Does economic complexity tame the stock markets? International evidence

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Abstract

Using panel data from 81 countries, we test whether economic complexity influences stock market volatility. Our results show that countries with more diverse and unique products (i.e., higher economic complexity) tend to experience higher asset-price stability. This relationship is particularly strong for emerging market economies. In additional tests, we find that the benefit of lower volatility kicks in after economic complexity breaches a certain threshold, below which the gains are either lower or insignificant. Our results are robust in response to concerns about endogeneity. Further analysis reveals that trade complexity significantly influences stock market stability more than technology and research complexities.

Keywords: Economic complexity, Financial markets, Non-linearity, Panel threshold, Trade complexity, Emerging markets

JEL Codes: G12, G15, G18

1. Introduction

Economic complexity, defined as the level of knowledge embedded in a country's production, influences a wide range of economic outcomes. According to Balland et al. (2022), the idea of economic complexity dates back as far as Adam Smith, and they write that "societies with very specialized individuals have access to a greater variety of knowledge and are, therefore, more diversified". Balland et al. (2022) argue that access to collective knowledge allows developed countries to supply a highly diversified set of products and services, which further fuels economic growth. As a result, countries with more complex economies can produce products and services where the knowledge requirements are diverse and unique (Hausmann et al., 2007).

The argument for economic complexity can also be connected to the Schumpeterian ideals of creative destruction and technological innovation as drivers of economic growth. However, economic complexity (i.e., the ability to integrate diverse technical know-how and convert it into production) has effects far beyond just economic growth. For instance, Hartmann et al. (2017) show that economic complexity is inversely related to income inequality, suggesting that as a nation's productivity increases, so does the quality of its education, thus contributing to greater income equality. Similarly, economic complexity is associated with lower sovereign risk premia (Özmen, 2019) and unemployment rates (Adam et al., 2023), and higher levels of foreign direct investments (Ranjbar and Rassekh, 2022) and long-run environmental quality (Lee and Williams, 2024; Li et al., 2024). Collectively, this strand of literature highlights the broad influence of economic complexity on key outcomes such as growth, inequality, sovereign risk, and labour market dynamics.

While complexity has an obvious connection with the real sector of the economy, it is unknown whether the effects are large enough to significantly impact the financial sector. For example, it remains unclear whether economic complexity as a metric is relevant to stock market investors. Therefore, to deepen our understanding of the linkages between economic complexity and financial markets, in this study, we examine whether economic complexity contains unique information about stock-market volatility. To our understanding, we are the first to analyse the impact of the economic complexity index (ECI) on the idiosyncratic volatility (IVOL) of stock indices of 81 countries.

Since economic complexity reflects the spatial and technological diversity of a country's production capabilities, it is reasonable to expect that it could influence business risks. Therefore, we address the following three research questions concerning the relationship between economic complexity and market volatility:

- RQ1: Does economic complexity (ECI) impact stock indices' idiosyncratic volatility (IVOL)? We consider idiosyncratic volatility instead of overall volatility because we want to remove the effects of global market returns on a country's stock markets.
- RQ2: Does the effect of ECI on IVOL vary across economies? Specifically, is there cross-sectional heterogeneity in this relationship among developed, emerging, and frontier markets?
- RQ3: Is there a non-linear relationship between ECI and IVOL, suggesting that the effect of complexity on volatility might change at different levels of economic sophistication?

Our results demonstrate a significant negative relationship between economic complexity and volatility, with idiosyncratic volatility decreasing as economic sophistication increases. However, the effect varies across different economies. We find that the impact of economic complexity on idiosyncratic volatility is more pronounced in emerging markets than in developed or frontier economies. Hence, for emerging markets, diversifying and enhancing the sophistication of production and knowledge creation is likely to contribute towards greater asset-price stability. Further, we use decomposed ECI indices to better understand the source of the complexity-volatility relationship. We find that the negative relationship between ECI and IVOL is driven by trade complexity, rather than technological or research complexity.

To address endogeneity concerns, we use an alternate econometric method, i.e., the dynamic panel regression (Arellano and Bond, 1991; Blundell and Bond, 1998). Our results are consistent across both fixed effects and dynamic panel methods, reinforcing the validity of our findings.

Further, to test for non-linearity, we used panel threshold regressions (Wang, 2015) and find the impact of complexity to be different across two regimes, i.e., above and below certain thresholds identified by the model. Following Neagu (2021), we find that economic complexity has a beneficial effect of reducing volatility when it surpasses a threshold (e.g., for emerging economies, volatility reduction is higher if the ECI is above the 60^{th} percentile of the ECI of all emerging markets). To summarize, our results show that economic complexity mitigates stock market risk, especially when a country reaches a threshold of sophistication in its production capabilities.

Our study contributes to the literature on economic complexity and finance in multiple ways. The existing literature on economic complexity primarily concerns the relationship between complexity and other macroeconomic factors. To our understanding, we are the first to explore the connection between economic complexity and asset price volatility. Second, we also explore non-linearity in the volatility-complexity relationship by estimating the effect across economies with different levels of development and complexity. Our results carry important evidence for policymakers, allowing them to better look into the cost of sophistication of the production process vs its benefits.

The rest of the paper is structured as follows: we discuss the existing literature on economic complexity and our hypotheses in section 2. The data and methodology are in section 3, and the results are in section 4. Section 5 addresses endogeneity concerns. We conclude the study in section 6.

2. Literature Review

2.1 Economic Complexity and the Economy

Economic complexity reflects the level of knowledge incorporated in an economy's productive structure. Literature has ample evidence that the development of a nation depends on the number of activities in the economy and the complexity emerging from the interaction of these activities. Hidalgo and Hausmann (2009) discuss that a country's productivity comes from unexplored combinations of existing capabilities or developing new ones. Economic complexity has a greater potential role in the growth of economies that are yet to explore existing capabilities, as these are expected to grow faster than countries that can only grow through new capabilities.

The higher the products of a country are placed on the quality spectrum, the better the country's performance. Hence, countries that export more complex goods have higher economic growth (Hausmann et al., 2007). Stojkoski et al. (2016) analyse the contribution of the service sector to economic development and report that sophistication and diversification of services contribute to economic growth in developed and developing nations. Lapatinas (2016) report a positive correlation between social development (or quality of life) and economic diversification. Economic complexity also positively relates to human capital and enhances the positive effect of human capital or education level on short- and long-term economic growth (Hausmann et al., 2014; Zhu and Li, 2017).

Further, literature provides evidence on the influence of economic complexity on various parameters. Higher economic complexity leads to higher GDP growth (Koch, 2021), employment (Adam et al., 2023), environmental patents and better environmental policies (Mealy and Teytelboym, 2022). It is also negatively related to industrial inefficiency in developed countries (Ghasemkhani et al, 2023), CO_2 emissions (Mealy and Teytelboym, 2022), and carbon emission spillover (Ren et al., 2025).

2.2 Measuring Economic Complexity

Complexity research in economics deals with the modelling of economies with multiple heterogeneous agents interacting with each other in a dynamically evolving system. Scholars in the domain often invoke parallels to other complex systems in natural sciences (e.g. dissipative systems, chaos theory, etc.). A reader is referred to Nomaler and Verspagen (2024) for a brief review of the state of complexity research in economics. With the high level of interaction among various economic agents (firms, countries, national, regional, and global institutions), the measurement of economic complexity becomes a complex task in itself.

Therefore, capturing the complexity of an economy in a single indicator is a challenging task that involves capturing the diversity and technical know-how of products and services produced into a unified metric. Studies have proposed various indicators to capture the dimensions of economic complexity (Cristelli et al., 2013; Koch, 2021; Inoua, 2023). In this study, we use the Economic Complexity Index (hereafter *ECI*) from Harvard Growth Lab's website (https://atlas.hks.harvard.edu/rankings) as a measure of economic complexity (Hausmann et al., 2014). The method employed to compute ECI is similar to Google's algorithm to rank webpages, i.e., the complexity of a country is computed relative to that of other countries (Inoua, 2023). While constructing the ECI, an economy is considered to be more complex if it exports more complex and diversified products. The measure mainly considers two components based on the basket of products being exported: (a) diversity and (b) ubiquity. The first component captures the number of products in the export basket, and the second represents the number of countries exporting similar products. The index is standardized and usually ranges between -3 (low complexity) and +3 (high complexity), with a higher score indicating stronger and more sophisticated production capabilities. Hence, a lower ECI would either mean that the country is exporting fewer types of products or that many other nations are also exporting the products exported by them.

The data for the ECI is available via the *'Atlas of Economic Complexity'*, a visualisation tool that tracks export-import data of different countries to generate their complexity index and ranking.

2.3 Hypotheses

Higher output volatility, proxied by the standard deviation of real GDP per capita growth rate, has a negative relationship with economic growth (Ramey and Ramey, 1995; Acemoglu et al., 2003). Recent studies show that higher economic complexity is associated with reduced output volatility (Güneri and Yalta, 2021 and Nguyen and Schinckus, 2023), leading to higher economic growth and lower vulnerability to external shocks. Gomez-Gonzalez et al. (2023), using a comprehensive dataset of 172 countries, show that a one-point increase in economic complexity reduces the probability of a fiscal crisis by half, thus contributing to overall economic stability. Overall, the literature shows the potential of economic complexity to contribute to the stability of various economic parameters. Extending this finding to the stock market, we hypothesize the following effect of economic complexity on stock market volatility:

H1: *Economic complexity is negatively related to the idiosyncratic volatility.*

Economic complexity is broadly shown to contribute to the growth and resilience of an economy. However, its effect can vary depending on the maturity and institutional structure of the country. While developed countries hold more than half of the global wealth, other nations are still working on their human capital, economic growth, technology infrastructure, etc (Huang et al., 2022). The variation in economic factors can have different implications on these nations. For instance, Mushtaq et al. (2025) demonstrate that government expenditures, institutional quality, and capital flows increase economic growth volatility in developing countries, while decreasing it for developed countries. Similarly, economic complexity negatively impacts the pollution level and GINI index in developed or high-income countries but increases the same for developing or low-income nations (Huang et al., 2022; Lee and Vu, 2020). Hence, we consider the following hypothesis to examine this heterogeneity.

H2: *The effect of economic complexity varies with the level of economic development.*

Economic complexity may impact outcomes differently at a lower level compared to a higher level. Nguyen et al. (2023) report that economic complexity increases income inequality till a certain threshold. Thereafter, inequality decreases with higher complexity. Similarly, Peng et al. (2022) exhibit an inverted U-shaped relationship between economic complexity and CO_2 emissions, such that low levels of complexity increase emissions, whereas high levels may help curb them. In the initial stages, countries produce products that lead to environmental degradation. However, a higher level of development increases the preference for cleaner and innovative technologies. Our following hypothesis explores the possibility of a similar nonlinear relationship between economic complexity and idiosyncratic volatility, where the effect of economic complexity on volatility depends upon the complexity level.

H3: *Economic complexity has a non-linear relation with the idiosyncratic volatility.*

3. Data and methodology

We collect the data for stock indices of 81 countries from 2007 to 2022. The economic complexity indicator is available till 2022. The names of the countries, the stock index chosen from each country, and the countries' MSCI classification are listed in Table A1 (Appendix). Variables considered in this study are discussed below.

3.1 Dependent variable

Idiosyncratic volatility (IVOL) is computed using the Fama-French 3-factor model (Fama and French, 1993) as shown in equation 1. We use the global asset-pricing factor data [namely, the market risk premium (MKT), size premium (SMB), and value premium (HML)] from Kenneth French's data library. We use the following model to eliminate the variation in a country's index return that can be attributed to global factors, thus leaving only the country-specific returns as the residuals of the regression. Thereafter, we calculate the IVOL for a given year as the standard deviation of daily residuals for that year (in % per day).

$$Return_{i,t} = \beta_0 + \beta_1.MKT_t + \beta_2.SMB_t + \beta_3.HML_t + e_{i,t} \tag{1}$$

Where, $Return_{i,t}$ is the daily return of the stock index of country i on day t. Similarly, MKT_t, SMB_t, and HML_t are the daily factor returns of the global Fama-French factors on day t.

3.2 Independent variable

Following Hausmann et al. (2014), we consider Economic Complexity Index (ECI) as the proxy for economic complexity. Harvard Growth Lab publishes ECI data for countries that meet the following criteria-

(a) Published GDP and export data

(b) A population greater than 1 million

(c) Average trade above $ 1 Bn

Considering the above criteria, reliable ECI data is available for 133 countries. From this cohort, the countries with a stock index have been considered for the analysis, leading us to a sample of 81 countries worldwide.

3.3 Control variables

Following Caglayan et al. (2020), we include the following variables known to affect idiosyncratic volatility in our model:

- *GDP growth rate (GDPG):* downloaded from the World Development Indicators (WDI) database. It indicates economic growth (Diebold and Yilmaz, 2008).
- *Forex and gold reserves (RESERVES):* Total reserves as a percentage of GDP (both in US$). Also from the WDI database, it is a measure of foreign exchange stability (Blau, 2018; Raza et al., 2016).
- *Stock market performance (MKT-PERF)*: logarithmic difference of respective stock index prices (Li et al., 2005).
- *Corruption perception index (CPI)*: published by Transparency International (https://www.transparency.org/en/cpi/), controls for the political stability of an economy. The index ranges from 0 to 100, with 0 being the most corrupt and 100 the cleanest country. As discussed in the literature, higher corruption increases idiosyncratic risk (Zhang, 2012).

Table 1: Descriptive statistics

	N	Mean	Std. dev.	Min	Max
IVOL	1,201	0.011	0.006	0.002	0.045
ECI	1,201	0.519	0.915	-2.085	2.556
GDPG	1,201	0.029	0.042	-0.214	0.245
RESERVES	1,201	0.202	0.213	0.003	1.549
MKT-PERF	1,201	-0.003	0.317	-1.520	1.607
CPI	1,201	52.771	19.885	20.000	95.000

GDP growth rate, forex and gold reserves, and stock market performance generally have a negative impact on idiosyncratic volatility, whereas corruption is positively related to it. All variables are considered at an annual frequency. Tables 1 and 2 present the descriptive statistics and the correlation matrix, respectively, for all variables.

Table 2: Correlation matrix

	IVOL	ECI	GDPG	RESERVES	MKT-PERF	CPI
IVOL	1.000					
ECI	-0.180	1.000				
GDPG	-0.100	-0.197	1.000			
RESERVES	-0.023	0.071	-0.007	1.000		
MKT-PERF	-0.314	0.005	0.021	0.068	1.000	
CPI	-0.287	0.555	-0.150	-0.098	0.012	1.000

4. Empirical analysis

4.1 Baseline results

In this section, we analyse the impact of economic complexity on stock-market volatility. As discussed earlier, we use the GDP growth rate, forex and gold reserves, stock market performance, and corruption perception index as the control variables. Thus, we consider the following model to examine the relationship between complexity and volatility. We employ Panel OLS regressions with both country (μ) and time (τ) fixed-effects to control our variables' cross-sectional (country) and time (year) heterogeneity. The results of this model are presented in Table 3.

$$IVOL_{i,t} = \alpha_0 + \alpha_1.ECI_{i,t} + \alpha_2.GDPG_{i,t} + \alpha_3.RESERVES_{i,t} + \alpha_4.MKT - PERF_{i,t} + \alpha_5.\mathrm{CPI}_{i,t} + \mu + \tau + e_{i,t} \tag{2}$$

Where, i and t indicate country and year, respectively.

As shown in Table 3, the Economic Complexity Index (ECI) has a negative relationship with stock market volatility (IVOL). Hence, as an economy becomes more complex, its stock market becomes more stable. These results support our first hypothesis and align with Gnangnon (2022) and Eichengreen and Gupta (2013), who argue that higher complexity increases the economy's penetration into the international market, thereby developing a network and diversifying its exports. An increased ability to produce technologically sophisticated products and services can lead to stronger economic growth, attracting both domestic and international investments. Furthermore, a diversified economy not reliant on a single sector faces lower economic fluctuations, which helps stabilize corporate earnings and cash flows (Canh and Thanh, 2022; Balland et al., 2022). Overall, on average, higher complexity contributes to more business and economic stability and subsequently, lower volatility in stock market returns.

Table 3: Results of fixed effects panel regressions of idiosyncratic volatility on economic complexity and other control variables.

	All Countries (1)	Developed (2)	Emerging (3)	Frontier & Standalone (4)
ECI	-0.004**	0.000	-0.006**	-0.005
	(-2.870)	(0.540)	(-2.730)	(-1.370)
GDPG	-0.015**	-0.007*	-0.016	-0.021**
	(-2.150)	(-1.760)	(-0.990)	(-2.600)
RESERVES	-0.001	0.001	-0.001	-0.008
	(-0.340)	(1.640)	(-0.420)	(-1.100)
MKT-PERF	-0.003*	-0.002	-0.002	-0.003**
	(-2.130)	(-1.320)	(-0.720)	(-2.220)
CPI	-0.000	0.000	-0.000**	-0.000
	(-0.830)	(1.410)	(-2.900)	(-1.180)
Constant	0.016***	0.003	0.027***	0.018***
	(4.580)	(0.940)	(7.120)	(3.440)
N	1,201	352	365	363
R^2 (Within)	0.087	0.074	0.170	0.140

*Note: Table 3 presents the results of specification (1) using panel fixed effects regression with IVOL as the dependent variable. Both time and cross-section fixed effects have been controlled for. T-statistics are given in parentheses. *** denotes a significance level of 1%, ** for 5%, and * for 10%. 0.000(-0.000) shows a coefficient lower than 0.0005(-0.0005).*

4.2 Effect of the level of economic development on the complexity-volatility relationship

Our sample includes countries at different levels of development and from various geographical regions. Combining all these countries into a single homogeneous group could obscure their cross-sectional diversity. Although fixed effects can account for time-invariant factors influencing our model, they do not capture the cross-sectional differences in effect sizes across countries.

Therefore, to account for differences in market structure, regulations, governance, and information disclosure practices across countries, we conduct a sub-sample analysis of developed, emerging, and frontier economies. These results are reported in Table 3. As per the results, the effect of economic complexity on volatility is most pronounced in emerging economies. Therefore, diversity and ubiquity of products bring more stability in countries that are in an intermediate stage of development. Our findings support Rondeau and Roudaut (2014), who argue that the benefits of trade diversification tend to decrease with the level of GDP per capita, i.e. economic development. Overall, in support of our second hypothesis, we find that the impact of economic complexity on stock market volatility varies with the level of economic development, with the effects mainly concentrated in emerging economies.

4.3 Non-linearity

In the earlier sections, we observe a negative relationship between ECI and IVOL. However, these analyses do not account for potential nonlinearity in the relationship between the explanatory and dependent variables. There are multiple reasons to believe that the relationship between economic complexity and idiosyncratic volatility may be non-linear. While product sophistication might bring development and stability, highly complex economies are likely to be deeply integrated into global value chains. For example, Acemoglu et al. (2016) show that shocks to individual firms can propagate to the entire economy via complex input-output linkages. Highly complex systems can, therefore, counterintuitively become more exposed to certain shocks, and any additional complexity in such a situation is likely to create more volatility rather than less. Ranjbar and Rassekh (2022) also argue that for foreign direct investment to induce growth in an economy, it must surpass a certain threshold level of complexity. These studies indicate the non-linear effects of economic complexity on economic outcomes.

Therefore, we test for non-linear relation between ECI and IVOL using panel threshold regressions (Wang, 2015). This method computes a threshold value (q) of the independent variable and splits it into two (or more) regimes. It then tests whether the relation between explanatory and dependent variables changes across regimes. Table 4 presents the results of the panel threshold analysis. For the overall sample, ECI has a weak influence over IVOL below the threshold value. However, the effect is more substantial once the ECI crosses a threshold. These findings support our third hypothesis regarding non-linearity in the relation between complexity and volatility. The results also align with findings on the advantageous impact of economic complexity after surpassing a certain threshold (Nguyen et al., 2023; Peng et al., 2022).

Table 4: Panel threshold analysis for full sample and sub-samples

	All Countries (1)	Developed (2)	Emerging (3)	Frontier & Standalone (4)
ECI (<q)	-0.003* (-1.680)	0.006*** (4.920)	-0.008*** (-3.670)	-0.002 (-1.010)
ECI (>q)	-0.005*** (-3.180)	0.001 (0.700)	-0.015*** (-9.480)	-0.005** (-2.620)
GDPG	-0.025***	-0.032***	-0.034***	-0.013*
	(-4.610)	(-6.880)	(-2.900)	(-1.830)
RESERVES	-0.000	-0.000	-0.003	0.002
	(-0.180)	(-0.220)	(-1.170)	(0.460)
MKT-PERF	-0.005***	-0.006***	-0.005***	-0.004***
	(-5.890)	(-25.750)	(-3.550)	(-7.780)
CPI	-0.000	0.000**	-0.000**	-0.000**
	(-1.450)	(2.340)	(-2.860)	(-2.280)
Constant	0.021***	-0.003	0.034***	0.020***
	(4.630)	(-0.590)	(9.180)	(4.690)
N	1,040	352	336	288
R^2 (Within)	0.227	0.468	0.361	0.253

*Note: Table 4 presents the results of specification (1) using panel threshold regression with IVOL as the dependent variable. T-statistics are given in parentheses. *** denotes a significance level of 1%, ** for 5%, and * for 10%. 0.000(-0.000) shows a coefficient lower than 0.0005(-0.0005).*

Another interesting story emerges in the sub-sample analyses. In the case of developed economies, complexity below a threshold increases volatility, whereas there is no significant relation above the threshold. For emerging economies, complexity reduces volatility in both regimes, but the decrease is higher when complexity breaches the threshold value. Finally, the frontier markets only benefit from ECI if it is above a certain threshold. We further analyse the dynamics of these findings by reporting the threshold values in Table 5.

Table 5 shows a clear pattern where threshold values and percentiles increase as we move from developed to frontier economies. Specifically, this indicates that less developed economies need to achieve a higher level of complexity relative to their peers to avail of the benefits of economic complexity. In other words, the more underdeveloped an economy is, the greater the level of sophistication and diversity in its production capabilities required to observe a reduction in asset-price volatility. Therefore, economic complexity is more critical in driving stability and risk reduction in less advanced economies than their more developed counterparts.

Table 5: ECI threshold statistics

	All Countries (1)	Developed (2)	Emerging (3)	Frontier & Standalone (4)
Min	-2.085	-0.708	-1.502	-2.085
Threshold value	*0.979*	*-0.503*	*0.678*	*0.967*
Threshold Percentile	*65.00%*	*2.20%*	*62.60%*	*90.80%*
Median	0.542	1.378	0.292	-0.073
Max	2.556	2.556	2.170	1.711

Note: Table 5 presents the values of thresholds obtained in the panel threshold regressions and compares them with the minimum, median, and maximum values of economic complexity in the sample. The threshold value gives the threshold value, whereas the threshold percentile shows the proportion of values in the sample that lie below the threshold value.

To summarize the evidence, the less developed an economy, the more they have to be above their peers in economic complexity to gain the advantages of reduced business risks. For developed economies, higher complexity is needed to maintain their stability rather than as a tool to become more stable. Our results demonstrate a non-linear relationship between ECI and IVOL, wherein higher economic complexity stabilizes stock markets. However, the effect primarily exists when the ECI breaches a threshold value.

4.4 Sub-component analysis

Most of the complexity measures used in the literature are centred on trade data. This approach underrates the complexity of the countries that are developing advanced technologies but are not linked to global markets. It also misses out on certain critical and innovative aspects, such as research publications and patent applications (Stojkoski et al., 2023). These factors can play a significant role in transforming production techniques, which can potentially affect workers' skills and compensation. To overcome these limitations of prior measures, Stojkoski et al. (2023) introduced a multi-dimensional approach to complexity that includes data on exports, patents, and scientific publications. They compute three distinct indices for economic complexity, namely, *trade complexity* (based on export data), *technology complexity* (based on patent applications data), and *research complexity* (utilising published documents data).

Table 6: Results of fixed effects panel regressions of idiosyncratic volatility on the trade complexity and other control variables.

	All Countries (1)	Developed (2)	Emerging (3)	Frontier & Standalone (4)
TRADE ECI	-0.005***	-0.001	-0.006**	-0.003
	(-3.360)	(-0.780)	(-2.660)	(-1.220)
GDPG	-0.012*	-0.007**	-0.010	-0.023**
	(-1.800)	(-2.410)	(-0.610)	(-2.160)
RESERVES	0.000	0.002*	0.001	-0.006
	(0.100)	(2.030)	(0.450)	(-0.720)
MKT-PERF	-0.003*	-0.002	-0.002	-0.004**
	(-2.050)	(-1.510)	(-0.790)	(-2.850)
CPI	-0.000**	0.000*	-0.000***	-0.000
	(-2.180)	(1.790)	(-3.230)	(-0.740)
Constant	0.019***	0.004	0.028***	0.016**
	(7.620)	(1.380)	(7.540)	(2.650)
N	1,168	374	388	312
R^2 (Within)	0.079	0.083	0.138	0.112

*Note: Table 6 presents the results of specification (1) using panel threshold regression with IVOL as the dependent variable and the Trade complexity as the independent variable. T-statistics are given in parentheses. *** denotes a significance level of 1%, ** for 5%, and * for 10%. 0.000(-0.000) shows a coefficient lower than 0.0005(-0.0005).*

In this section, we analyse the potential of all three sub-components to influence the stock market stability. The sub-component complexity data have been downloaded from the Observatory of Economic Complexity (OEC) website[1]. We analyse the impact of ECI on idiosyncratic volatility, but this time replacing the aggregated ECI (the independent variable) with trade, technology, and research ECI scores. The results are summarized in Tables 6, 7, and 8. We use Panel regressions with both country and time fixed effects. As seen in the tables below, it can be said that trade complexity has a significant influence over stock markets, as IVOL decreases with an increase in trade complexity. On the other hand, technology and research complexities are largely insignificant. Hence, we can say that our aggregate ECI findings are driven by trade complexity, rather than technological or research complexity. These findings extend support to Sezgin et al. (2025), who describe a negative association between international trade and idiosyncratic volatility.

[1] https://oec.world/en/rankings/eci/hs6/hs96?tab=table

Table 7: Results of fixed effects panel regressions of idiosyncratic volatility on the technology complexity and other control variables.

	All Countries (1)	Developed (2)	Emerging (3)	Frontier & Standalone (4)
TECH ECI	0.000	-0.001	0.001	-0.001
	(0.330)	(-1.230)	(1.080)	(-0.930)
GDPG	-0.012*	-0.009**	-0.002	-0.032***
	(-1.900)	(-2.530)	(-0.090)	(-3.080)
RESERVES	0.001	0.001***	0.002	-0.003
	(0.480)	(2.980)	(0.550)	(-0.630)
MKT-PERF	-0.002	-0.002	-0.001	-0.003*
	(-1.270)	(-1.060)	(-0.440)	(-1.940)
CPI	-0.000*	0.000	-0.000***	-0.000
	(-2.100)	(1.250)	(-3.360)	(-0.720)
Constant	0.018***	0.005	0.026***	0.015**
	(5.250)	(1.320)	(6.150)	(2.510)
N	974	330	340	245
R^2 (Within)	0.051	0.068	0.004	0.172

*Note: Table 7 presents the results of specification (1) using panel threshold regression with IVOL as the dependent variable and the Technology complexity as the independent variable. T-statistics are given in parentheses. *** denotes a significance level of 1%, ** for 5%, and * for 10%. 0.000(-0.000) shows a coefficient lower than 0.0005(-0.0005).*

Table 8: Results of fixed effects panel regressions of idiosyncratic volatility on the research complexity and other control variables.

	All Countries (1)	Developed (2)	Emerging (3)	Frontier & Standalone (4)
RESEARCH ECI	0.002**	0.001	0.001	0.001
	(2.840)	(1.340)	(1.040)	(1.250)
GDPG	-0.011	-0.007**	-0.012	-0.024**
	(-1.620)	(-2.280)	(-0.720)	(-2.400)
RESERVES	-0.001	0.001	0.002	-0.006
	(-0.350)	(1.230)	(0.910)	(-0.740)
MKT-PERF	-0.002*	-0.002	-0.002	-0.004**
	(-1.850)	(-1.580)	(-0.650)	(-2.810)
CPI	-0.000*	0.000*	-0.000***	-0.000

	(-1.920)	(1.770)	(-3.360)	(-0.870)
Constant	0.016***	0.002	0.025***	0.018**
	(5.240)	(0.750)	(6.670)	(2.820)
N	1,177	374	388	314
R^2 (Within)	0.061	0.091	0.111	0.114

*Note: Table 8 presents the results of specification (1) using panel threshold regression with IVOL as the dependent variable and the Research complexity as the independent variable. T-statistics are given in parentheses. *** denotes a significance level of 1%, ** for 5%, and * for 10%. 0.000(-0.000) shows a coefficient lower than 0.0005(-0.0005).*

5. Additional tests for endogeneity

To assess the robustness of our baseline results, we estimate a dynamic panel model using the system GMM estimation procedure (Arellano and Bond, 1991; Blundell and Bond, 1998). This approach addresses key issues such as omitted variable bias, endogeneity, and the inherent inertia in the variables by incorporating lagged values of the dependent variable as independent variables (Amidu and Harvey, 2016). The results from the dynamic panel estimation are presented in Table 9. We find a significant negative relationship between ECI and IVOL for the overall sample. In the sub-sample analysis, similar to the previous findings, the IVOL of developed economies is not influenced by ECI, while in emerging and frontier markets, the coefficients for ECI are negative and significant at the 10% level. Since the results in Table 9 are consistent with those in Table 3, we conclude that an increase in economic complexity reduces stock market volatility.

Table 9: Dynamic panel analysis for full sample and sub-samples

	All Countries (1)	Developed (2)	Emerging (3)	Frontier & Standalone (4)
ECI	-0.005**	0.001	-0.006*	-0.005*
	(-2.480)	(0.820)	(-1.660)	(-1.680)
GDPG	-0.030***	-0.033***	-0.030***	-0.025**
	(-5.250)	(-5.200)	(-3.530)	(-2.010)
RESERVES	0.002	0.000	0.001	-0.001
	(0.940)	(0.030)	(0.340)	(-0.240)
MKT-PERF	-0.005***	-0.005***	-0.005***	-0.004***
	(-8.060)	(-18.200)	(-4.200)	(-7.900)

CPI	0.000	0.000	-0.000*	0.000
	(0.580)	(0.450)	(-1.760)	(1.150)
Constant	0.012***	0.007***	0.021***	0.007*
	(6.120)	(2.590)	(7.110)	(1.910)
N	1,201	352	365	363
AR(1) p-value	0.000	0.002	0.008	0.038
AR(2) p-value	0.016	0.127	0.115	0.545
Hansen p-value	0.517	0.142	0.988	0.203

*Note: Table 9 presents the results of specification (1) using dynamic panel estimation with IVOL as the dependent variable. T-statistics are given in parentheses. *** denotes a significance level of 1%, ** for 5%, and * for 10%. 0.000(-0.000) shows a value lower than 0.0005(-0.0005).*

6. Concluding remarks

We examine the impact of economic complexity on stock-market volatility in 81 countries. Our findings show that stock markets experience a drop in idiosyncratic volatility following an increase in economic complexity. This effect is much more substantial for emerging markets. The observed decline in volatility tends to be higher when complexity crosses a particular threshold value, and the threshold value is relatively higher at lower levels of development. Our results remain robust to concerns about endogeneity. Further, trade complexity appears to be a higher explanation for volatility in the emerging markets. The findings suggest that the economic complexity of a country is a crucial factor affecting its stock market volatility. Therefore, ECI has the potential to be an input factor while designing investment strategies and developing volatility forecasting models.

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Appendix

Table A1: Countries with their respective indices and MSCI classification.

Country	Index	Classification	Country	Index	Classification
Australia	AS51 Index	Developed	Saudi Arabia	SASEIDX Index	Emerging
Austria	ATX Index	Developed	South Africa	JALSH Index	Emerging
Belgium	BEL20 Index	Developed	Thailand	SET Index	Emerging
Canada	SPTSX Index	Developed	Turkey	MXTR Index	Emerging
Denmark	KFX Index	Developed	United Arab Emirates	ADSMI Index	Emerging
Finland	HEX25 Index	Developed	Bahrain	BHSEASI Index	Frontier
France	CAC Index	Developed	Bangladesh	DSEX Index	Frontier
Germany	DAX Index	Developed	Croatia	CRO Index	Frontier
Ireland	ISEQ Index	Developed	Estonia	TALSE Index	Frontier
Israel	TA-125 Index	Developed	Jordan	JOSMGNFF Index	Frontier
Italy	FTSEMIB Index	Developed	Kazakhstan	KZKAK Index	Frontier
Japan	NKY Index	Developed	Kenya	NSEASI Index	Frontier
Netherlands	AEX Index	Developed	Latvia	RIGSE Index	Frontier
New Zealand	NZSE Index	Developed	Lithuania	VILSE Index	Frontier
Norway	OSEAX Index	Developed	Mauritius	SEMDEX Index	Frontier
Portugal	PSI20 Index	Developed	Morocco	MXMA Index	Frontier

Singapore	STI Index	Developed	Oman	MSM30 Index	Frontier
Spain	IBEX Index	Developed	Pakistan	KSE100 Index	Frontier
Sweden	OMX Index	Developed	Romania	BET Index	Frontier
Switzerland	SMI Index	Developed	Serbia	BELEXLIN Index	Frontier
United Kingdom	UKX Index	Developed	Slovenia	SBITOP Index	Frontier
United States of America	SPX Index	Developed	Sri Lanka	CSEALL Index	Frontier
Chile	IPSASD Index	Emerging	Tunisia	TUSISE Index	Frontier
China	SHCOMP Index	Emerging	Argentina	SPMERVAL Index	Standalone
Colombia	COLCAP Index	Emerging	Botswana	MXBW Index	Standalone
Brazil	IBOV Index	Emerging	Jamaica	JMSMX Index	Standalone
Czechia	PX Index	Emerging	Nigeria	NGXINDX Index	Standalone
Egypt	EGX30 Index	Emerging	Ukraine	UX Index	Standalone
Greece	ASE Index	Emerging	Zambia	LUSEIDX Index	Standalone
Hungary	BUX Index	Emerging	Lebanon	BLOM Index	Standalone
India	SENSEX Index	Emerging	Armenia	MXAR Index	Unclassified
Indonesia	JCI Index	Emerging	Cambodia	CSX Index	Unclassified
Korea, Republic of	KOSPI Index	Emerging	Cyprus	CYSMMAPA Index	Unclassified

Kuwait	KWSEAS Index	Emerging	Ghana	GGSECI Index	Unclassified
Malaysia	FBMKLCI Index	Emerging	Mongolia	MSETOP Index	Unclassified
Mexico	MXMX Index	Emerging	Namibia	NSEIL Index	Unclassified
Peru	SPBLPGPP Index	Emerging	Rwanda	RSEASI Index	Unclassified
Philippines	PSE PM Equity	Emerging	Slovakia	SKSM Index	Unclassified
Poland	WIG20 Index	Emerging	Uganda	UGSINDX Index	Unclassified
Qatar	MXQA Index	Emerging	United Republic of Tanzania	DARSDSEI Index	Unclassified
Russian Federation	IMOEX Index	Emerging			