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Global power and Stock market co-movements: A study of G20 markets

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ABSTRACT

It is well understood that a handful of countries such as members of G7 and G20 influence the direction of the trade policy of nations across the world. Such influence places significant pressure on other countries to adapt their own policies to suit G7 and G20 as these two groups of countries control international agencies such as the World Bank and the United Nations. This influence is also evident from the deliberations of G7 and G20 member countries and how such more powerful nations seem to shape and influence the global economic agenda. This study aims to investigate the relationship between global power (as measured by the global power index GPI) and globalisation (as measured by the co-movements of stock markets time varying correlations). Previous studies have investigated various factors influencing stock market correlations; however, the relationship between GPI and stock market correlations has not been addressed thus far. To investigate this relationship, we created an index of correlations of each stock market with other stock markets in G20 countries. Our empirical results indicate that GPI has a positive and statistically significant impact on the stock market correlations in G20 nations. This is the first study to establish such relationship between GPI and change in relative stock market performance. In the past changes in relative stock market returns were mainly attributed to the economic factors and relative volatility of the underlying stock markets. As such this study makes an important contribution to body of knowledge by developing a theoretical argument to show how change in relative global power, influences changes in stock market correlations via changes in relative risk premium and returns. The findings of the study have implications for the development of global policies as global power influences stock market co-movements. The findings of this study may also have implications for investors who aim to construct globally diversified portfolios.

1. Introduction

Since the 1970s, the convergence of global markets has interested economists, policymakers and investors. Mishkin (1999) discusses how instability in the global market has led to a greater increase in uncertainties in financial markets, making it challenging for lenders to differentiate good and bad credit risks. This body of literature identifies causes for global market convergence in economic and financial market indicators. However, contemporary debates in popular media suggest that the global economic and trade agenda

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is regularly dominated by influential nations. For example, the G7 group[1] of countries is considered the most powerful nations shaping the global economic agenda. The ongoing interest in globalisation and the perceived impact of global power (GP) on this convergence of global economies motivates this study. Thus, our study investigates the role of GP on the changes in the convergence of markets via stock market correlations.

Previous research primarily attributes stock market returns to economic factors and relative stock market volatility (Dimic, Kiviaho, Piljak, & Äijö, 2016; Prasad, Grant, & Kim, 2018). Furthermore, research examines the long-run cointegration of economies measured by gross domestic product (GDP; Arouri, Ben Youssef, M'henni, & Rault, 2012). Scholars argue that economic integration elicits short- or long-run economic benefits for economies (Badinger, 2001; Baldwin, 1993). However, while GP has the potential to significantly influence the economic, trade and political policies of nations, it has not been sufficiently investigated in the context of its impact on the globalisation of economies.[2] Hence, we address this research gap by investigating the relationship between stock market co-movements and GP using stock market correlations. This study is the first to investigate the relationship between GP and globalisation while testing the relationship between GP and the change in relative stock market performance. To this end, we pose the following question. Does the GP of nations positively affect stock market correlations over time? We use a sample of G20 markets to investigate this relationship. Using stock market indexes, we estimate indexes of return correlations of each market with other markets. We employ an appropriate panel dataset to examine the relationship between stock market correlations and GP.

To the best of our knowledge, this study is the first to develop a theoretical framework that analyses the relationship between relative GP and changes in stock market correlations via changes in relative returns and risk premia. Changes in investor confidence across markets are expected to reallocate resources in an economy, reflected in stock market returns. Moreover, this study is the first to test the relationship between relative GP and stock market returns[3] across countries. Our study makes significant contributions towards understanding convergence in stock markets, specifically the impact of GP on stock markets. Prior research examines the cause of changes in correlations from the lens of relative overall market risk changes. In contrast, our study investigates the cause of changes in correlation from a GP perspective. The study's findings reveal a positive and statistically significant relationship between GP and stock market correlations. The results are robust and statistically significant. Understanding this relationship has implications for policymakers for bilateral and multilateral trade and investment negotiations. Furthermore, the findings have implications for investors and fund managers who seek to diversify their portfolios internationally since GP has implications for correlation changes. Diversification benefits are primarily dependent on the presence of lower return correlations among markets.

The remainder of the study is organised as follows. Section 2 presents the literature review followed by the conceptual framework. Section 3 discusses the study variables. Section 4 describes the model. Section 5 introduces the model and estimation techniques. Section 6 presents the results, and Section 7 provides concluding comments.

2. Literature Review

Globalisation can be seen as the end of the Cold War (1947–1991), causing economies to be segmented in production, transport and other aspects of the international economy. With the abolition of capital controls in the early 1980s in developed economies and the late 1980s for developing economies, global markets started to integrate. There has been significant interest in testing the extent of market integration[4] for global economies since then. Research suggests the process of integration differs across developed and developing markets. Developed markets are understood as fully integrated, whereas developing markets are largely segmented (Akbari, Ng, & Solnik, 2020). If markets are integrated, local economic factors are redundant, and market returns are determined by global factors. However, if markets are completely segmented, global factors may not affect returns, while domestic factors determine market returns (Akbari & Ng, 2020). Over time, researchers have examined economic, financial, overall market risk and cultural differences affecting correlation changes (Liu, 2020). Globalisation has caused a significant shift in economic policies worldwide. In the current economic milieu, economic policies are no longer managed in a purely domestic context but developed considering the economic policies of other nations. Despite more powerful nations exerting significant influence on the policies of less powerful economies, research has not specifically examined the relationship between GP and market integration. This lack of understanding of the influence of GP on stock markets motivates the current research.

Market integration is examined from various aspects, primarily regarding financial and economic integration. However, most studies have considered the former more than the latter. This may be due to the complexity of measuring economic integration through trade barriers, labour and capital mobility, the openness of economies and testing the law of one price (Ammer & Mei, 1996; Baele & Soriano, 2010; Bekaert, Harvey, Lundblad, & Siegel, 2013). Distinct from market integration, Bekaert, Harvey, and Ng (2005) examine equity market contagion using factor models.[5]

Several salient findings and modelling choices emerge from current research. Theoretically, cointegration is employed to test long-

[1] The G7 countries include Canada, France, Germany, Italy, Japan, the United Kingdom and the United States.

[2] While the economic impact of GP on global economies may be wide and far reaching, this study focuses on its impact on stock market integration.

[3] Change in returns of stock markets worldwide can be caused by common factors influencing stock returns across countries. When underlying factors affect returns across markets differently the returns may change across markets differently. These can be measured as time varying correlations using conditional GARCH processes.

[4] See Akbari and Ng (2020) for a comprehensive review of literature on stock market integration.

[5] Kearney and Lucey (2004) provide a review of methodological advancement in equity market integration.

run equilibrium relationships. The most common types of tests are the Engle and Granger (1987) for bivariate datasets (Gupta & Guidi, 2012) and the Johansen (1991, 1995) for multivariate datasets (Kalaitzi & Chamberlain, 2020). Another critical aspect is market connectedness, bringing markets closer, enabling an increasingly integrated economy and portfolio diversification. For example, Bouri, Demirer, Gabauer, and Gupta (2022) investigate the relationship between investor sentiment and connectedness patterns across global markets to determine an asymmetric relationship regarding return and volatility connectedness. Portfolio diversification requires a certain level of connectedness that allows for cross-border investment. However, if markets are fully integrated, few benefits are left to exploit from a portfolio diversification perspective (Gupta & Donleavy, 2009). Similarly, Diebold and Yilmaz (2009) examine various measures of return and volatility spillovers. Their results show that returns spillovers display an increasing trend without bursts, whereas volatility spillovers present no trend but clear bursts. Furthermore, Diebold and Yilmaz (2012) explore volatility spillovers using a cross-market volatility transmission while focusing on the importance of stock market volatility spillovers to other markets during times of crisis.

The following section provides an overview of the broader literature on globalisation encompassing market integration. Section 2.1 reviews the literature in the field of market integration, including financial and stock market integration. Since we use time-varying correlations as our measure of stock market integration, we follow the literature on time-varying correlations. The current study analyses the impact of GP on the co-movements (i.e. time-varying correlations) among financial markets. Section 2.3 reviews the literature on GP and its likely relationship with stock markets. Section 2.4 discusses common global factors we include as control variables in our study. Section 2.5 discusses other factors, including cultural and political factors, that may influence correlations but are not included in this study due to data unavailability.

2.1. *Market integration*

Integration refers to how individual economies (or markets) move with other markets. Market integration also refers to the co-movements of markets and economies and how markets react to common influencing factors. This motivates researchers to identify factors that influence the changes in the degree of integration. The following sections discuss studies on integration and the factors likely to impact the convergence of economies and markets.

2.1.1. *Economic integration*

Greenspan (2000) suggests that economic integration can take various forms, including free trade areas, customs unions, common markets, and economic unions. Monetary union is often considered the final step in the integration of economies; participating economies adopt a common currency and monetary and shared fiscal policies. Tariffs between participating countries in a free trade area are abolished, while each country retains tariffs for non-members. Other factors influencing integration can include trade, monetary and fiscal policies, culture and personal preferences. Mussa (2000) explains that these factors can be broadly divided into three groups, namely, (1) technological factors, (2) individuals' preferences in reducing transport costs, production and communication and (3) public policies. Studies evaluate economic integration from the perspective of deviations from the law of one price in international goods and services. Another approach involves testing lead–lag relationships in national output growth, volatility and macroeconomic variables (Imbs, 2006; Kose, Prasad, & Terrones, 2003). Similarly, Phylaktis and Ravazzolo (2002) employ data from a group of Pacific-Basin countries from 1980 to 1998 to identify that financial integration accompanies economic integration.

2.1.2. *Stock market integration*

Research examines the integration of global markets from the perspective of introducing geographical union. For instance, Kim, Moshirian, and Wu (2005) examine time-varying correlations to indicate that European stock markets become more integrated in the eurozone. Similarly, Hardouvelis, Malliaropulos, and Priestley (2006) indicate that introducing a single currency means the individual eurozone country stock indexes had completely integrated with the EU market by the second half of the 1990s. Another body of literature investigates stock market integration from the perspective of industry-level market integration. For instance, Carrieri, Errunza, and Hogan (2007) suggest that country markets are integrated if the industries across markets are also integrated. In this context, research suggests that stock market convergence may be affected by underlying stock market volatility (Gupta & Mollik, 2008). Other studies (Ang & Chen, 2002; Longin & Solnik, 2001) examine volatility levels while testing whether international equity correlation increases in volatile times during 'bear and bull' markets, which can often lead to spurious relationships between correlations and volatility. Patel, Goodell, Oriani, Paltrinieri, and Yarovaya (2022) provides a review on financial markets in their quantitative analysis examining 1980 to 2022; they focus on investor benefits and changes in financial market integration, including time-varying correlations.

2.2. *Time-varying correlations*

Estimating co-movements of financial markets using a moving time window or conditional co-variances in the form of time-varying correlations is another method of testing global financial market integration. In this case, researchers examine how closely each financial market moves with other financial markets by estimating correlations among market pairs. The use of correlations is intuitive to understand financial market integration; the measure provides information on how closely two markets move with each other. Correlations (or co-variances) are a common input in the portfolio diversification literature and help to construct a diversified portfolio (domestic or international). Specifically, the exploit gains accrued by incorporating assets that are less than perfectly correlated (Gupta & Donleavy, 2009; Lee & Lee, 2023; Markowitz, 1959).

The co-movements of financial markets can be estimated in numerous ways, including entropy (Kuang, 2021), fuzzy sets (Chiang & Lin, 1999) and copula (Albulescu, Aubin, Goyeau, & Tiwari, 2018). A more commonly used correlation measure is Pearson's correlation analysis, implicitly using a single measure of correlations over time. Pearson's correlation coefficient is estimated based on the volatility of underlying variables. Researchers employ a moving time window to model the changing nature of correlations over time. Based on autoregressive conditional heteroskedasticity (ARCH) and generalised autoregressive conditional heteroskedasticity (GARCH; Engle, 1982) models, several conditional GARCH models have been introduced to estimate time-varying correlations, for example, dynamic conditional correlation (DCC) and asymmetric dynamic conditional correlation (ADCC; Sukumaran, Gupta, & Jithendranathan, 2015) and Golsten, Jagannathan and Runkle and GARCH (Alexander, Lazar, & Stanescu, 2021). The ADCC-GARCH model is extensively used in studies of asset pricing and investment literature (Basher & Sadorsky, 2016).

ADCC is a commonly used model for estimating time series datasets (Yahya, Abbas, & Lee, 2023). Several factors can influence time-varying correlations via risk premia and return, including trade, macroeconomics, labour movements, policy frameworks and globalisation. Correlations are mathematically estimated as the volatility of these underlying factors. Gupta and Mollik (2008) and Loretan and English (2000) discuss these factors through the underlying theories of market integration and correlation changes. Loretan and English (2000) also indicate that correlations can be affected by other factors without affecting the variances of the underlying series.

2.3. Global power

Global Power refers to a political unit that is powerful enough to affect the policies of the world through its influence or actions (Goddard & Nexon, 2016). Within GP, power is a critical instrument, prominent in developing countries where international donors and institutions of global governance exert considerable influence (Davis, Fisher, Kingsbury, & Engle Merry, 2012). From the 19th to the 21st century, global economic integration has strengthened international trade, developed negotiations with global actors and assisted development of legal and institutional frameworks. Previous studies (Hopewell, 2021) examine global dynamics of export credit transformation while finding significant impacts on global governance. Shifts in GP challenge global governance while influencing changes in theoretical frameworks. Moreover, Stephen (2018) provides a theoretical framework for change in international relations and the regime. Shifts in GP create systematic diversity between rising and establishing powers (Ikenberry, 2014). Global economic integration enables communication and trade between remote countries. Shin (2000) argues that three fundamental factors affect the economic globalisation process driving the future. The first factor is improvements in transportation technology. The second is opportunities provided by declining transportation costs and increasing economic integration. Finally, public policies influence the pace of economic integration. In the current context, GPI offers a comprehensive measure of political, military and economic strength in one measurable index, allowing for empirical testing of its influence on market integration.

Changes in global financial markets influence the development of international investments and institutional works. The development of international institutions allows GP to influence developed and developing countries, where both experience varying levels of integration and benefits. Given the importance of GP and its potential to affect stock market correlations, it is essential to examine GP's impact on relative changes in overall stock market returns across different nations over time.

2.4. Common global factors

Stock market correlations are affected by local and common global factors, including global economic conditions, geopolitical strengths and events, trade policies and tariffs, global market sentiments and global monetary policies. These factors can influence the returns of stocks differently in each market. Collectively, each country's market return may be affected differently.

2.4.1. Environmental awareness

Increasing global focus on environmental sustainability has significantly changed the stock market landscape. Driven by concerns over climate change, pollution and resource depletion, environmental awareness causes shifts in investor behaviour, regulations and corporate strategies while ultimately influencing stock market dynamics. Investors are increasingly considering a company's environmental performance alongside financial metrics when making investment decisions. Furthermore, environmental awareness has spurred innovation in clean energy, sustainable transportation and resource-efficient technologies. Companies at the forefront of these innovations may experience increased investor interest and higher stock prices as they capitalise on the increasing demand for sustainable solutions. Differences in investor's environmental awareness across nations may influence investment returns differently across countries. Research has looked at the impact of environmental awareness of the public on stock market performance, for example Paramati, Mo, and Gupta (2017) find a link between stock market returns and CO_2 emissions internationally.

2.4.2. Education level

The relationship between a population's average education level and stock market returns is complex and multifaceted. While education can enhance financial literacy and investment acumen, various other factors influence its impact on stock market returns. Specifically, financial literacy, risk perception, access to information and behavioural biases are significant. Lusardi and Mitchell (2011) determine that higher financial literacy results in better investment decisions. Van Rooij, Lusardi, and Alessie (2011) suggest that highly educated individuals may understand investment risk better and be more willing to invest in riskier assets, potentially leading to higher stock market returns. Baker and Haslem (1974) identify that individuals with higher education levels are more likely to participate in financial markets while investing in stocks. Furthermore, Demirgüç-Kunt and Levine (1996) document similar findings in a cross-country study. Thus, education can play a role in shaping investor behaviour while influencing stock market returns. Its impact is intertwined with various other factors. While higher education levels may correlate with better investment outcomes, individual circumstances and market dynamics ultimately determine stock market returns.

2.4.3. Overall economic growth

The economic levels of individuals and countries can significantly affect stock market returns while reflecting the broader economic conditions and financial health of investors. Researchers examine the relationship between economic strength and stock market growth. Shapiro (1988) indicates that stock market returns should not decouple from overall economic activity over long periods since stocks reflect expected discounted earnings from investment. However, evidence for the relationship between the economic activity and stock market performance is mixed. Fischer and Merton (1984) find positive relationships between economic activity and stock market returns. In contrast, Ritter (2004) identifies negative relationships between per capita GDP and stock returns between 1900 and 2002 among 16 countries.

2.4.4. International trade

International trade plays a pivotal role in shaping the stock market returns of different countries by influencing various economic factors and market dynamics. For example, countries heavily reliant on exports often experience stock market returns closely tied to global trade dynamics. Moreover, stock markets in export-driven economies are sensitive to changes in global demand, trade policies and exchange rates. Stronger export performance typically results in higher stock market returns, while trade disruptions or protectionist measures can lead to volatility and lower returns. Meanwhile, international trade patterns may influence the performance of specific sectors within a country's stock market. Trade agreements and tariff policies influence market sentiment and investment decisions. Positive developments, such as trade liberalisation or tariff reductions, can stimulate investor confidence while driving higher stock market returns, specifically for export-oriented countries benefitting from increased market access. Understanding the interplay between international trade dynamics and stock market returns is essential for investors navigating global markets. Kose, Prasad, and Terrones (2006) reveal that higher stock returns in countries are more integrated into the global economy. As such, international trade can be considered a common factor across markets that can affect correlations of stock market returns.

2.5. Other factors

2.5.1. Cultural factors

The importance of culture has not been sufficiently understood from a financial market perspective. However, it is expected to play a major role in economic integration and stock market co-movements. Participants from similar cultural backgrounds ought to act similarly in their decision-making (Yates & de Oliveira, 2016). This includes economic relations, the formation of transnational corporations and investment in the global market. Research uses cross-cultural experiments to test complex societal and cultural impacts on fairness and business interactions (Woodside & Zhang, 2013). The influence of culture on investors, businesses and policy frameworks should not be overlooked. Singh, Li, and Roca (2017) examine data from G20 countries in their analysis of the impact of culture on stock market co-movements. They find cultural similarities to have a positive impact on stock market integration (Singh et al., 2017).

2.5.2. Political and other factors

Political power positively affects economic integration by balancing the power between politics and markets to best suit the needs of international institutions and policymakers (Underhill, 2000). Previous studies identify lobbying and political influence on private sector investment while showing how political choices influence private sector decisions and, subsequently, politics (Callander, Foarta, & Sugaya, 2021). Lobbying is used to enhance corporate power and firm performance (Ward, 2004; Woll, 2019). A similar study (Kurecic, 2017) mentions economic integration in the multi-polar world works as levelling powers; however, the author does not test this empirically. Political science recognises the legitimate and vital role of public and private interests in public policy (Coen, 2007). Coen's (2007) study incorporates the effect of migration and travel on economic integration. Changes to the world regime influence the costs of travel through visa issuance and transport costs. However, certain migration policies fail to achieve their declared objectives or have unintended consequences. For example, Castles (2004) examines factors arising from the social dynamics of the migratory process. These factors are linked to globalisation and the political system. Effective policies are often hampered by the one-sided models used to explain migration, as well as by conflicts of interest in domestic and international politics. However, insufficient research exists to understand the impact of political factors on integration. Political factors are important in terms of understanding integration but are not the primary focus of the study.

The literature review offers an overview of the relationship between globalisation, economic integration and stock market returns. Furthermore, it underscores the evolution of globalisation since the Cold War era and its implications for market integration. Notably, the research emphasises differences in integration levels between developed and developing economies. This review reveals the importance of understanding the impact of GP dynamics on stock market correlations—a dimension that has been overlooked in the current literature.

Accordingly, the literature gap we identify is the limited exploration of the impact of GP on financial market integration, particularly regarding the changes in stock market correlations over time. Previous studies examine economic and financial integration from various perspectives, such as trade policies, monetary unions and industry-level integration. However, limited studies specifically address the influence of GP dynamics on stock market co-movements. This gap presents an opportunity for this study to contribute by investigating how shifts in GP affect the correlations of stock markets across different nations over time.

3. Conceptual Framework

Fig. 1 presents the study's conceptual framework. It illustrates the relationship between the dependent and independent variables via intermediary factors. We posit the independent variables GPI, environmental awareness, overall economic growth and education levels affect the intermediary variables. We examine the impact of GP on the returns of the overall stock market in an economy. The impact of GP on stock market returns is complex and not well understood.

Changes in policies are influenced by international trade negotiations and other international economic agreements, such as World Trade Organisation (WTO) membership, removing export subsidies, etc. Relative GP is an influential factor in trade changes and investment policies. The United Nations Conference on Trade and Development (UNCTAD) recognises that large and rich countries are more likely to make rules while developing countries are more likely to be followers of these rules (UNCTAD, 2018).[6] Motivated by the perceived influence rich and powerful nations can exert on less powerful nations, we investigate this relationship between the GP and global market integration.

From a theoretical perspective, the reallocation of resources across and within firms can be affected by the expected efficiencies from the reallocation of resources within an economy and firms. Overall changes in firm performance in this study are proxied by the broad-based stock market index of the respective market (country). This reallocation of resources can lead to increased economic efficiency and overall productivity while contributing to better firm performance and competitiveness. Epifani (2003) offer evidence of trade-induced efficiency gains that can potentially improve individual firm productivity and, thus, profitability. In agency theory, the reallocation of resources in firms is related to the alignment of interests between a principal and agents (Kochar, 1996). The need to reduce agency costs and ensure that resources are effectively used to maximise shareholder value drive reallocation decisions. The argument that trade liberalisation leads to productivity gains is well documented. For example, Brandt, van Biesebroeck, Wang and Zhang (2017) reveals that Chinese firms improved productivity after joining the WTO. Similar evidence is reported by Schmitz (2005) in the context of US iron ore firms after the reduction of import tariffs in the 1980s.

This study's conceptual framework illustrates the interaction of different economic variables and how the independent variables impact stock market correlations. Correlations are not directly affected by independent variables but via intermediary variables. The changes in independent variables (GP, environmental awareness, education level and GDP per capita) impact the intermediatory variables, which subsequently impact the stock returns across markets differently and, thus, are reflected by time-varying correlations. The impact on market returns is either via influencing overall returns in each market differently (without affecting risk premium) and or via influencing the risk premia across markets, thus influencing returns across financial markets differently. The linkage and effect of GP on stock market returns directly or via changes in risk across markets is the primary contribution of this study.

Table 1 presents the variables used in this study and provides details on the variable measures. Following Bekaert and Harvey (1995), we use time-varying correlation estimates to measure the co-movements of stock market return changes over time. The impact of GP in economic studies[7] may have been previously overlooked since GP has been primarily considered from a military power perspective. Heim and Miller (2020) suggest that GP include economic factors since economic strength has significant bearing on how different nations exert their power over others; they indicate GPI considers economic power and the GP index is currently published by the Rand Corporation. As such, the current study uses Rand Corporation data for measuring GP.

Jänicke et al. (2000) examine carbon (CO_2) emissions per tonne to measure people's awareness of the impact of economic activities on the environment. Environmental awareness is critical in terms of investors' perceptions and decisions. Environmentally aware populations are more likely to make similar investment decisions that are more environmentally conscious. We use CO_2 emissions as a measure for environmental awareness. Niesten and Jolink (2020) demonstrate how investors with similar environmental awareness influence asset allocation to companies based on their environmental credentials. Moreover, environmental awareness is found to be an important variable in the study of sustainable finance by Fatemi and Fooladi (2013), and this factor may influence overall stock market returns. Changes in the environmental awareness of economies may affect stock markets differently, thus influencing co-movements. Similarly, an individual investor with higher education level may influence investors' asset allocation by making more informed decisions (Haritha & Rishad, 2020; Jones, 2007). This study measures the number of educated people in the tertiary sector

[6] UNCTAD., 2018. Only words? How power in trade agreement texts affects international trade flows. https://unctad.org/publication/only-words-how-power-trade-agreement-texts-affects-international-trade-flows

[7] A recent economic study by Svobodova, Owen, Harris, and Worden (2020) indicates a direct correlation between CO_2 emissions and the size of national economies; they further expand into the 118 markets by examining coal using energy-efficient technologies to test the correlations. However, the study does not factor in the effect it may have on GP. Wu (2020) explore the issue of financial integration in stock markets while examining ASEAN economies by constructing a matrix using correlation coefficients to rank markets. Wu's (2020) study overlooks the relationship it may have with GP since it mainly focuses on market interconnectedness.

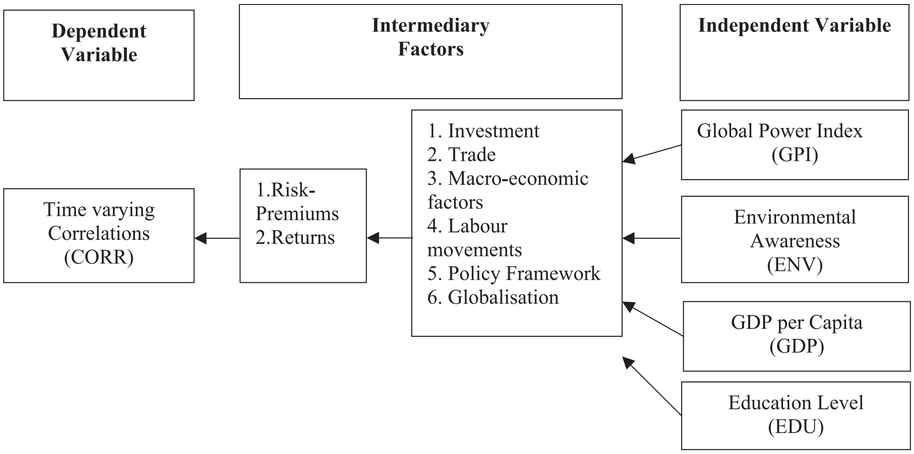

Fig. 1. Conceptual Framework.
Note: This conceptual model shows the relationship between the dependent and independent variables and correlations via the intermediary factors.

Table 1
Variables.

Variable Names	Descriptive Measures
Time-varying correlations[a] **(Corr)**	Dependent variable: Measures change over time in co-movements of returns of the stock market. Pairs for the stock market or the stock market integration (Bekaert & Harvey, 1995; Cappiello, Engle, & Sheppard, 2006).
Global Power Index (GPI) **Variable of interest**	Measures change over time regarding a nation's power compared to other nations (Song & Yuan, 2012). A nation stronger in global power is more dominant in negotiating bilateral and multilateral trade agreements. They are also more likely to exert greater influence on the global policy framework. This index is constructed by Rand Corporation.
CO_2emissions in metric tonne per capita (ENV)	Measures aggregate awareness of individuals in a country with sustainability of the environment (Jänicke, Blazejczak, Edler, & Hemmelskamp, 2000). The affect is more (or less) if the public is environmentally aware; they are more (or less) likely to behave similarly with the public of other countries. This influences the relative policy framework. For instance, environmentally friendly firms may exhibit higher prices for goods and services across countries.
Education, Tertiary level (EDU) **School enrolment, Tertiary education (percentage of population)**	Average education of the public in a given country (Jones, 2007). A higher level of education is likely to influence individuals in making more informed decisions that are likely to influence policy makers. We include all education post-secondary school against other measures that only include education in a particular age group or only bachelor's degree and above in tertiary education.
GDP per capita[b]	Aggregate GDP per capita (Topuz, 2022). Measures the per capita wealth of individuals in the country. Commonly used control variable in most economic studies.
Trade **Used as a common factor**	Sum of exports and imports of goods and services measured as a share of gross domestic product. Trade measures all exports and imports in a country to which can be used as a common factor for trade.

Note: This table provides a summary of variables used in the study: time-varying correlations; GPI as a measure of the relative GP of nations; CO_2 emissions as a measure of awareness of sustainability; tertiary level education as the percentage of population to measure education levels and as an indirect proxy for technological advancement in a country; GDP per capita as a measure for overall economic growth of a country; trade as a measure for exports and imports of goods and services; correlation indexes measure the relationship of the stock market of a country with other stock markets.

[a] The time varying correlations for each market pair are estimated using the returns of the individual stock market index (source: Refinitiv workspaces). To estimate the correlations, we first collect data for market indexes of all markets, calculate log returns and time varying correlations using the ADCC GARCH model (details this model and estimation are provided in Section 4).

[b] We control for economic factors despite the inclusion of economics in the GPI index. The GDP variable allows us to measure the capital wealth of each country separate to the economic power of each country.

based on the percentage of population. GDP per capita measures the wealth of the citizens in any particular country (Topuz, 2022). Since GDP is part of the GPI variable we use another common factor, Trade instead of GDP. Trade measures total exports and imports of local and international goods and services.

The motivation for this study is based on the perceived influence of major economies on the market and on policy agendas worldwide. Past studies have examined the various factors that may influence the financial and economic integration of global markets. However, the effects of the relative GP of economies on stock market correlations have been overlooked. By constructing a scaled correlation index for each market with other stock markets, our study aims to answer the question, 'Does the global power of nations positively influence stock market correlations over time?' The correlation indexes have been tested against the market GPIs. The analysis involved using panel data estimations covering 11 countries from 1995 to 2019.

4. Estimating correlation index

The analysis involves three steps. The first step estimates pairwise time-varying correlations for market pairs, comprising 55 correlation pairs. The second step constructs a scaled correlation index for each market using the 55 pairs across 11 markets. Scaling is carried out using the capitalisation of each market and the total market capitalisations of all markets.

4.1. Estimating pairwise time-varying correlations

We describe the method of constructing pairwise time-varying correlations for each market pair below. We use Cappiello et al. (2006) ADCC-GARCH model to construct pairwise time-varying correlations for each market pair.[8] ADCC is a multivariate model, but we use the model as a bivariate model to estimate pairwise correlations. The ADCC model has been extensively used to estimate time-varying correlations (Tiwari, Raheem, & Kang, 2019). While we describe Cappiello et al.'s (2006) ADCC-GARCH approach below, first, we discuss the DCC-GARCH framework.

Let r_t be a n x 1 vector of asset returns and assume they are conditionally normal with a mean of 0 and conditional covariance matrix H_t as follows:

$$\mathrm{r_t} \mid \mathrm{I_{t-1}} \sim \text{Normal}\,(0, H_t)$$

The matrix H_t can be decomposed:

$$H_t = D_t R_t D_t$$

where $D_t = diag\left(h_{1,t}^{\frac{1}{2}}, \dots h_{n,t}^{\frac{1}{2}}\right)$ is a n x n diagonal matrix of time-varying standard deviations from the univariate GARCH model with $h_{i,t}^{\frac{1}{2}}$ is on the i^{th} diagonal and $R_t = diag\left(q_{1,t}^{-\frac{1}{2}}, \dots q_{n,t}^{-\frac{1}{2}}\right)$ is the time-varying correlation matrix.

The DCC model follows a two-stage estimation of the conditional covariance matrix H_t.

Stage 1:

Use a univariate volatility model, such as GARCH (Bollerslev & Ghysels, 1996) or EGARCH (Nelson, 1991) to fit for r_t and obtain the estimate for $h_{i,t}$.

Stage 2:

Asset return r_t is transformed by their estimated standard deviations resulting from Stage 1. Use them to estimate the parameters of the conditional correlations.

For example, consider a case where the asset returns r_t follows an AR(1) process, which can be written as follows:

$$r_t = \mu + a r_{t-1} + e_t \qquad \mathrm{e_t} \mid \mathrm{I_{t-1}} \sim \text{Normal}\,(0, H_t) \tag{1}$$

and the time-varying variance $h_{i,t}$ follows a GARCH (1,1) model:

$$h_{i,t} = w_i + \alpha_i e_{i,t-1}^2 + \beta_i h_{i,t-1} \; \mathrm{\alpha_i + \beta_i} < 1 \tag{2}$$

When (1) is estimated under (2), the standardised residuals $\varepsilon_{\mathrm{it}}$ can be calculated as follows:

$$\varepsilon_{\mathrm{it}} = \mathrm{e_{it}} / \sqrt{(\mathrm{h_{it}})} \text{ or } \varepsilon_{\mathrm{t}} = \mathrm{D_t}^{-1} \mathrm{e_t}$$

Obviously, $\mathrm{E}\,(\varepsilon_t \varepsilon_t') = \mathrm{D_t^{-1} E(e_t\, e_t')\, D_t^{-1} = D_t^{-1} H_t D_t^{-1} = R_t}$.

Following Engle (2002), we can write the resulting correlation matrix in the standard DCC model as follows:

$$Q_t = S(1 - \alpha - \beta) + \alpha\left(\varepsilon_{t-1}\varepsilon_{t-1}'\right) + \beta Q_{t-1} \tag{3}$$

where Q_t is a symmetric positive definite matrix and S is the unconditional correlation matrix of the standardised residuals ε_t.

Since this model does not allow for asymmetries and asset-specific news impacts, the modified model of Cappiello et al. (2006) incorporating the asymmetrical effect and the asset-specific news impacts can be written as follows:

[8] Correlations can also be estimated using non-parametric methods (Amira, Taamouti, & Tsafack, 2011; Skintzi & Refenes, 2005) such as Fuzzy sets (Chiang & Lin, 1999) or Copulas (Osseiran & Segonne, 2019; Gospondinov, 2017) and different GARCH specifications (Cappiello et al. (2006)). However, conditional GARCH models is most common especially in the context of investment literature where correlation estimates are central to the construction of risk adjusted portfolios.

$$h_{i,t} = w_i + \alpha_i \varepsilon^2_{i,t-1} + \beta_i h_{i,t-1} + d_i \varepsilon^2_{i,t-1} I(\varepsilon_{i,t-1}) \tag{4}$$

The indicator function $I(\varepsilon_{i,t-1})$ is equal to 1 if $\varepsilon_{i,t-1} < 0$, and 0 otherwise. For this specification, a positive value for d implies that negative residuals tend to increase the variance more than positive residuals. The asymmetric or leverage effect is designed to capture an often-observed characteristic of financial assets, which is that an unexpected drop in asset prices tends to increase volatility more than an unexpected increase of the same magnitude. This can be interpreted to suggest that bad news increases volatility more than good news. For the ADCC model, the dynamics of Q are given as follows:

$$Q_t = (\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{N}G) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'Q_{t+1}B + G'n_{t-1}n'_{t-1}G \tag{5}$$

Eq. (5) estimates the correlations for the dependent variable. The matrices A, B and G are diagonal parameter matrices. The indicator function $n_t = I(\varepsilon_{i,t-1})$ is equal to 1 if $\varepsilon_{i,t-1} < 0$, and 0 otherwise and $\overline{N} = E[n_t n'_t]$. In addition, for $\overline{Q}$ and $\overline{N}$, expectations are infeasible and are replaced with sample analogues, $T^{-1}\sum_{t=1}^{T}\varepsilon_t\varepsilon'_t$ and $T^{-1}\sum_{t=1}^{T}n_t n'_t$, respectively. In this context, Cappiello et al. (2006) only examine the asymmetrical effects and not the asset-specific news impacts.

4.2. Scaled correlation index construction

We construct the capitalisation-weighted scaled correlation indexes using the correlations of each market pair from the pairwise correlations calculated using the ADCC-GARCH model. We estimate 55 pairs[9] of correlations for 11 markets.[10] Using time series data for the period of 1995–2019 for the 55 pairs of correlations, we construct an index for each stock market in our study. To obtain the capitalisation-weighted scaled index for market $i (i = 1, 2, .., 11)$, we first multiply the market correlation of market i and j, by the capitalisation of market $i(Cap_i)$ and divide by the total capitalisation of all markets (Cap_m). Since $i = 1,2,..,11$, we have 11 such indexes in relation to market i. We then sum these 11 scaled indexes to obtain an index of correlation for market i. Since $i = 1, 2, .., 11$, we construct 11 indexes, one for each market.

To calculate the index for country i (I_i) we use the following formula:

$$I_i = \frac{\sum_{j=2}^{11} \rho_{i,j} \times Cap_j}{Cap_m} \tag{6}$$

For example, to construct the index for Australia, $I_{Australia}$; j = Canada, China, France, Germany, India, Italy, Korea, Mexico, the UK and the US.

4.3. Data source and preliminary data analysis

As noted above, this study uses data on 11 subjects (stock markets) over 25 years (1995–2019) to perform panel data estimation.

The variables of interest include time-varying correlations, GPI, education (EDU), environment (ENV) and GDP per capita. GPI is a measure of the relative power of nations compared with other nations globally. The Rand Corporation (Heim & Miller, 2020) constructed this index, incorporating economic factors, and it is a valid proxy for an individual country's power relative to overall GP. The EDU variable is determined by the tertiary level education as the percentage of population (Barro & Lee, 2013). ENV is the overall awareness of sustainability in a country proxied by the CO_2 emissions in metric tonne per capita (The World Bank, 2023). GDP per capita, proxying for the overall growth of the country (Topuz, 2022). Data for CO_2 emissions, EDU and GDP per capita are sourced from the World Bank database[11] and GPI from the Rand Corporation.[12] We use annual data from 1995 to 2019 for all variables under consideration, except the stock market indexes. These data calculate the correlations, collected from Refinitiv workspace databases. The stock market data is used monthly for estimating an ADCC-GARCH model (Gupta & Donleavy, 2009). After estimating monthly correlations, we select end of year correlations to construct an annual time series.

Appendix A presents the descriptive statistics for each variable in our estimation model. The data for GPI, environment (CO_2

[9] We construct the correlation matrix by examining the unique pairs. To construct the correlation indexes, we use 55 pairs.

[10] The G20 comprises 19 countries and the European Union (EU). Putting aside the EU countries, we elicit data from the other 19 countries. For each, there is available data for GPI, ENV and GDP for 1995–2019. However, EDU data is not available for Argentina, Brazil, Indonesia, Japan, Russia, Saudi Arabia, South Africa and Turkey. Thus, we omit them; the stock markets in the study are Australia, Canada, China, Germany, France, India, Italy, Korea, Mexico, the United Kingdom and the US.

[11] Data for these variables have been collected from the various world bank tables: The World Bank. (n.d). World Bank National Accounts data and OECD National Accounts data files. https://data.worldbank.org/indicator/NY.GDP.MKTP.PP.CD. The World Bank. (n.d). 2020. Washington, DC: World Resources Institute. https://data.worldbank.org/indicator/EN.ATM.CO2E.PC The World Bank. (n.d). 2022. UNESCO Institute for Statistics. https://data.worldbank.org/indicator/SE.TER.ENRR

[12] We thank Jacob L Heim from Rand Corporation for providing data and methodology for estimation of GPI, allowing us to complete GPI for all 20 economies. The published paper only shows data for a limited number of nations.

emissions in metric tonne per capita),[13] education (tertiary level education as the percentage of population)[14] and GDP per capita[15] for all the 11 markets, namely, Australia, Canada, China, Germany, France, India, Italy, Korea, Mexico, the UK and the US for the sample period 1995–2019. Canada has the lowest level of mean GPI at 0.003, while the US has the highest GPI at 0.280, followed by China at 0.138. Furthermore, Australia has the lowest level of SD for GPI at 8.501E-4, and China has the highest SD at 0.049, followed by the US at 0.023.

Appendix A reveals that CO_2 emissions are lowest for India and highest for the US. Education level for India is the lowest with a tertiary qualification of 14.42% against the highest level of 82.65% for Australia. The US has the highest per capita GDP, and India has the lowest. The SD of GDP for Germany, Korea and the US is low, showing minimal fluctuations in GDP per capita compared with other countries. The SD of stock market returns for all countries is high. Stock market returns are generally volatile and dependent on different underlying factors. The SD for trade is high for all countries except Australia, the UK and the US. The *p*-value of most J-B statistics (except stock market returns) is larger than 0.05, suggesting the variables are normally distributed. The stock market returns for all countries are not normally distributed. However, we use returns of stock markets for the correlation calculations, which are found to be normally distributed.[16] Moreover, returns for these markets range between 3.6% in the UK to 16.3% in India with a standard deviation of 13.7% and 34.9%, respectively. Meanwhile, the lowest standard deviation of returns is for the UK and the highest is for Korea, with 41.2%.

Fig. 2 plots GPI on a graph for a visual understanding of changes in GPI across markets. The GPI for the US declines and that for China increases over the sample period. The movement in GPI has relevance for understanding the relationship between GPI and the correlations.

We also investigate multicollinearity issues by estimating the variance inflation factor (VIF). Table 2 presents the centred VIF values. The table shows that all VIF values are well below 5, indicating a low level of multicollinearity.

5. Model and estimation

Since we have data on 11 subjects (stock markets) over 25 years (1995–2019), we perform panel data estimation.[17]

We consider the following model for estimation:

$$Corr_{i,t} = B + \beta_{GPI}GPI_{i,t} + \beta_{EDU}EDU_{i,t} + \beta_{ENV}ENV_{it,} + \beta_{GDP}GDP_{i,t} + u_{i,t} \tag{7}$$

In (7), we have the dependent variable $Corr_{i,t}$ (correlation index) and where $GPI_{i,t}$, $EDU_{i,t}$, $ENV_{i,t}$ and $GDP_{i,t}$ per capita are the explanatory/independent variables. Variable descriptions are given in Table 1.

Returns on assets (overall stock market) across economies may be impacted different by global factors. Differential changes in market returns will influence correlations in stock markets over time. Past studies have examined underlying factors that influence correlations (Luo, Thompson, & Detterman, 2003). Similarly, the relative GP of economies also has the potential to change correlations of markets over time. As such, we test the following hypotheses.

H_0: $\beta_{GPI} = 0$ (Changes in correlation are not influenced by changes in GPI).

H_1: $\beta_{GPI} \neq 0$ (Changes in correlations are influenced by changes in GPI).

We expect the relationship between GPI and correlations to be positive. We do not make a priori expectations for the relationship signs between correlations and the control variables (EDU, ENV and GDP per capita). Depending on investors' perceptions, the impact of environmental awareness on correlations can have a positive or negative impact. CO_2 emissions proxy environmental awareness while the impact of high level emissions may influence investors to look for stock investments that conserve energy by improving energy efficiency and/or investment in renewable energy, thus segmenting the domestic market. However, industries that rely more on imports to save emissions result in integrating with global markets. Thus, the overall influences of CO_2 emissions in metric tonne per capita (environmental awareness) can be negative or positive on market integration. Higher education levels may suggest that investors will make more informed decisions. As such, their decisions may similarly affect returns, resulting in positive correlations.

However, a higher level of education may indicate that investors are more aware of their domestic national policies. They make decisions in a domestic context, thus deviating from convergence and resulting in a negative relationship. Financial literacy has a significant international presence within education systems. It assists students in improving their financial skills, enabling them to make informed financial decisions internationally (Widdowson & Hailwood, 2007). In a domestic context, wealthier investors, as well as those with more education and access to financial information, invest in foreign securities from an early age (Abreu, Mendes, & Santos, 2011; Orihara & Eshraghi, 2022). Finally, GDP per capita is a proxy for a country's overall economic growth, and its impact on

[13] https://data.worldbank.org/indicator/EN.ATM.CO2E.PC

[14] OECD. (2023b). Population with tertiary education (EDU) (indicator). doi: https://doi.org/10.1787/0b8f90e9-en

[15] OECD.0 (2023a). Gross domestic product (GDP) (indicator). doi: https://doi.org/10.1787/dc2f7aec-en

[16] Based on the minimum and maximum GPI, we established four quarters for the GPI range. When we allocate countries based on the GPI index, only one country is in the first quartile (US), none in the second, and the third has two (China and Mexico). All other eight countries are in the bottom quartile (India, Canada, Italy, Korea, France, the UK, Germany and Australia). This eliminates the use of the quartile analysis. We then consider placing countries into three groups; however, the distributions of countries do not present an even spread. There is only one country in first group, one in the second group, and nine countries in the third group.

[17] Multivariate GARCH models can estimate relationships between more than two variables. However, Cappiello et al., (2006) propose model reduced multivariate GARCH models to estimate time varying correlations in a bivariate context.

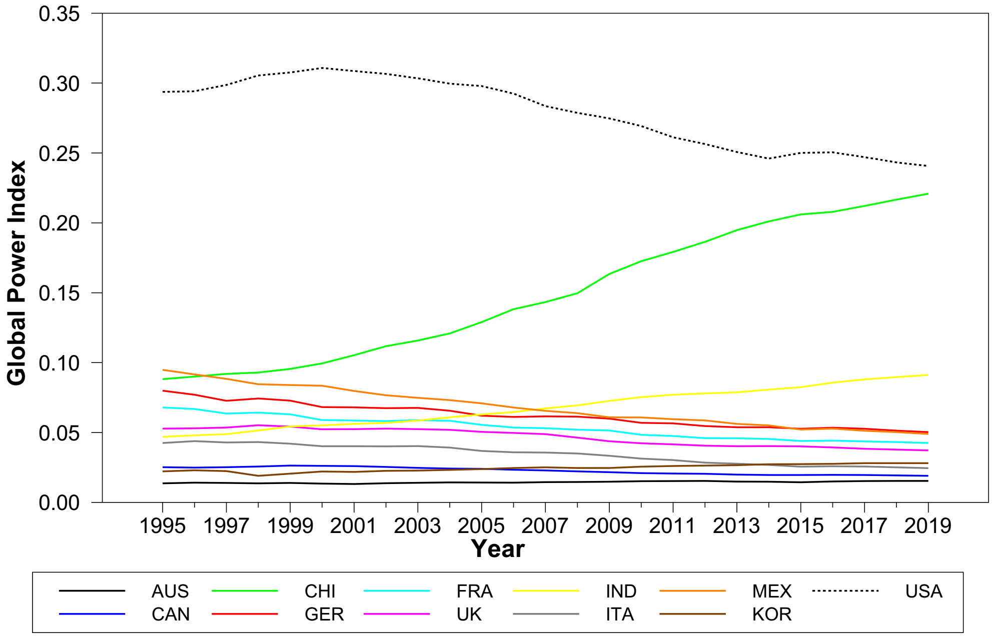

Fig. 2. Country GPI.
Note: This figure provides the GPI for each of the 11 markets.

Table 2
Testing Multicollinearity.

Multicollinearity Test (Coefficient Table)								
Unstandardised Coefficients				Standardised Coefficients			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	0.600	0.020		29.548	<0.001		
	GPI	−1.766	0.198	−0.873	−8.913	<0.001	0.271	3.686
	ENV x 10^8	3.300	0.000	0.502	5.101	<0.001	0.269	3.720
	EDU	−0.002	0.001	−0.418	−4.779	<0.001	0.340	2.939
	GDP x 10^6	−3.900	0.000	0.394	4.330	<0.001	0.315	3.173

a. Dependent Variable: Corr
Note: Testing for multicollinearity using the independent variables (GPI, ENV, EDU and GDP per capita) and the dependent variable (correlations).

correlations can be positive or negative depending on the overall maturity of the stock market and economy.

6. Estimation results

Results of the analyses are presented regarding the correlation indexes that we have estimated for the 11 markets. In constructing the indexes, we use the ADCC model discussed in Section 4 to estimate time-varying correlations for each market pair from the 11 markets (i.e. Australia, Canada, China, Germany, France, India, Italy, Korea, Mexico, the UK and the US). We further use the time-varying correlations for market pairs to construct the scaled correlations index for each market with other markets. Moreover, the scaled correlation index is the dependent variable in the panel analysis to test if GPI influences the correlations.

6.1. Correlation movements

Notably, some markets have lower correlations that are stable over time, whereas other markets have correlations that change significantly over time. From a theoretical standpoint, testing and understanding the factors that may influence these changes are interesting. As discussed, this study is motivated by the perceived impact of GP and its potential to influence trade and political and economic policies of weaker nations. This influence potentially affects economic and trade policies, thus affecting the profitability of firms, which is reflected in stock market returns. The impact on stock markets is not uniform, as reflected in stock market return correlations. This is evident in the variations in correlations across different markets over time.[18]

[18] Detailed results for correlation pairs have not been presented here but can be requested from the authors.

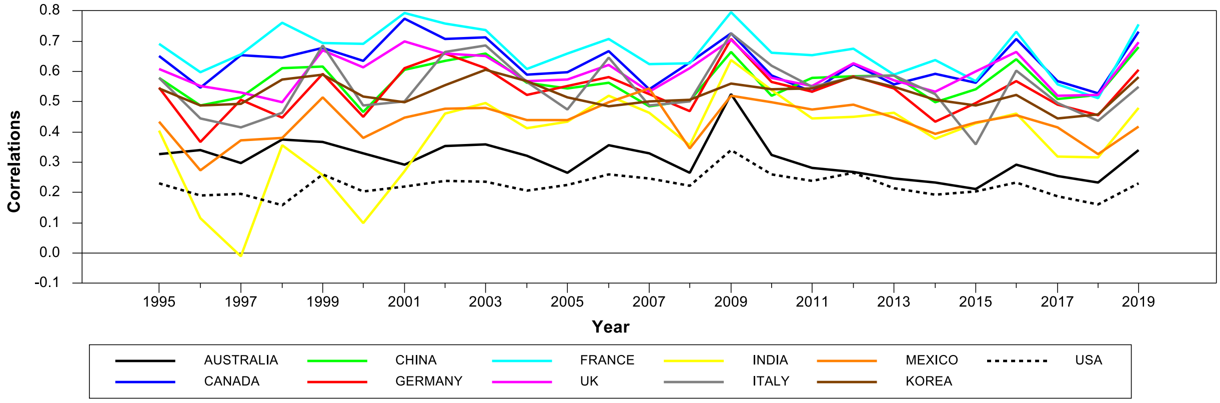

Fig. 3. Year-wise Indexes of Correlations.
Note: The graph shows the year-wise correlations for each country: Australia, China, Canada, Germany, France, India, Italy, Korea, Mexico, the UK and the US.

Using correlation pairs, we construct scaled correlation indexes for each stock market with other markets, leading to 11 correlation indexes for the period 1995–2019. Fig. 3 presents this as a year-wise line graph for 1995–2019. The indexes show that correlations for Australia and the US are stable and lower than for other markets. Correlations for India are most volatile, followed by China. Correlations for China are much higher than most markets except France, Canada and the UK. However, towards the end of study period, most markets have higher correlations and are seen to be moving together.

6.2. *Estimation results*

Since we perform panel data estimation, the first step is investigating the cross-sectional panel independence, since the selection of tests for stationarity (or panel unit root test) of the time series variables is based on whether a panel time series represents cross-sectional independence (CI) or cross-sectional dependence (CD). We conduct a Breusch and Pagan (1979) (BP) LM test and Pesaran Scaled LM test to determine CI. The null hypothesis for the test is H_0 : time series is CI and $H_{A:}$ time series is CD. The results are presented in Table 3. Since the *p*-value for the two CI tests is <1%, we reject the null hypothesis at the 1% level and conclude that the time series are CD (Pesaran, 2007; Selvanathan, Jayasinghe, & Selvanathan, 2022).

Since, the panel dataset variables are CD, we cannot use traditional/conventional tests for the existence of panel unit roots. In this situation, we need to perform the commonly used second generation panel unit root tests, such as CIPS panel unit tests, assuming CD. Table 4 presents the CIPS panel unit test results for each variable under CD. Evidently, the variables CORR, ENV, EDU and GDP per capita are stationary (i.e. I(0)] and GPI and TRADE are non-stationary and their first-differences are stationary [i.e. I(1)]).

We include a Pedroni (2004) panel cointegration test under three categories: (1) no trend/no intercept, (2) no trend/intercept and (3) with trend/with intercept. This is illustrated in Table 5a with GDP per capita and Table 5b with trade variables replacing GDP. This test uses a residual based test for the null of no cointegration for dynamic panels, considering the pool within dimension test and groups mean between dimension tests. Evidently, almost all test statistic values are less than the corresponding critical values at the 5% or 10% level of significance. We reject the null hypothesis of no cointegration and conclude there is support for the variables under consideration are panel cointegrated.

Since some of the variables in (7) are I(1) and others are I(0), we consider using the ARDL formulation of (7), which can be written in the following two forms:

The first ARDL formulation of (7) with long and short run terms can be written as follows:

$$\begin{aligned}\Delta\left(Corr_{i,t}\right) = \beta_0 + \beta_1 Corr_{i,t-1} + \beta_2 GPI_{i,t-1} + \beta_3 EDU_{i,t-1} + \beta_4 ENV_{i,t-1} + \beta_5 GDP_{i,t-1} \\ +\sum_{j=1}^{q}\gamma_{0j}\Delta\left(Corr_{i,t-j}\right) \\ +\sum_{j=0}^{q}\gamma_{1j}\Delta\left(GPI_{i,t-j}\right) \\ +\sum_{j=0}^{q}\gamma_{2j}\Delta\left(EDU_{i,t-j}\right) \\ +\sum_{j=0}^{q}\gamma_{3j}\Delta\left(ENV_{i,t-j}\right) \\ +\sum_{j=0}^{q}\gamma_{4j}\Delta\left(GDP_{i,t-j}\right) + u_{it.}\end{aligned} \quad (8)$$

Table 3
Cross-sectional Dependence (CD) Test.

Variable	Cross-sectional dependence (CD) test	
	Breusch–Pagan LM test	Pesaran Scaled LM
(1)	**(2)**	**(3)**
CORR	428.438 (0.000)	35.606 (0.000)
GPI	965.270 (0.000)	86.790 (0.000)
ENV	683.196 (0.000)	59.896 (0.000)
EDU	512.020 (0.000)	43.575 (0.000)
GDP	1013.606 (0.000)	91.399 (0.000)
TRADE	375.602 (0.000)	30.568 (0.000)

Note: Statistical significance is given in parenthesis.

Table 4
CIPS Panel Unit Root Test Under Cross-sectional Dependence. H_0: The series has a unit root.

Variable	CIPS	P-value	Conclusion
(1)	(2)	(3)	(4)
CORR	−3.56	<0.01	Since the p-value is <0.01, we reject H_0 at the 5% level of significance and conclude CORR has no unit root and hence CORR is stationary in level form. That is, CORR is I(0).
GPI	−0.93	>0.10	Since the p-value is >0.10, we do not reject H_0 at the 5% level of significance and conclude that GPI has a unit root and hence non-stationary.
DGPI	−2.24	<0.01	Since the p-value is <0.01, we reject H_0 at the 5% level and conclude that the first difference of GPI, which is DGPI, has no unit root and hence DGPI is stationary. Therefore DGPI is I(0) and GPI is I(1).
ENV	−2.61	<0.01	Since the p-value is <0.01, we reject H_0 at the 5% level and conclude ENV has no unit root and hence ENV is stationary in level form. That is, ENV is I(0).
EDU	−3.21	<0.01	Since the p-value is <0.01, we reject H_0 at the 5% level and conclude EDU has no unit root and hence EDU is stationary in level form. That is, EDU is I(0).
GDP	−2.24	<0.10	Since the p-value is <0.10, we reject H_0 at the 10% level and conclude GDP has no unit root and hence GDP is stationary in level form. That is, GDP is I(0).
TRADE	−2.39	>0.10	Since the p-value is >0.10, we do not reject H_0 at the 5% level of significance and conclude that the TRADE has a unit root and hence TRADE is non-stationary.
DTRADE	−2.85	<0.01	Since the p-value is <0.01, we reject H_0 at the 5% level and conclude that the first difference of TRADE, which is DTRADE, has no unit root and hence DTRADE is stationary. Therefore DTRADE is I(0) and TRADE is I(1).

Note: p-values are given in column 3.

If cointegration between Corr, GPI, EDU, ENV and GDP exists, then an error-correction model can estimate the speed of adjustments of the disequilibrium caused by previous period shocks that re-converges with the long-run equilibrium (e.g. Selvanathan, Jayasinghe, Selvanathan, Abbas, & Iftekhar, 2023). The error correction form corresponding to (7) and (8) can be written as follows:

$$
\begin{aligned}
\Delta\left(Corr_{i,t}\right) = \alpha_0 + \sum_{j=1}^{q}\gamma_{0j}\Delta\left(Corr_{i,t-j}\right) \\
+\sum_{j=0}^{q}\gamma_{1j}\Delta\left(GPI_{i,t-j}\right) \\
+\sum_{j=0}^{q}\gamma_{1j}\Delta\left(EDU_{i,t-j}\right) \\
+\sum_{j=0}^{q}\gamma_{1j}\Delta\left(ENV_{i,t-j}\right) \\
+\sum_{j=0}^{q}\gamma_{1j}\Delta\left(GDP_{i,t-j}\right) + \mu \mathrm{EC}_{t-1} + u_{i,t}
\end{aligned}
\tag{9}
$$

To test the relationship between GPI and the time-varying correlations, we estimate panel regression using time-varying correlation indexes. We calculate these as described in Section 6.1 and the variable of interest (GPI) with other control variables for a panel of 11

Table 5a
Pedroni Residual Cointegration Test Results with GDP per Capita (Dependent variable = Corr).

No Trend/No Intercept				No Trend/Intercept				With Trend/ With Intercept			
Within Dimensions		Between Dimensions		Within Dimensions		Between Dimensions		Within Dimensions		Between Dimensions	
Group	**Statistics**	**Group**	**Statistics**	**Group**	**Statistics**	**Group**	**Statistics**	**Group**	**Statistics**	**Group**	**Statistics**
Panel rho-Statistic	−1.948	Group PP-Statistics	−14.361	Panel rho-Statistic	−1.223	Group PP-Statistics	−13.126	Panel rho-Statistic	0.010	Group PP-Statistics	−15.101
Panel PP-Statistic	−7.938	Group ADF-Statistics	−8.782	Panel PP-Statistic	−10.865	Group ADF-Statistics	−8.333	Panel PP-Statistic	−12.020	Group ADF-Statistics	−7.296
Panel ADF-Statistics	−6.725			Panel ADF-Statistics	−8.577			Panel ADF-Statistics	−8.554		

Note: Critical values are 10% = −1.28, 5% = −1.64 and 1% = −2.33. Within and between dimensions Pedroni test.

Table 5b
Pedroni Residual Cointegration Test Results with Trade (Dependent variable = Corr).

No Trend/No Intercept				No Trend/Intercept				With Trend/ With Intercept			
Within Dimensions		Between Dimensions		Within Dimensions		Between Dimensions		Within Dimensions		Between Dimensions	
Group	Statistics	Group	Statistics	Group	Statistics	Group	Statistics	Group	Statistics	Group	Statistics
Panel rho-Statistic	−2.125	Group PP-Statistics	−18.341	Panel rho-Statistic	−1.425	Group PP-Statistics	−16.567	Panel rho-Statistic	−0.100	Group PP-Statistics	−16.369
Panel PP-Statistic	−9.186	Group ADF-Statistics	−9.236	Panel PP-Statistic	−10.890	Group ADF-Statistics	−9.097	Panel PP-Statistic	−11.150	Group ADF-Statistics	−7.294
Panel ADF-Statistics	−7.746			Panel ADF-Statistics	−8.751			Panel ADF-Statistics	−8.411		

Note: Critical values are 10% = −1.28, 5% = −1.64 and 1% = −2.33. Within and between dimensions Pedroni test.

Table 6
Panel Estimation Results with GDP per Capita (Dependent variable = Corr).

Variables	Models			
	MGE	CCEMG	CCEP	PMG
Long run: GPI	13.863 (0.006)*	16.881 (0.098)**	0.020 (0.999)	4.997 (0.000)*
ENV $\times 10^7$	−1.35 (0.716)	−7.59 (0.282)	0.197 (0.940)	−1.03 (0.093)**
EDU	0.004 (0.210)	−0.002 (0.749)	0.006 (0.292)	0.006 (0.000)*
GDP $\times 10^5$	0.016 (0.425)	−0.093 (0.298)	−0.018 (0.990)	0.144 (0.403)
Short run: GPI	15.130 (0.064)**	29.824 (0.035)	4.826 (0.663)	8.994 (0.091)**
ENV $\times 10^7$	−1.87 (0.712)	−5.59 (0.283)	−0.764 (0.939)	0.593 (0.931)
EDU	0.001 (0.633)	911.713 (0.317)	4.38E−04 (0.960)	−0.010 (0.100)**
GDP $\times 10^5$	−0.482 (0.518)	−12.57 (0.171)	0.0799 (0.979)	−0.519 (0.612)
ECT	−1.027 (0.000)*	−0.185 (0.221)	−0.058 (0.606)	−0.497 (0.000)*

Note: *Statistical significance at the 5% level. ** Statistical significance at the 10% level. The *p*-values are given in parenthesis. Mean group estimates (MGE), common correlated effects mean group (CCEMG), common correlated effects pooled (CCEP) and pooled mean group (PMG).

markets over 25 years of data.

Table 6 presents the group mean estimates based on Pesaran, Shin, and Smith (1999), common correlated effects mean group (CCEMG) estimates, common correlated effects pooled (CCEP) estimates and pooled mean group (PMG) estimates based on Pesaran (2015).[19] The estimated long-run coefficients of GPI under all estimation methods are positive. Under mean group estimates (MGE), CCEMG and PMG methods, estimates are statistically significant. This finding indicates that a positive relationship exists between GPI and time-varying correlations for all 11 countries. The PMG long-run coefficient estimate of EDU is positive and statistically significant. Furthermore, the PMG long-run coefficient estimate of ENV is negative and statistically significant. Across the four estimation methods, the estimated coefficients for GDP per capita is positive but not statistically significant. The findings based on various estimation methods suggest that GPI has a positive relationship with the correlations. Most of the estimated coefficients across the four estimation methods for short run estimates are not statistically significant. However, the error-correction term is negative across the four estimation methods. The MGE and PMG estimates are statistically significant.

We recognise that the economic activity of countries is factored into the GPI compiled by the Rand Corporation. As such, we use an alternative variable (international trade) considered a common factor across financial markets with the potential to impact stock market returns and, thus, market correlations. International trade allows firms to exploit the comparative advantage that they may have, thus influencing profitability (Knudsen, Lien, Timmermans, Belik, & Pandey, 2021). This, in turn, has the potential to influence correlations over time. Stock and Watson (2005) examine international trade (exports and imports) as a factor that has the potential to influence business cycles across economies. The estimated model results with trade are presented in Table 7.

As in Table 6, Table 7 reports the MGE, CCEMG, CCEP and PMG estimates, generating similar results. The estimated long-run coefficient of GPI across all four estimation methods are positive. Furthermore, the PMG and MGE estimates are statistically significant. The estimated long-run coefficient for ENV is generally negative and the PMG estimate is statistically significant. The estimated EDU coefficients are generally positive, and the PMG estimate is statistically significant. Moreover, the trade coefficient estimate across the four methods is positive, and the CCEMG and PMG estimates are statistically significant. The error-correction term estimate across the four estimation methods is negative and statistically significant, within the expected range (−1,0). Among the four sets of estimates presented in Tables 6 and 7, the PMG estimates are considered the most preferred as most of the estimated coefficients are of the correct sign and the majority are statistically significant. The estimated Table 6 PMG estimates lead to the following interpretation. One unit change in GPI is expected to cause an average of approximately 5-unit changes in the correlations. A unit change in the environment causes only a small change in correlations. A unit change in education causes an average of 0.006 units change in correlations. Similarly, a unit change in GDP per capita is expected to cause economically insignificant (extremely small) changes in correlations. The error-correction term of −0.497 suggests that approximately 50% of the discrepancy between long- and short-term correlations is corrected within one year, indicating a reasonably fast rate of adjustment (approximately two years) to equilibrium.

Among the four sets of estimates presented in Table 7, based on the Table 6 results, we consider the PMG estimates to be the preferred estimated results. According to the PMG estimates in Table 7, a unit change in trade is expected to cause, on average, 0.007 units of change in correlations in the long run. Furthermore, Table 7 indicates that environmental awareness and overall individual wealth of nations may have a statistically significant relationship with correlations but are not economically significant.[20] Since the variation in GPI in certain markets is small compared with others, we divide the 11 countries into four quartiles based on GPI values and re-estimate (9). We present the four sets of estimates for the four groups of countries (with GDP per capita and trade as control variables) in Appendix D.

For robustness, we also use the 11 country panel dataset to estimate models excluding the control variables trade and GDP per capita from (9), as these variables are included in the Rand Corporation's GPI construction.[21] Table 8 presents the panel data estimation results for (9), excluding the GDP per capita and trade variables. These estimation results allow us to observe the direct changes

[19] We thank the anonymous referee for the suggestion and references for using different estimators.
[20] We thank the anonymous referee for their suggestion and helpful citation in this instance.
[21] Rand corporation uses a weight of 25% for GDP and 15% for trade in their construction of the GPI index.

Table 7
Panel Estimation Results with Trade (Dependent variable = Corr).[a]

Variables	Models			
	MGE	CCEMG	CCEP	PMG
Long run: GPI	9.827 (0.015)*	8.798 (0.407)	0.123 (0.983)	2.540 (0.000)*
ENV × 10^7	−0.184 (0.948)	−1.48 (0.826)	0.182 (0.856)	−0.764 (0.088)**
EDU	0.001 (0.320)	−0.004 (0.345)	−0.0006(0.918)	0.001 (0.032)*
TRADE	0.001 (0.372)	0.004 (0.026)*	0.008 (0.197)	0.007 (0.000)*
Short run: GPI	13.524 (0.121)	5.011 (0.677)	1.095 (0.875)	−0.260 (0.978)
ENV × 10^7	0.921 (0.753)	2.52 (0.631)	−0.283 (0.830)	3.85 (0.461)
EDU × 10^3	1.136 (0.619)	−7.026 (0.247)	0.598 (0.911)	−7.244 (0.162)
TRADE	−0.005 (0.012)*	−0.008 (0.009)*	−0.005 (0.249)	−0.011 (0.000)*
ECT	−0.295 (0.017)*	−0.295 (0.017)*	−0.217 (0.093)**	−0.463 (0.000)*

Note: *Statistical significance is at the 5% level. ** Statistical significance at the 10% level. The *p*-values are given in parenthesis. Mean group estimates (MGE), common correlated effects mean group (CCEMG), common correlated effects pooled (CCEP) and pooled mean group (PMG).

[a] The ARDL method uses the least squares method. The least squares method refers to the conditional distribution of the mean of the dependent variable given by the independent variables. If the distribution of data has an unequal variation, then we consider the conditional distribution of the median of the dependent variable given the independent variables. The resulting estimation method is quantile regression. In quantile regressions, the conditional distribution of the dependent variable is divided into different quantiles. The 50th quantile represents the median. We have estimated (7) using the quantile regression method. The results are reported in Appendix B and C of this paper. The results are similar to the long run estimates reported in Tables 6 and 7.

Table 8
Panel Estimation Results Excluding GDP per Capita and Trade (Dependent variable = Corr).

Variables	Models			
	MGE	CCEMG	CCEP	PMG
Long run: GPI	10.209 (0.008)*	6.361 (0.402)	−0.251 (0.992)	4.655 (0.000)*
ENV × 10^7	1.99 (0.442)	−3.51 (0.542)	0.270 (0.970)	−0.843 (0.009)*
EDU	0.001 (0.316)	0.001 (0.782)	0.006 (0.308)	0.006 (0.000)*
Short run: GPI	13.179 (0.073)**	29.414 (0.008)*	4.610 (0.282)	4.970 (0.428)
ENV × 10^7	−1.09 (0.740)	−12.9 (0.040)*	−0.733 (0.906)	−2.11 (0.772)
EDU	−0.0007 (0.766)	1117.072 (0.317)	0.0007 (0.912)	−0.008 (0.142)
ECT	−0.960 (0.000)*	−0.146 (0.232)	−0.060 (0.162)	−0.462 (0.000) *

Note: *Statistical significance is at the 5% level. ** Statistical significance is at the 10% level. The *p*-values are given in parenthesis. Mean group estimates (MGE), common correlated effects mean group (CCEMG), common correlated effects pooled (CCEP) and pooled mean group (PMG).

Table 9
Panel Estimation Results with GPI Only (Dependent variable = Corr).

Variables	Models			
	MGE	CCEMG	CCEP	PMG
Long run: GPI	12.271 (0.000)*	−5.764 (0.298)	2.830 (0.710)	3.636 (0.000)*
Short run: GPI	5.209 (0.442)	15.765 (0.044)*	1.161 (0.670)	7.534 (0.387)
ECT	−0.504 (0.000)*	−0.768 (0.000)*	−0.023 (0.421)	−0.1174 (0.067)**

Note: *Statistical significance is at the 5% level. ** Statistical significance is at the 10% level. The p-values are given in parenthesis. Mean group estimates (MGE), common correlated effects mean group (CCEMG), common correlated effects pooled (CCEP) and pooled mean group (PMG).

between GPI and the correlations without additional economic factors. This is because GPI contains elements of economic capacity, including GDP measurements using PPP and trade (exports plus imports). The estimated long-run coefficients of GPI are generally positive, and the MGE and PMG estimates are statistically significant. The estimated long-run PMG and short-run CCEMG estimates for ENV are negative and statistically significant. The PMG long-run EDU estimates are positive and statistically significant.

Since our variable of interest is GPI, we also estimate (9) with GPI as the only independent variable, excluding all other control variables. The results are presented in Table 9 and are similar and mostly statistically significant.

7. Concluding comments

The study's motivation is to explore the impact of powerful nations on the economy and trade policies of less powerful nations. By answering the question, 'Does the global power of nations positively influence stock market correlations over time?' we fill the research gap regarding the impact of GPI on financial market integration. This is the first study to develop such a theoretical relationship between GP and market integration. Moreover, it provides empirical evidence for the theoretical relationship using data from a selected number of markets from G20 countries. The findings from our study enhance the understanding of the factors that drive changes in time-varying correlations. Previously, changes in market integration have been examined from a financial market perspective or by considering macroeconomic factors. However, the impact of GP, albeit intuitive, has not been previously examined from the standpoint of market integration.

Research on time-varying correlations to date has implicitly assumed that changes in correlations among market pairs are owing to changes in the volatility of the underlying market pairs. However, the relevant literature does not adequately address the reasons for these changes in the relative risk of these markets. Our study specifically offers a theoretical argument to establish the relationship between GP and the intermediary variables that feed into the risk premium and returns of underlying markets. Changes in risk premium in the underlying markets may cause changes in relative market returns, thus changing co-movements over time.

Time-varying correlations have been estimated from stock market returns using Cappiello et al.'s (2006) ADCC-GARCH model. We estimate scaled correlation indexes for each of the stock markets with others. The correlation indexes are used as a dependent variable in the panel regression. Independent variables include GPI, education level (EDU), environmental awareness (ENV) and GDP per capita. Moreover, we use trade as an alternative control variable. Based on panel unit root tests with CD, we use the ARDL model for our analysis. Our estimated results support the hypothesis that GP positively influences the correlations of the stock markets. The GPI coefficient is statistically significant at the 1% level.

The estimated coefficients for the environment and education variables are statistically significant, and the magnitudes of the estimated coefficients are extremely small, suggesting that the relationship may not be economically significant. We did not have a priori expectations of the direction of the impact of ENV, EDU and GDP per capita on correlations. The results imply that environmental awareness has a negative relationship with the correlations. This finding may be because environmentally aware people may focus more on local factors, thus affecting the correlations negatively. Coefficients for environment, education, GDP per capita and trade are small. This is unsurprising as correlations and GPI are indexes, whereas other variables are absolute numbers (e.g. GDP per capita and trade as a proportion of GDP). The environment variable is measured as CO_2 emissions in metric tonnes per capita and education as a gross percentage of tertiary enrolled students.

Furthermore, we find coefficients in some cases to be extremely small but statistically significant. A small change to the correlations across markets may have significant economic impacts in terms of systemic risk and portfolio implications. According to Eisenberg and Noe (2001), small changes in the structure of financial networks and asset correlations can amplify systemic risk and lead to cascading failure. Das and Hanouna (2009) reveal how small changes in correlations between credit instruments can have significant implications for portfolio risk management and the assessment of systemic risk in credit markets. Elton, Gruber, and Rentzler (1990) demonstrate how small changes in asset correlations across different markets can significantly affect portfolio diversification benefits.

Li, Zhuang, Wang, and Dong (2021) determine similar results in their study of spillover effects. Developed markets are transmitters of volatility and developing markets are receivers (Li et al., 2021). Their study differs from ours, as Li et al. (2021) consider the impact of the COVID−19 pandemic across G20 markets, while we examine the cause of changes over time. Studies examining underlying factors for changes in co-movements are scant while typically examining pairwise correlations. For example, Gupta and Mollik (2009) investigate the relative volatility of market pairs as the primary factor. Recently, Shi (2022) determines co-movements to be influenced by bilateral trade and market similarities. Moreover, the present study finds trade to be positively related to correlation indexes. However, the findings of the aforementioned studies are not directly comparable with ours, as we examine the relationship of one market with other markets by constructing scaled correlation indexes. Studies testing long-run equilibrium relationships between markets are numerous (Aggarwal & Kyaw, 2005; Caporale, You, & Chen, 2019; Saji, 2022); however, they do not test for the cause of change. Notably, equilibrium studies test for a long-run equilibrium while not providing an understanding of the time-varying nature of the relationship.

Our study contributes to the body of knowledge by elucidating the role of powerful nations on stock market performance. The findings provide additional evidence on the debate regarding changes in correlations over time. Prior to this study, the role of GP on time-varying correlations had not been investigated. Furthermore, this study contributes to methodology by constructing correlation indexes for each market with other markets, thus allowing for analysis in a global context rather than being restricted to pairwise analysis.

The findings of this study have essential implications for practitioners who seek investment opportunities worldwide. For example, a portfolio manager from a market with a strong GP who seeks diversification benefits is less likely to benefit from diversifying into markets that have stronger/increasing GP. Furthermore, our findings have implications for policymakers who seek to develop policies conducive to future investments. Policymakers must be mindful of policy impacts on market integration when negotiating trade policies in bilateral and multilateral trade negotiations.

This study involves certain limitations. First, stock market data are generally available on a daily, weekly and monthly frequency basis (we use monthly data for stock prices). However, data for other variables are only available on a quarterly or annual basis. The exception is for GPI data, which is only available on an annual basis. We recognise this limitation, especially regarding estimating panel models where time series observations are assumed to be large. With 25 observations from 1995 to 2019 and with only 11 individuals, model can be considered appropriate. To further address the issue of heterogeneity and lower variations in GPI for some markets, we divide data into quartiles based on GPI levels. Results based on this analysis are similar to the base analysis. Second, due to the unavailability of data for certain markets, we eliminate eight markets while working with only 11 markets, representing 58.05% of the GDP of global markets[22] and 46.17% of the global population.[23] As such, findings from these 11 markets can be generalised.

Finally, some of the unique differences in pairwise correlations are lost due to the construction of scaled indexes. The benefit of index construction is that we draw conclusions for global markets, which would not be possible otherwise. However, these limitations would not cause problems in drawing conclusions for this study. These 11 markets are a good representation of G20 markets. From a methodological perspective, we are able to construct annual time series data for the correlations using monthly data. The construction of indexes allows for analysis in a broader context. We can estimate cross-country relationships over a length of time. Thus, 25 years of data provide a sufficient time window for the analysis and the conclusions drawn to be valid.

CRediT authorship contribution statement

Rakesh Gupta: Writing – original draft, Supervision, Software, Formal analysis, Conceptualization. **Sama Haddad:** Writing – review & editing, Writing – original draft, Validation, Investigation, Formal analysis. **E.A. Selvanathan:** Writing – review & editing, Software, Formal analysis.

Declaration of competing interest

During the preparation of this work the author(s) did not use any generative AI tool. Authors take(s) full responsibility for the content of the publication.

Data availability

Data will be made available on request.

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Appendix A. Descriptive Statistics for Country-wise Data for All Variables

Country	GPI (1)			ENV (2)			EDU (3)			GDP per capita growth (4)			Stock market returns (5)			Trade (6)		
	Mean	SD	J-B test (p-value)	Mean (x 10^5)	SD (x 10^5)	J-B test (p-value)	Mean	SD	J-B test (p-value)	Mean (%)	SD (%)	J-B test (p-value)	Mean (%)	SD (%)	J-B test (p-value)	Mean	SD	J-B test (p-value)
1. Australia	0.014	0.0009	1.305 (0.521)	3.473	0.449	5.233 (0.073)	82.645	19.865	1.500 (0.472)	3.8	2.3	6.275 (0.036)	5.8	14.3	30.057 (0.000)	40.015	3.574	2.6877 (0.260)
2. Canada	0.003	0.023	2.969 (0.226)	5.145	0.530	3.396 (0.183)	70.553	12.592	24.847 (0.000)	2.9	2.5	6.275 (0.433)	7.6	16.7	2.941 (0.229)	66.473	8.144	0.145 (0.929)
3. China	0.138	0.049	2.628 (0.269)	6.024	31.13	3.106 (0.211)	20.304	16.632	2.310 (0.315)	9.6	3.2	0.098 (0.952)	7.1	36.1	2.615 (0.270)	41.836	11.653	1.152 (0.562)
4. Germany	0.065	0.010	1.659 (0.436)	8.122	0.711	0.277 (0.871)	54.030	10.923	1.630 (0.443)	3.7	2.3	3.195 (0.202)	7.2	20.7	6.611 (0.036)	67.124	17.140	3.355 (0.186)
5. France	0.055	0.008	1.866 (0.393)	3.514	0.254	2.600 (0.273)	53.928	7.468	4.390 (0.111)	3.7	2.1	3.607 (0.164)	7.5	19.8	4.276 (0.117)	53.123	7.378	1.794 (0.407)
6. UK	0.047	0.006	3.328 (0.189)	4.941	0.668	3.576 (0.167)	54.095	10.055	8.109 (0.017)	3.7	2.2	62.554 (0.000)	3.6	13.7	10.623 (0.004)	54.543	5.470	1.920 (0.382)
7. India	0.063	0.015	1.793 (0.408)	1.329	6.205	2.573 (0.276)	14.426	8.353	3.031 (0.220)	6.4	2.0	2.373 (0.305)	16.3	34.9	2.668 (0.263)	35.328	12.994	2.580 (0.275)
8. Italy	0.036	0.007	2.666 (0.264)	4.030	0.477	2.278 (0.320)	54.719	11.977	3.976 (0.137)	2.9	2.5	0.073 (0.963)	4.3	22.0	2.143 (0.342)	48.976	7.429	1.547 (0.461)
9. Mexico	0.072	0.015	1.859 (0.394)	4.020	0.693	3.003 (0.223)	24.669	8.348	2.068 (0.356)	3.7	2.7	0.041 (0.979)	14.1	25.4	0.310 (0.856)	54.916	13.720	0.150 (0.927)

(continued on next page)

[22] For the percentage of GDP for global markets (2023), see: https://www.imf.org/external/datamapper/PPPSH@WEO/AUS/CAN/CHN/DEU/FRA/IND/ITA/KOR/MEX/GBR/USA

[23] For the Percentage of global population (2023), see: https://www.worldometers.info/world-population/population-by-country/

(*continued*)

Country	GPI (1)			ENV (2)			EDU (3)			GDP per capita growth (4)			Stock market returns (5)			Trade (6)		
	Mean	SD	J-B test (p-value)	Mean (x 10^5)	SD (x 10^5)	J-B test (p-value)	Mean	SD	J-B test (p-value)	Mean (%)	SD (%)	J-B test (p-value)	Mean (%)	SD (%)	J-B test (p-value)	Mean	SD	J-B test (p-value)
10. Korea	0.023	0.003	0.841 (0.656)	4.802	1.127	1.805 (0.406)	79.624	22.829	6.285 (0.043)	5.0	3.8	1.862 (0.394)	11.8	41.2	55.042 (0.000)	70.792	17.355	1.757 (0.145)
11. US	0.280	0.023	2.983 (0.225)	52.77	3.487	2.744 (0.254)	81.151	5.857	2.187 (0.335)	3.5	1.7	39.385 (0.000)	8.5	16.9	18.254 (0.000)	25.117	3.459	1.596 (0.450)

Note: Table provides descriptive statistics for all variables for the data used in the study.

Appendix B. Quantile Regression Results with GDP per Capita (Dependent Variable = Corr)

Variable	Quantile (25%)	Quantile (50%)	Quantile (75%)
GPI	−2.788 (0.000)	1.289 (0.7238)	4.977 (0.000)
ENV × 10^7	0.911 (0.000)	12.3 (0.8601)	−0.503 (0.002)
EDU × 10	0.004 (0.8187)	0.022 (0.006)	0.037 (0.003)
GDP × 10^5	1.04 (0.001)	0.848 (0.002)	0.590 (0.000)

Note: Statistical significance is given in parenthesis.

Appendix C. Quantile Regression results with Trade (Dependent Variable = Corr)

Variable	Quantile (25%)	Quantile (50%)	Quantile (75%)
GPI	−0.251 (0.1691)	−0.120 (0.542)	−0.004 (0.983)
ENV × 10^7	0.254 (0.000)	0.179 (0.010)	0.154 (0.044)
EDU × 10	−0.004 (0.124)	−0.007 (0.037)	−0.012 (0.011)
TRADE	0.006 (0.000)	0.009 (0.000)	0.011 (0.000)

Note: Statistical significance is given in parenthesis.

Appendix D. Appendix D: Panel Estimation Results for Quartiles (Dependent variable = Corr)

Table D1
Panel Estimation Results for 1st Quartile excluding GDP per Capita and Trade.

Variables	Models			
	MGE	CCEMG	CCEP	PMG
Long run: GPI	4.878 (0.112)	1.188 (0.759)	−1.127 (0.954)	5.931 (0.000)
ENV × 10^7	−0.131 (0.852)	−5.65 (0.290)	0.352 (0.957)	−0.927 (0.011)
EDU	−0.0008 (0.834)	−0.004 (0.701)	0.005 (0.655)	0.004 (0.001)
Short run: GPI	3.580 (0.023)	10.719 (0.011)	3.595 (0.629)	7.995 (0.005)
ENV × 10^7	−3.80 (0.184)	−8.65 (0.259)	−0.601 (0.911)	−3.98 (0.147)
EDU	−0.002 (0.693)	0.019 (0.441)	0.0007 (0.945)	−0.008 (0.293)
ECT	−0.918 (0.000)	−0.423 (0.137)	−0.034 (0.764)	−0.351 (0.129)

Note: Countries include China, Germany and the US. Mean group estimates (MGE), common correlated effects mean group (CCEMG), common correlated effects pooled (CCEP) and pooled mean group (PMG). Statistical significance is given in parenthesis.

Table D2
Panel Estimation Results for 2nd Quartile excluding GDP per Capita and Trade.

Variables	Models			
	MGE	CCEMG	CCEP	PMG
Long run: GPI	3.678 (0.223)	3.003 (0.833)	5.797 (0.510)	6.169 (0.000)
ENV × 10^7	4.36 (0.409)	−4.46 (0.001)	−1.03 (0.918)	−1.87 (0.009)
EDU	0.007 (0.006)	0.011 (0.200)	0.006 (0.086)	0.006 (0.000)
Short run: GPI	9.544 (0.453)	19.000 (0.007)	7.789 (0.451)	7.098 (0.785)
ENV × 10^7	1.48 (0.682)	−0.572 (0.904)	−1.76 (0.892)	−4.31 (0.274)
EDU	0.002 (0.689)	−0.012 (0.521)	0.007 (0.033)	0.0001 (0.975)
ECT	−0.940 (0.000)	0.086 (0.570)	−0.650 (0.000)	−0.774 (0.000)

Note: Countries include France, the UK and India. Mean group estimates (MGE), common correlated effects mean group (CCEMG), common correlated effects pooled (CCEP) and pooled mean group (PMG). Statistical significance is given in parenthesis.

Table D3
Panel Estimation Results for 3rd Quartile excluding GDP per Capita and Trade.

Variables	Models			
	MGE	CCEMG	CCEP	PMG
Long run: GPI	27.081 (0.116)	−7.085 (0.675)	17.860 (0.732)	10.213 (0.007)
ENV × 10^7	−9.83 (0.042)	−12.7 (0.500)	−17.1 (0.174)	−4.55 (0.384)
EDU	0.004 (0.052)	0.009 (0.410)	0.010 (0.180)	0.006 (0.001)
Short run: GPI	3.170 (0.585)	17.352 (0.014)	8.837 (0.672)	−6.735 (0.048)
ENV × 10^7	−10.6 (0.000)	−32.3 (0.247)	−16.5 (0.373)	−8.58 (0.000)
EDU	0.0004 (0.271)	0.024 (0.376)	0.017 (0.027)	−0.003 (0.430)
ECT	−0.629 (0.159)	−0.039 (0.912)	−0.362 (0.444)	−0.615 (0.183)

Note: Countries include Italy and Korea. Mean group estimates (MGE), common correlated effects mean group (CCEMG), common correlated effects pooled (CCEP) and pooled mean group (PMG). Statistical significance is given in parenthesis.

Table D4
Panel Estimation Results for 4th Quartile excluding GDP per Capita and Trade.

Variables	Models			
	MGE	CCEMG	CCEP	PMG
Long run: GPI	10.822 (0.026)	23.855 (0.290)	0.034 (0.999)	−1.405 (0.526)
ENV × 10^7	9.61 (0.000)	5.70 (0.772)	12.5 (0.549)	16.9 (0.000)
EDU	−0.002 (0.046)	−0.008 (0.045)	−0.001 (0.917)	−0.003 (0.001)
Short run: GPI	33.086 (0.152)	66.563 (0.052)	−2.816 (0.858)	31.244 (0.033)
ENV × 10^7	5.40 (0.613)	−16.6 (0.202)	9.78 (0.764)	−4.06 (0.760)
EDU	−0.002 (0.287)	4095.909 (0.317)	−0.004 (0.738)	−0.005 (0.005)
ECT	−1.241 (0.000)	−0.172 (0.475)	−0.531 (0.023)	−0.658 (0.003)

Note: Countries include Australia, Canada and Mexico. Mean group estimates (MGE), common correlated effects mean group (CCEMG), common correlated effects pooled (CCEP) and pooled mean group (PMG). Statistical significance is given in parenthesis.

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