

Quantile	TCI (Daily Interpolation)	TCI (Quarterly Interpolation)
25th	94.08	93.75
50th	94.14	94.02
75th	93.91	93.85

Source: Authors' calculations.