The role of stock markets in economic growth: Empirical evidence from panel data analysis

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Abstract: This study explores the link between stock market development and economic growth on a global scale. Analysing panel data from 37 countries over two decades (2003-2022), we investigate this relationship through a fully modified ordinary least squares (OLS) and panel vector error correction model to capture both short- and long-term dynamics. The empirical findings suggest a two-way influence between economic output and the stock market capitalisation in the short term, but only for high-income countries. In contrast, low- and middle-income countries experience a short-term effect where stock market capitalisation benefits economic growth, but not vice versa. The long-term analysis suggests a unidirectional positive influence of stock market capitalisation on economic growth, although this effect appears weaker in low- and middle-income countries. Policymakers, particularly in low- and middle-income countries, should thus focus on strengthening their stock markets to harness these growth benefits and support sustainable economic development.

Keywords: Stock market, economic growth development, cross-country difference, panel data, panel cointegration analysis.

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1 Introduction

The intricate relationship between financial markets development and economic growth has been a subject of extensive research, yielding mixed results. While cross-sectional and panel studies often reveal a positive relationship between different indicators of financial markets development and economic output growth (King and Levine (1993), Khan and Senhadji (2000), Levine et al. (2000)), others present a more nuanced picture (Demetriades and Hussein (1996), Luintel and Khan (1999))[1]. These discrepancies highlight the need for further exploration that addresses potential methodological limitations and considers the heterogeneity across countries at varying development stages. Within this context, the specific role of stock markets deserves particular attention. Understanding how stock exchanges contribute to economic performance is important for crafting effective economic policies.

Stock exchanges play a multifaceted role in the economy. They serve as a barometer of economic health by reflecting investor sentiment and expectations, and also contribute to economic growth through several mechanisms. Primarily, stock exchanges facilitate the efficient allocation and mobilisation of capital. By enabling companies to issue shares, they provide access to vast pools of savings that can be channelled into investments for expansion, innovation and productivity enhancements. These investments are fundamental drivers of job creation, promoting a robust economy.

Furthermore, stock exchanges enhance liquidity by allowing investors to buy and sell shares with relative ease. This improved liquidity reduces trading cost and mitigates the risks associated with holding stocks over time, thereby encouraging higher levels of investment. Increased investment, in turn, equips businesses with capital for growth and development. Additionally, stock exchanges enable risk diversification, allowing investors to spread their investments across various sectors. This diversification mitigates overall portfolio risk and fosters an environment where capital flows towards the most promising ventures.

This study discusses the conditions under which stock exchanges contribute to economic growth. By gaining a deeper understanding, policymakers can tailor financial regulations and economic strategies to maximise these benefits. This research aims to provide an analysis of the stock exchange-economic growth nexus, offering valuable insights for academic inquiry and practical policy formulation.

Previous studies on the relationship between stock markets and economic growth have addressed issues of simultaneity and omitted variables, yet limitations remain. The use of small samples can distort power in standard tests, leading to misleading conclusions (Levine et al. (2000), Beck et al. (2000)). Additionally, some studies might estimate spurious long-run relationships due to a lack of attention to data-integration properties.

Our robust panel data approach addresses these limitations. By employing a comprehensive dataset encompassing 37 developed and developing countries, we overcome the limitations of small sample sizes. Furthermore, our use of panel vector error correction models and fully modified OLS techniques ensures that our analysis considers short-term and long-term dynamics, while accounting for potential data-integration issues. Unlike much of the existing literature that focuses predominantly on general financial markets and banking sectors, our study zeroes in on stock markets. We contribute to the literature in three ways:

(i) We utilise a recent dataset encompassing 37 developed and developing countries, offering a broader perspective than studies that focus primarily on individual economies or regionally confined datasets. Panel time series methods are employed to re-examine the relationship while controlling for other relevant macroeconomic variables.

(ii) We move beyond a focus on long-run relationships by analysing both short-term and long-term dynamics. This is achieved through a panel vector error correction model and fully modified OLS, providing a nuanced understanding of how the stock market influences economic growth over time.

[1] See Popov (2017) for a recent summary of this literature.

(iii) We examine the potential moderating effect of a country's economic development level. By categorising countries by income group, we explore whether the stock market-growth relationship varies across different stages of development. This focus on the stock markets complements the traditional literature's emphasis on financial development through the banking sector.

The findings of this study suggest a two-way influence between economic output and stock market capitalisation in the short-term, but only for high-income countries. In contrast, low- and middle-income countries show a short-term effect where stock market development benefits economic growth, but not vice versa. The long-term analysis reveals a unidirectional positive influence of stock market development on economic growth, although this effect appears weaker in low- and middle-income countries.

The rest of the paper is structured as follows. Section 2 presents the relationship between economic growth and market activities with a short summary of literature. Section 3 introduces the econometric model, followed by a description of the data in Section 4. Section 5 presents and discusses the empirical results. Section 6 explores the policy implications and concludes the paper.

2 A review of the relationship between stock market development and economic growth

Over the past century there has been a growing body of theoretical and empirical literature studying the link between economic growth and financial markets and intermediation[2]. Overall, this literature suggests that financial markets development has a substantial effect on economic growth.

In this paper we focus specifically on connection between the stock market segment of the financial market and economic growth, emphasising the role of stock exchanges in facilitating capital formation and allocation, key drivers of economic expansion. The contribution of the stock market, either direct or indirect, to economic growth can be grouped into several primary channels:

Efficient allocation of capital and capital mobilisation channel: A well-functioning stock market facilitates the efficient allocation and mobilisation of capital, which in turn fuels economic growth (Greenwood and Smith (1997)). By issuing shares, companies gain access to a vast pool of savings, enabling them to invest in endeavours that drive expansion, innovation and make productivity gains. These investments translate ultimately into job creation and a more robust economy.

The stock market also allows investors to manage risk through diversification. This process fosters an environment where capital flows towards enterprises with demonstrably strong performance and promising prospects. Companies with a proven track record and the potential for significant growth attract greater investment, empowering them to act as catalysts for broader economic activity.

Liquidity channel: A liquid stock market is characterised by ease of entry and exit for investors, who can buy and sell shares readily. This reduces trading costs and fosters a more attractive investment environment, as investors are more confident about holding illiquid assets. Consequently, increased investment translates into a larger pool of capital accessible to businesses, ultimately fuelling economic growth.

Several studies, including those by Levine (1991), Fulghieri and Rovelli (1998), Levine and Zervos (1996) and Bencivenga et al. (1996), advocate for the positive effects of stock market liquidity on long-term growth and investment in innovative technologies. They argue that the ability to buy and sell assets quickly and cheaply allows savers to adjust their portfolios as needed and minimise perceived risk. This, in turn, encourages investment and facilitates easier access to capital for companies through equity issuance. By lowering risk and enhancing access to capital, liquid markets promote an efficient allocation of resources, which is a critical driver of economic growth. However, increased liquidity can have negative

[2] See Schumpeter (1912), McKinnon (1973), Shaw (1973), Greenwood and Jovanovic (1990), Pagano (1993), Levine (1997), Patinkin (1955) for historical discussions.

consequences. Bhide (1993), Demirgüc-Kunt and Levine (1996) and Levine (1997) identify three potential channels for this. First, higher returns associated with liquid markets may incentivise lower savings rates. Second, reduced uncertainty due to increased liquidity might discourage precautionary savings, further impacting savings rates. Finally, highly liquid markets can foster euphoria and short-termism, which can discourage internal monitoring by companies. Dissatisfied shareholders can exit easily by selling their shares, reducing the pressure to exert control and improve corporate governance. This, in turn, can impact corporate decision-making and ultimately hinder economic growth.

Information aggregation channel or signalling mechanism: Beyond the primary function of capital allocation, stock markets also play an important informational role by aggregating and signalling valuable information about a company's health and prospects[3]. As Grossman (1976) emphasises, these markets aggregate information about the prospects of listed firms. This information becomes accessible to investors and creditors, thereby facilitating corporate monitoring and leading to more efficient resource allocation (Grossman and Stiglitz (1980)).

Stock prices act as a signal, conveying valuable information about a company's health and future prospects. This information then guides crucial economic decisions, influencing both resource allocation and investment behaviour. For instance, rising stock prices are a positive signal, indicating investor confidence in a company's ability to grow and generate future profits. This confidence translates into real-world effects, potentially boosting consumer spending and business investment. Increased spending and investment stimulate economic activity further, creating a positive feedback loop.

Risk sharing and diversification channel: This channel emphasises the stock market's key function of enabling investors to manage risk through diversification (Levine (1991)). By investing in a variety of companies across different sectors and asset classes, investors can spread their risk, potentially reducing the overall volatility of their portfolio[4]. This increased risk tolerance allows for greater investment in companies with high growth potential, even if they are inherently riskier. This, in turn, leads to a more efficient allocation of capital towards ventures that can drive economic growth. However, capital allocation becomes less effective when the market lacks risk-diversification opportunities, as the benefits of exchanging ownership for a portfolio of financial assets diminish.

Wealth effect channel: When stock prices rise, shareholders' wealth increases. This can lead to increased consumer spending, as people feel more confident about their financial situation (Poterba (2000) and Karl et al. (2005)). Higher spending boosts demand for goods and services, which can encourage businesses to invest and expand, contributing to economic growth.

Although many empirical studies have explored the relationship between stock market development and economic growth, the findings are inconclusive.

Several studies support a positive association between stock markets and growth. King and Levine (1993), Khan and Senhadji (2000) and Levine et al. (2000) utilise cross-country and panel data analysis to demonstrate that financial markets, including stock markets, positively impact output growth. Levine and Zervos (1996) further highlight the unique role of stock markets in facilitating investment through increased liquidity, fostering long-term growth, especially in developing economies. Atje and Jovanovic (1993) find a significant positive correlation between stock market activity and growth across 40 countries. Similarly, Beck et al. (2000) and Rousseau and Wachtel (1998) report positive influences of stock markets on subsequent growth.

However, other studies present contrasting results. Harris (1997) finds that the stock market adds little incremental explanatory power in accounting for growth across 49 countries, including developed and developing. In the subsample of developed countries, while the level of stock market activity offers some explanatory power, its statistical significance remains weak. Arestis et al. (2001) uses quarterly data for five developed economies. This research finds that banking sector development and stock mar-

[3] This information aggregation mechanism is well-documented in the literature such as Greenwood and Jovanovic (1990) and King and Levine (1993)

[4] Pagano (1993) further emphasises the importance of diversification for entrepreneurs.

ket development contribute to growth. However, the effect of banking development is demonstrably larger, suggesting potential limitations of stock markets in promoting growth, particularly in developed economies with established banking systems.

The literature also suggests a distinction between long-term and short-term effects. Demirgüc-Kunt and Levine (1996) find a long-term association between well-developed stock markets and overall financial development, leading to higher growth. Conversely, Al-Awad and Harb (2005) suggest a short-term causality running from growth to credit-market development in Middle Eastern countries. Cooray (2010) provides further support for the argument for the stock market's significance in long-term growth for developing economies.

3 The model and econometric methodology

This section discusses the methodology for estimating short-run and long-run relationship between the stock market and growth.

3.1 The model

The long-run relationship between economic growth and stock market capitalisation is captured by the following equation:

$$y_{it} = \alpha_{it} + \beta_1 m + \beta_2 X + \epsilon_{it} \tag{1}$$

The subscripts i and t represent country and time, respectively. y stands for the growth rate for real GDP, m represents stock market capitalisation ratio to nominal GDP, and finally X represents a group of control macroeconomic variables that can potentially influence a country's output growth including the fixed capital ratio to nominal GDP, inflation rate, real interest rate, and real exchange rate.

3.2 Econometric methodology

The following steps are followed to estimate the model:

(i) A cross-sectional dependence (CD) test is performed to verify whether there is cross-sectional dependence across the panel.

(ii) Once cross-sectional dependence is observed, an appropriate panel unit root test (i.e. CIPS) is conducted to examine the stationarity of the series.

(iii) A Panel Fully Modified Ordinary Least Squares (FMOLS) is employed to estimate the long-run relationship, while a Panel Vector Error Correction Model (VECM) estimation technique is applied to estimate the short-run and long-run relationships among the variables.

(iv) A VECM Granger causality test is conducted to assess causality between the variables.

(v) Finally, we analyse the generalized impulse response function (IRF) to trace positive or negative impacts and both short- and long-run effects, preferring this approach over simple Choleski factorization, which is insensitive to the VECM's ordering.

3.2.1 Cross-sectional dependence and panel unit root test

Panel data analysis utilises observations across entities (e.g. countries, firms) and time periods, offering a powerful tool for empirical investigations. A critical assumption in this framework is the cross-sectional independence of the error terms. This implies that unobserved factors that influence the outcome of one entity in a given period do not affect the outcome of another entity in the same period. However, in macroeconomic studies, this assumption is typically violated. Common shocks, spillover effects and regional trends can induce cross-sectional dependence, where the error terms exhibit correlation across entities. Ignoring this dependence can have severe consequences for panel data estimation.

One major implication of neglecting cross-sectional dependence is the loss of estimator efficiency[5]. Standard errors become unreliable, potentially leading to spurious significance levels for estimated coefficients. Consequently, inferences about the relationships between variables in the model become compromised. Additionally, test statistics predicated on the assumption of independent errors become invalid. This undermines the ability to draw accurate conclusions about the model's parameters.

Given the prevalence of cross-sectional dependence in macroeconomic data, it is crucial to assess its presence before panel unit root testing and estimating panel data models. Fortunately, there are several diagnostic tests for this purpose such as Pesaran (2004) CD test[6]. This test utilises the residuals from a panel regression with individual fixed effects and constructs a statistic to evaluate the degree of cross-sectional dependence.

The presence of cross-sectional dependence renders conventional unit root tests invalid. To address this issue and analyse the stationarity properties of our series, we focus on the cross-sectionally augmented Im-Pesaran-Shin (CIPS) panel unit root test developed by Pesaran (2007). The CIPS test builds upon the Panel Analysis of Non-stationarity in Idiosyncratic and Common components (PANIC) test proposed by Bai and Ng (2004), which decomposes data into common factors and idiosyncratic components. While PANIC assesses the stationarity of each component separately, the CIPS test assumes that cross-sectional dependence arises from common unobserved factors influencing the residuals and calculates the average of individual cross-sectionally augmented Dickey-Fuller (CADF) statistics to determine the presence of unit roots[7].

By utilising the CIPS test, which is informed by the foundational PANIC approach, we can address the challenges posed by cross-sectional dependence and assess the stationarity of our macroeconomic data series.

3.2.2 *Panel cointegration equation and testing*

To assess the presence of long-run equilibrium relationships among the variables, we followed Pedroni (2004) the panel cointegration equation which can be defined as follows:

$$Y_{it} = \alpha_i + \lambda_i t + \sum_{i=1}^{l} \beta_{it} X_{it} + \varepsilon_{it} \tag{2}$$

$$\varepsilon_{it} = \rho_i \varepsilon_{it-1} + u_{it} \tag{3}$$

where Y_{it} and X_{it} represent the observable variables with dimensions of (N*T), l denotes the number of cross-sectional units, α_i denotes individual fixed effects, λ_i refers to individual time trends, capturing country-specific deterministic trend effects. Additionally, the vector of slope coefficients, denoted by β_{it}, is permitted to vary by countries, and ε_{it} represents the error term which represented in autoregressive form.

Pedroni (2004)'s approach allows for heterogeneity in both the cointegration vectors (the long-term relationships) across the panel units and the panel structure itself (unbalanced panels with missing data). It proposes various statistics, categorised into "Within" and "Between" dimensions. Withing-dimension tests ($panel - \nu, panel - rho, panel - PP$, and $panel - ADF$) analyse individual unit residuals and then average the results across units. They focus on rejecting the null hypothesis of no cointegration for each unit individually. On the other side, between-dimension tests (group-rho, group-PP, and group-ADF) focus on the average behaviour of the residuals across all units. They test the null hypothesis

[5]The implication of cross section dependence can be seen from Gengenbach et al. (2009)

[6]This test is summarised in the section B.1. For more details about the CD test see Pesaran (2004)

[7]Further details about these tests are provided in Section B.2

of no cointegration for the entire panel collectively. Both sets aim to test the null hypothesis of no cointegration, $H_0 : \rho_i = 1$; but differ in how they approach the alternative hypothesis.

For additional robustness checks, we employ Kao (1999)'s tests, which are akin to the panel ADF statistic within the framework in Pedroni (2004), employing Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) frameworks to examine cointegration. However, Kao's test distinguishes itself from Pedroni (2004)'s within-dimension ADF test by several characteristics: First, it introduces cross-sectional intercepts in the first-stage regression (Eq. 3), enabling the incorporation of individual intercepts across units. Second, it assumes homogeneous coefficients in the first-stage regression, implying uniform slope coefficients in the cointegration relationship across all units. Third, it excludes any trend coefficients in the first-stage regression, thereby eliminating trends from consideration. Despite these distinctions, Kao's test shares the same null hypothesis (no cointegration) and similar alternative hypotheses as Pedroni's tests[8].

3.2.3 Panel FMOLS estimates

Once cointegration is confirmed, we estimate the long-run relationship between the variables (in Eq.1) using the Fully Modified Ordinary Least Squares (FMOLS) method developed by Pedroni (2000).

While Ordinary Least Squares (OLS) is a popular choice for panel regressions, it suffers from two limitations in our context. First, OLS assumes no serial correlation in the error terms. However, in cointegrated panels, the residuals often exhibit serial dependence, leading to biased and inefficient estimates. Second, in the presence of cointegration, the independent variable (X_{it}) may be endogenous, meaning it's potentially correlated with the error term. This can also lead to biased OLS estimates.

To address these limitations, we employ the FMOLS method proposed by Pedroni (2000). FMOLS incorporates adjustments to account for serial correlation in the error terms, providing more reliable and efficient estimates. Additionally, the method addresses endogeneity bias by modifying the regression framework, allowing for the estimation of consistent long-run coefficients.

FMOLS modifies the conventional OLS estimator to account for both serial correlation and endogeneity. It achieves this by augmenting the cointegrating regression with lagged differences of the regressors, controlling for the feedback effect between variables. The FMOLS model is represented as follows:

$$Y_{it} = \alpha_i + \beta X_{it} + \sum_{k}^{K} \gamma_{ik} \Delta X_{it-k} + \varepsilon_{it} \tag{4}$$

Here, FMOLS incorporates the constant term, α_i, and the potential correlation between the error term and the differenced regressors (ΔX_{it}). Vector error process $X_{it} = (\epsilon_{it}, \Delta X_{it})$ is assumed to be stationary with long-run covariance matrix Ω_i. This covariance matrix can be decomposed into Ω_i^0 and a weighted sum of autocovariances $\Gamma_i + \Gamma_i^{'}$.

Non-parametric adjustments are applied to the dependent variable and the estimated long-run coefficients obtained from regressing the adjusted dependent variable on the regressors. The FMOLS estimator can be written as follows:

$$\hat{\beta}_{FMOLS} = N^{-1} + \sum_{i=1}^{N} \Big(\sum_{t=1}^{T} (X_{it} - \bar{X}_i)^2 \Big)^{-1} \Big(\sum_{t=1}^{T} (X_{it} - \bar{X}_i) Y_{it}^{*} - T\tau_i \Big) \tag{5}$$

where $Y_{it}^{*} = (Y_{it} - \bar{Y}_i) - \Big(\frac{\Omega_{21i}}{\Omega_{22i}}\Big)\Delta X_{it}$ and $\tau_i = \hat{\Gamma}_{21i} + \hat{\Omega}_{21i}^{0} - (\frac{\hat{\Omega}_{21i}}{\hat{\Omega}_{22i}})(\hat{\Gamma}_{22i} + \hat{\Omega}_{22i})$. The corresponding t-statistic for the FMOLS estimator converges asymptotically to a standard normal distribution:

$$\hat{t}_{\hat{\beta}_{FMOLS}} = N^{-1/2} \sum_{t=1}^{T} (\hat{\beta}_{FMOLS,i}^{*} - \beta) \Big(\hat{L}_{11i}^{-1} \sum_{t=1}^{T} (X_{it} - \bar{X}_{it})^2 \Big)^{1/2} \tag{6}$$

[8]For comprehensive insights into these tests and their critical values, it is advisable to refer to the original works by Pedroni (2004) and Kao (1999).

where the traditional FMOLS estimator applied to each panel member is $\hat{\beta}^*_{FMOLS,i}$.

This approach provides reliable estimates of the long-run relationships within our panel data, addressing the limitations associated with OLS in the context of cointegrated variables.

3.2.4 Panel Granger Causality test and VECM

The cointegrating relationship indicates a potential causal relationship, but the direction is unclear. To explore the direction of short-run and long-run causality among economic growth and market capitalisation, a Panel VECM with a dynamic error correction term is employed. A key advantage of panel VECM is its ability to capture the feedback effects among variables. This allows us to examine the dynamic causal relationships within a temporal framework, as suggested by Li (2001).

Our approach follows the Engle and Granger (1987) two-step procedure. In the first step, we estimate the long-run model (Eq. 3). Next, we employ the residuals obtained from this first-step regression to estimate a Panel VECM which is specified as follows:

$$\Delta y_{it} = c + \sum_{i=1}^{n} \beta_i \Delta m + \sum_{i=1}^{n} \Delta x'_{t-1}\gamma_i + \lambda(y_{t-1} - x'_{t-1}\delta - \delta_0 m_{t-1}) + v_t \tag{7}$$

Here, the error correction term, $(y_{t-1} - x'_t - 1\delta - \delta_0 m_{t-1})$, represents the equilibrium error that is a deviation from the long-run relationship. In Equation (7), the long-run causality is assessed by the statistical significance of the error correction term ($H_0 : \lambda \neq 0$). If this is not the case, the cointegration finding would not be reliable. Conversely, short-run causality is established by the statistical significance of the corresponding independent regressors ($H_0 : \beta_i = 0 \forall i \in \{1, \ldots, n\}$). If it can be rejected, there is no evidence of short-run causality.

Although the VECM is valuable for identifying the direction of causal relationships among variables, it has some limitations. Specifically, it is restricted to the selected sample period and does not provide insight into the sign of the impact. To address these shortcomings, we employ generalised impulse response analysis. This approach offers a comprehensive examination of the dynamic causal effects and reveals whether the impacts of innovations are positive or negative, as well as their short-run or long-run[9].

4 Data

The sample for this study comprises quarterly data series from 37 countries, spanning the period from 2003q1 to 2022q3[10]. The selection of countries was based on the availability of continuous data records throughout this time frame. It covers real growth rate, market capitalisation ratio, real fixed capital to ratio, inflation, real interest rate and real exchange rate. Data is obtained from the WFE and IMF databases. Economic growth is measured as the percentage change in the natural logarithm of real GDP which addresses potential issues with data normality and facilitates the analysis of long-term trends. The market capitalisation ratio is the market capitalisation to nominal GDP ratio, reflecting the relative size of the stock market compared to the overall economy. Inflation is measured as the annualised percentage change in the quarterly Consumer Price Index (CPI), indicating changes in the general level of prices for goods and services. The real exchange rate is measured as the percentage change in the natural logarithm of the real effective exchange rate index. This metric reflects the relative value of a country's currency compared to a basket of its trading partners' currencies, adjusted for inflation. Finally, the real interest rate is calculated as the annual short-term nominal interest rate minus annual inflation. Market

[9]Detailed explanations of this technique can be found in the foundational works of Sims (1980) and Bernanke (1986).

[10]See appendix for data details. We consolidate certain countries into groups to align with stock exchanges. For example, the Nordic and Baltic group includes Denmark, Finland, and Sweden; the Euronext region comprises Belgium, France, Ireland, Netherlands, Norway and Portugal.

capitalisation data was sourced from the World Federation of Exchanges database, while the remaining data were obtained from the International Financial Statistics published by IMF.

5 Empirical results

In this section, we first present the cross-section dependence, panel unit root and panel cointegration test results. Second, Panel FMOLS were employed to estimate the long-run relationship, while the VECM estimation technique was applied to estimate the short-run and long-run relationships among the variables. Third, a VECM Granger causality test was conducted to assess causality between the variables. Finally, we analyse the generalised IRF over simple Choleski Factorization which is insensitive to the VECM's order.

5.1 Cross-section dependence, panel unit root and panel cointegration test results

5.1.1 Cross-section dependence and panel unit root test results

Table 1 reports the results of the Pesaran (2004) CD test for individual series and the overall panel model with fixed effects. The null hypothesis of no cross-sectional dependence is rejected at the 1% significance level for all series and the panel model. This indicates the presence of significant error dependence across the countries, suggesting that the residuals are not independent and identically distributed.

Table 1: Cross-section dependence and panel unit root tests

Variables	CD statistics	CIPS statistics
Output (y)	124.83*	-2.15
Market cap. ratio (m)	54.42*	2.55
Capital share (c)	8.08*	-2.54
Inflation (p)	59.20*	-2.23
Real interest rate (r)	64.21*	-1.92
Real exchange rate (rer)	9.99*	-2.31
Model 1	124.06*	–

Notes: For the Pesaran CD statistics, *, ** and *** indicate that the test statistics are significant at the 1%, 5% and 10% levels, respectively. In Model 1, growth (dependent variable) is regressed on market cap ratio (independent variable) while controlling for capital share, inflation, real interest rate and real exchange rate. The CIPS test employs a constant and a trend under the null hypothesis of a unit root. The critical values for CIPS statistics from Pesaran (2007) are -2.78 (1%), -2.65 (5%), and -2.57 (10%).

The presence of cross-sectional dependence impacts unit root testing in panel data significantly. Since first-generation panel unit root tests assume independence across entities, they are unsuitable for our data, which shows dependency across countries[11]. Therefore, it is essential to use second-generation panel unit root tests that explicitly account for cross-sectional dependence to obtain reliable results.

Table 1 displays the outcomes of the CIPS tests for the panel. The findings indicate that we cannot reject the null hypothesis of a unit root for all series at 5% significance level, in the model with intercept and trend. In essence, all series appear to exhibit non-stationary behaviour within the panel[12].

[11] Consequently, the outcomes of first-generation panel unit root tests are not reported here.

[12] It's important to note that while the overall panel results indicate non-stationarity, further investigation of the idiosyncratic elements for each country might reveal stationarity in some individual cases, with lag selection varying across

5.1.2 *Panel cointegration test results*

The results of seven panel cointegration tests suggested by Pedroni (2004) and Kao (1999) are reported in Table 2. The test results indicate that most statistics are statistically significant, and therefore the null hypothesis of no cointegration can be rejected at 1% significance levels. They support for the presence of cointegration among the economic growth, market capitalisation ratio and other macroeconomic variables.

Table 2: Panel cointegration tests

	Model 1				*Model 2*			
	F.E.		F.E.T.		F.E.		F.E.T.	
	Value	p-Value	Value	p-Value	Value	p-Value	Value	p-Value
				Between-dimension				
Panel v-Statistic	3.19*	0.001	0.22	0.412	0.59	0.276	2.87*	0.002
Panel rho-Statistic	-32.55*	0.000	-29.68*	0.000	-0.87	0.193	-1.53**	0.062
Panel PP-Statistic	-44.98*	0.000	-48.65*	0.000	-2.57*	0.005	-3.18*	0.001
Panel ADF-Statistic	-43.79*	0.000	-44.85*	0.000	-2.88*	0.002	-3.72*	0.000
				Within-dimension				
Group rho-Statistic	-33.41*	0.000	-28.60*	0.000	1.11	0.866	0.80	0.788
Group PP-Statistic	-54.42*	0.000	-59.83*	0.000	-1.92*	0.027	-2.59*	0.005
Group ADF-Statistic	-51.13*	0.000	-49.58*	0.000	-0.41	0.341	-2.26*	0.012
Kao ADF	-7.12*	0.000			-2.18*	0.015		

Notes: F.E. indicates t-tests employing fixed effects but no time effects in the regression model, while F.E.T. encompasses both fixed and time effects. In Model 1, the output is the dependent variable, and in Model 2, the market capitalisation ratio serves as the dependent variable. The lag length is determined by selecting the model with the minimum Schwarz Information Criterion (SIC), which balances model fit with complexity.

5.1.3 *Panel FMOLS results*

Given the cointegration identified among our variables, we employ the FMOLS estimation methods, suitable for heterogeneous panels, to estimate the long-run equilibrium relationship. The results are presented in Table 3. Focusing on the core variables of our analysis, economic growth and market capitalisation ratio, the empirical findings reveal a statistically significant and positive association. This suggests that higher market capitalisation is positively associated with economic growth and vice versa. Quantitatively, a 10% increase in the market capitalisation ratio is associated with a 0.028% increase in long-run economic growth. Conversely, a 1% rise in economic growth leads to a 4% increase in long-run market capitalisation ratio to GDP.

Furthermore, the sample is stratified based on income level classifications established by the World Bank, dividing countries into high-income and low- and middle-income categories as the impact of stock market on long-term economic growth can vary by overall economic development and the level of financial markets development[13]. The empirical results reveal a statistically significant and positive coefficient of 0.45 for the market capitalisation ratio in high-income countries. This indicates that 10% increase in the market capitalisation ratio is associated with a 0.045 % increase in real economic growth in the long term. This finding suggests a more pronounced positive correlation between stock market development and

countries. Additionally, the PANIC test yields similar results, supporting our conclusions.

[13]Country classification by income data obtained from the World Bank's World Development Indicators www.databank.worldbank.org/source/world-development-indicators"

Table 3: Panel FMOLS results

	Output	Market cap. ratio	Fixed capital ratio	Inflation	Real exchange rate	Real rate
Output is the dependent variable						
Full panel FMOLS - weighted pooling		0.36*	0.05*	0.11	0.04	-0.05*
		(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Full panel FMOLS - Grouped estimation	-	0.29*	-0.07*	0.19	-0.05*	0.11
		(0.09)	(0.03)	(0.20)	(0.02)	(0.20)
Market cap. ratio is the dependent variable						
Full panel FMOLS - weighted pooling	0.04	-	0.03*	-0.09*	0.00	-0.03*
	(0.03)		(0.01)	(0.02)	(0.02)	(0.01)
Full panel FMOLS - Grouped estimation	0.04	-	-0.08*	0.52*	0.01	0.48*
	(0.03)		(0.03)	(0.23)	(0.03)	(0.23)
Output is the dependent variable						
High income group panel - Grouped estimation	-	0.45*	-0.13*	0.25	-0.05	0.17
		(0.09)	(0.04)	(0.28)	(0.03)	(0.28)
Low/Middle income group panel FMOLS - Grouped estimation	-	-0.27	0.10*	0.05	0.13*	-0.03
		(0.22)	(0.04)	(0.05)	(0.02)	(0.05)
Market cap. ratio is the dependent variable						
High income group panel FMOLS - Grouped estimation	0.06	-	-0.13*	0.75*	-0.01	0.70*
	(0.05)		(0.05)	(0.31)	(0.04)	(0.31)
Low/Middle income group panel FMOLS - Grouped estimation	-0.02	-	0.06	-0.16*	0.04*	-0.18*
	(0.02)		(0.04)	(0.04)	(0.02)	(0.03)

Notes: * and ** denote statistical significance at the 1% and 5% levels, respectively. Figures in parentheses are standard errors. In our estimation, we employ a fixed effects term to account for unobserved country-specific characteristics that remain constant over time.

long-term economic growth within high-income economies compared to the overall sample. Conversely, the coefficient for low- and middle-income countries is negative, albeit statistically insignificant. This implies that the market capitalisation ratio does not show a clear long-term association with economic growth in these countries, and any observed negative association is insufficiently robust to draw definitive conclusions. These results align with the established notion that well-developed stock markets offer greater benefits to high-income countries by facilitating increased savings and efficient capital allocation towards more productive investments, ultimately driving economic growth.[14] They are also parallel with the findings of Demirguc-Kunt and Maksimovic (1996), who argue that firms with access to more developed stock markets grow faster.

Additionally, the empirical findings suggest that the share of fixed capital and the real exchange rate have a negative impact on growth, while inflation and real interest rate have a positive but statistically insignificant impact.

5.1.4 VECM results

The long-run estimates presented in Table 3 do not provide information on the direction of causality between the variables. The results of VECM and panel Granger causality test is reported in Table 4 and Table 5, respectively.

The estimated error correction term (ECT) coefficient, representing the long-run dynamics, exhibits a statistically significant negative sign at the 5% significance level for the model, where output growth is the dependent variable, as expected (see Table 4). This finding suggests the presence of cointegration between the variables, implying a long-run equilibrium relationship. In simpler terms, the model exhibits mean reversion, indicating that any deviations from the long-run equilibrium level are corrected over time. Consequently, any instantaneous shocks to market capitalisation and other macroeconomic variables on economic growth will be adjusted fully in the long run, leading the system back to its equilibrium state. Notably, the low- and middle-income group exhibits the most rapid adjustment compared to high-income group. Conversely, the ECT for the model where market capitalisation is the dependent variable is

[14] See Levine (1991), Levine (1997) and Capasso (2006).

Table 4: Panel VECM results

	Full panel		High income group		Low/middle income group	
	Output (y)	Market Cap (m)	Output (y)	Market Cap (m)	Output (y)	Market Cap (m)
y_{t-1}	-0.38* (0.04)	0.08** (0.02)	-0.53* (0.04)	0.09* (0.02)	0.01 (0.13)	-0.02 (0.02)
y_{t-2}	-0.35* (0.04)	0.06** (0.02)	-0.42* (0.04)	0.08* (0.02)	-0.11 (0.10)	-0.01 (0.02)
y_{t-3}	-0.24* (0.03)	0.04** (0.01)	-0.24* (0.04)	0.05* (0.02)	-0.15** (0.07)	-0.01 (0.01)
y_{t-4}	-0.10* (0.02)	0.01 (0.01)	-0.10* (0.03)	0.01 (0.02)	-0.04 (0.04)	0.00 (0.01)
m_{t-1}	0.37* (0.05)	0.02 (0.02)	0.23* (0.05)	0.03 (0.03)	2.45* (0.27)	-0.21* (0.04)
m_{t-2}	0.10** (0.05)	-0.13* (0.02)	0.08*** (0.05)	-0.12* (0.03)	0.66** (0.29)	-0.05 (0.05)
m_{t-3}	0.15* (0.05)	0.04*** (0.02)	0.13* (0.05)	0.05*** (0.03)	0.24 (0.29)	-0.13* (0.05)
m_{t-4}	0.02 (0.05)	0.12* (0.02)	-0.01 (0.05)	0.13* (0.03)	0.72** (0.29)	-0.06 (0.05)
constant	-0.06 (0.05)	0.02 (0.02)	-0.07 (0.05)	0.03 (0.03)	-0.10 (0.11)	0.03 (0.02)
ECT_{t-1}	-0.73* (0.04)	-0.04*** (0.02)	-0.50* (0.04)	-0.00*** (0.00)	-1.27* (0.15)	-0.00*** (0.00)
R-squared	0.58	0.07	0.55	0.10	0.68	0.09
Adj. R-squared	0.57	0.05	0.54	0.09	0.66	0.06
F-statistic	117.68	5.95	74.81	7.07	47.27	2.43

Notes: *, **, and *** indicate statistical significance at the 1%, 5% and 10% levels, respectively. Figures in parentheses are standard errors. The analysis of lagged ECT in the output is negative and statistically significant, indicating that four variables play a role in the adjustment process when output deviates from its long-run equilibrium. In contrast, the market capitalisation ratio is very close to zero. Therefore, the results suggest the presence of unidirectional Granger causality from the stock market to output growth in the long run.

negative but very close to 0, indicating limited responsiveness to deviations from the long-run equilibrium for all groups.

Table 5: Short-run panel causality

	Full panel		High income group		Low/middle income group	
	Coeff.	p-Values	Coeff.	p-Values	Coeff.	p-Values
Dependent variable: output (y)						
Δm	69.52*	0.00	34.33*	0.00	87.51*	0.00
Δc	7.68*	0.10	1.70	0.79	5.71	0.22
Δp	26.13*	0.00	18.57*	0.00	23.08*	0.00
Δrer	94.24*	0.00	81.27*	0.00	24.53*	0.00
Δr	16.82*	0.00	14.55**	0.01	9.15***	0.06
All	255.90*	0.00	209.03*	0.00	185.26*	0.00
Dependent variable: market cap ratio (m)						
Δy	14.31*	0.00	16.65*	0.00	4.47	0.35
Δc	2.75	0.60	2.04	0.73	6.32	0.18
Δp	7.73	0.10	22.11*	0.00	4.20	0.38
Δrer	7.72	0.102	5.29	0.26	4.45	0.35
Δr	7.33	0.12	22.90*	0.00	4.40	0.35
All	66.69	0.00	112.85*	0.00	17.19	0.64

Notes: *, ** and *** indicate that the test statistics are significant at the 1%, 5% and 10% levels, respectively.).

The VECM results point to significant short-run causality between economic growth and market capitalisation activity (Table 4) for our full sample. The lagged changes in market capitalisation ratio influence output growth significantly, and vice versa, as evidenced by statistically significant coefficients at the 5% significance level in both models. This implies the presence of bidirectional short-run causality between our two main variables. This bidirectional causality in the short run is further confirmed when coefficients of market capitalisation and output growth for all lags are tested jointly as in Table 5. However, bidirectional short-term causality is absent in low- and middle-income group countries. Instead, short-term causality flows from stock market capitalisation to economic growth. This suggests that in these economies, stock markets play a foundational role in economic development. However, the feedback loop from economic growth to stock market development is weaker, possibly due to factors such as lower savings rates, which limit the capital available for investment in stock markets, limited investment capacity, which reduces firms' ability to expand and influence market capitalisation, and firms' limited appetite for expansion in weaker economies. In these environments, the lack of investor participation and limited business growth may inhibit the ability of economic growth to foster stock market development, due to these structural and institutional constraints.

Figure 1 plots the responses of our core variable to the shocks, unexpected changes, in each other, with 95% bootstrap confidence interval. We use the generalised impulses specification to construct an orthogonal set of innovations that do not depend on the VEC ordering (Pesaran and Shin (1998)).

We find a weak and statistically insignificant response of market capitalisation to an output growth shock (Figure 1, Panel B). In contrast, the response of output growth to a market capitalisation ratio shock is positive and significant (Figure 1, panel A). A doubling market capitalisation ratio leads to about 0.17% with this effect fading over time. Output growth returns to its normal level within roughly six quarters.

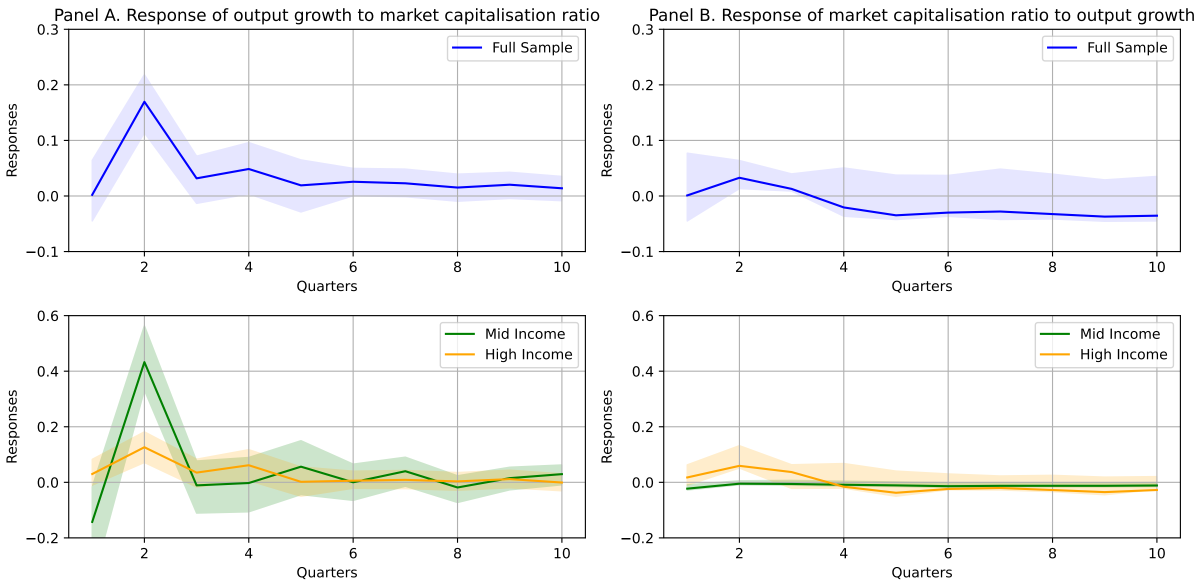

Figure 1: Generalised impulse responses

Note: Response to generalised one unit deviation innovations of core variables output growth, y, and market capitalisation ratio, m, with 95% confidence interval using Hall's percentile bootstrap with 999 bootstrap repetitions. The shock is applied in period 1, where a one-unit deviation innovation for y represents a 1% increase in output growth, and a one-unit deviation innovation for m reflects a doubling of market capitalisation relative to nominal GDP.

Further analysis categorised countries by income level. We found that low- and middle-income group experience a stronger response in output growth to changes in market capitalisation activity compared to high-income countries (Figure 1, Panel A). This finding suggests that policy interventions aimed at stimulating market capitalisation activity may have a more pronounced short-term impact on economic growth in low- and middle-income countries. However, the effectiveness of such interventions will depend on the specific economic and financial context of each country, and the long-term sustainability of economic growth in these countries may require a more comprehensive approach that addresses underlying structural issues and promotes sustainable development.

While the findings are compelling, it is also important to consider several factors that might influence the results. The dataset, while comprehensive, may have potential biases due to data availability issues, particularly in less developed markets. For countries with large shadow economies, official economic growth data may be misleading, potentially obscuring the true impact of stock market activity on growth. Additionally, micro-level factors, such as the structure of financial markets, sectoral differences across stock markets, corporate governance and investor behaviour, which also play a role in influencing economic growth. Furthermore, the study does not fully account for external structural economic shocks or policy changes during the study period, which could impact the observed relationships.

Moreover, while our analysis focuses on stock markets, understanding the broader relationship between financial markets and economic growth would require a more comprehensive study encompassing other financial sectors, such as banking, microfinance, and peer-to-peer lending. This expanded approach could provide deeper insights into the ways financial markets contribute to economic development.

6 Conclusion

This study presents a comprehensive examination of the relationship between stock market development and economic growth across 37 countries over two decades. The findings suggest a nuanced dynamic where high-income countries experience a bidirectional short-term causality between stock market capitalisation and economic output. In low- and middle-income countries, the effect is unidirectional, with stock market capitalisation influencing economic growth in the short term but not vice versa. In the long run, stock market capitalisation generally promotes economic growth across all income groups, although this long-term effect appears less pronounced in low- and middle-income economies.

This research underscores the critical role of stock markets in economic development, particularly by facilitating capital allocation and enhancing liquidity, which in turn stimulates investment and economic expansion. Policymakers, especially in low- and middle-income countries, should therefore focus on strengthening stock market infrastructure to harness these growth benefits, which could eventually translate into long-term economic gains. Future research could explore the specific mechanisms through which stock markets influence growth in low- and middle-income countries and identify strategies to optimise stock market contributions to economic growth. This work contributes to the existing literature by providing a robust analysis using a diverse dataset and econometric techniques address issues in the macroeconomic panel data, paving the way for informed policy formulation aimed at economic development through financial market advancements.

A Appendix: Data

Table 6: Country classification

Country	Income Group
Australia	High income
Austria	High income
Belgium	High income
Brazil	Upper middle income
Canada	High income
Chile	High income
China	Upper middle income
Denmark	High income
Finland	High income
France	High income
Germany	High income
Greece	High income
Hong Kong	High income
Hungary	High income
India	Lower middle income
Indonesia	Upper middle income
Ireland	High income
Israel	High income
Japan	High income
Luxembourg	High income
Malta	High income
Mexico	Upper middle income
Netherlands	High income
Norway	High income
Philippines	Lower middle income
Poland	High income
Portugal	High income
Singapore	High income
Slovenia	High income
South Africa	Upper middle income
South Korea	High income
Spain	High income
Sweden	High income
Switzerland	High income
Thailand	Upper middle income
Turkey	Upper middle income
United States	High income

Notes: Country income classifications are based on data from the World Bank's World Development Indicators.

B Appendix: Tests

B.1 Cross-section dependence Test

Following Pesaran (2004), suppose that we have a panel data model:

$$y_{it} = {\beta_{it}}' x_{it} + u_{it} \tag{8}$$

for $i = 1, 2, ..., N$ and $t = 1, 2, ..., T$ where x_{it} is a k-dimensional column vector of regressors, β_i are the corresponding cross-section specific vectors of parameters to be estimated. Pesaran points out that while this specification has cross-section specific coefficients, the tests described below are also applicable to the more restrictive fixed and random effects models. The general null hypothesis of no cross-section dependence may be stated in terms of the correlations between the disturbances in different cross-section units:

$$H_0 : P_{ij} = Corr(u_{it}, u_{jt}) = 0 \text{ for } i \neq j \tag{9}$$

For balanced samples, ρ_{ij} is the product-moment correlation coefficients of the residuals.

$$\hat{\rho}_{ij} = \frac{\sum_{i=1}^{T} \hat{u}_i \hat{u}_{it}}{(\sum_{i=1}^{T} \hat{u}_{jt}^2)^{1/2} (\sum_{i=1}^{T} \hat{u}_{jt}^2)^{1/2}} \tag{10}$$

To address the size distortion, Pesaran (2004) proposes an alternative statistic based on the average of the pairwise correlation coefficient, ρ_{ij} :

$$CD_p = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} T_{ij} \hat{\rho}_{ij}^2 \rightarrow N(0,1) \tag{11}$$

which is asymptotically standard normal for $T_{ij} \rightarrow \infty$ and $N \rightarrow \infty$ in any order. Further Pesaran (2004) points out that for a wide array of panel data models, the mean of CD is exactly equal to zero for all $T_{ij} > k + 1$ and all N, so that the CD test is likely to have good properties for both T_{ij} and N small which is supported by evidence of Monte Carlo simulations.

B.2 Panel Unit Root Tests

We consider the integrated panel data model:

$$Y_{it} = D_{it} + u_{it} \tag{12}$$

where Y_{it} represents the observed data at cross-section i and time t, D_{it} represents the model's deterministic dynamics (e.g., intercept, trend), and u_{it} is the innovation term capturing all deviations from the deterministic component.

To address cross-sectional dependence, we model u_{it} using a factor model structure:

$$u_{it} = \lambda_i F_t + \epsilon_{it} \tag{13}$$

$$(1 - L)F_t = C(L) + \eta_t \tag{14}$$

$$\epsilon_{it} = \rho \epsilon_{it-1} + v_{it} \tag{15}$$

where F_t is a vector of r common factors capturing the variation affecting multiple cross-sections, generated by a multivariate white noise process η_t. λ_i denotes a vector of cross-section-specific factor loadings, and ϵ_{it} is a multivariate idiosyncratic component assumed to be independent across cross-sections i. v_{it} is a mean-zero, stationary, and invertible MA process.

To test the presence of a unit root in the idiosyncratic component, an Augmented Dickey-Fuller (ADF) regression with lags is conducted for each cross-section. Failure to reject the null hypothesis for a specific cross-section indicates the presence of a unit root in that dataset.

Earlier panel unit root tests utilised pooled tests to address the issue of low statistical power associated with univariate tests, particularly when faced with limited time series observations (T). Likewise, a pooled test statistic can be calculated based on the methodologies proposed by Maddala and Wu (1999) and Choi (2001):

$$P_N^e = \frac{2\sum_{i=1}^{N}(\log(p_i^e) - 2N)}{\sqrt{4N}} \to N(0,1) \tag{16}$$

where p_i^e is the p-value associated with the idiosyncratic component ADF test for the i-th cross-section.

Pesaran (2007)'s Cross-Sectionally Augmented IPS (CIPS) test, a popular adopted modification of the PANIC test, addresses cross-sectional dependence by assuming it arises from a single stationary common factor.

When the deterministic terms in the model include both a trend and an intercept, we can express Eq. (12) in Augmented Dickey-Fuller (ADF) form as:

$$\Delta Y_{it} = \mu_i + \gamma_i t + \rho_i Y_{it-1} + \sum_{k=1}^{p} \phi_{ik} \Delta Y_{it-k} + \lambda_i F_t + \epsilon_{it} \tag{17}$$

The p lagged differences are added to account for correlation in the ϵ_{it}, and $\lambda_i F_t$ represents factor augmentation. Non-stationarity arises when the ρ_i autoregressive coefficient is equal to 0.

Let τ_i^{CADF} denote the t-statistic associated with the traditional ADF null hypothesis $H_0 : \rho_i = 0$ for cross-section i. The panel unit root test of interest is a pooled version of individual CADF statistics, or the cross-sectionally augmented (CIPS) statistic:

$$\tau^{CIPS} = \frac{1}{N} \sum_{i=1}^{N} \tau_i^{CADF} \tag{18}$$

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