Equity Home Bias in Space and Time

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‘*Play the game*’

Sir Henry Newbolt, 1862-1938

Vitaï Lampada

Abstract

Equity home bias (EHB) remains one of the most enduring puzzles in international finance. Despite the dominant narrative of deepening global financial integration over recent decades, investors continue to systematically overweight domestic equities, thereby foregoing the benefits of international diversification. Within the neoclassical finance tradition, EHB is typically regarded as a transient anomaly expected to dissipate as markets integrate and arbitrage opportunities are exhausted. In contrast, this study posits that EHB is a structural feature of international finance, sustained by clustering across space and path dependence through time. It addresses four guiding questions: how EHB is defined; how it is measured; whether clustering is present across neighbourhood structures; and whether, if present, such clustering persists in path-dependent ways.

The empirical chapters address these questions in turn. A Systematic Literature Review is undertaken in Chapter 2, showing that definitions of EHB fall into three forms (model-based, data-based, and hybrid), each derived from the neoclassical finance tradition that reduces space to domicile and time to an ordinal sequence. Drawing on data for 43 countries over the period 2001 through 2020, Chapter 3 constructs a panel of EHB estimates across the three forms and applies a non-parametric Quantile Shift Function, demonstrating that the distributions are statistically indistinguishable and that measurement debates are largely inconsequential. Chapter 4 computes the Global Moran's Index and Local Indicators of Spatial Association (LISA) for the panel's International Capital Asset Pricing Model series, finding that EHB is systematically clustered. Employing both Transition LISA and Directional LISA methodologies, Chapter 5 demonstrates that EHB clusters are persistent through time, with the directional results indicating a predominantly downward trajectory, particularly after the Global Financial Crisis.

By addressing the EHB puzzle through its definition, measurement, presence, and persistence, the study offers novel empirical insights with clear implications for theory and practice. The impact of financial integration has not been uniform, with clustering and path dependence associated with negligible EHB levels in European developed markets while reinforcing persistently high EHB in Asia's emerging markets. Likewise, the results confirm that the production of returns is systematically conditioned by neighbourhood structures, which dynamically shape the patterns of portfolio diversification. In short, investing is inherently geographical, structured through the intersection of space and time.

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This work is dedicated to Dr Jacqueline Drew, our two sons, Nicholas and Alexander, and the late Dawn Calam, my Nan. I love you more than words can show.

Michael E. Drew

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1. Introduction

1.1 The puzzle of Equity Home Bias

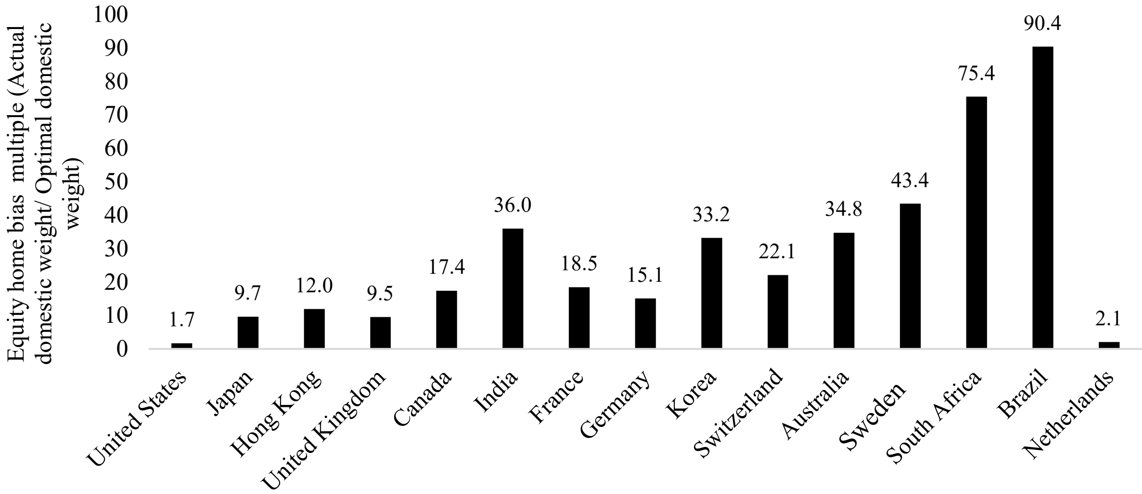
The case for international portfolio diversification seems compelling. The neoclassical finance tradition has long shown that global diversification minimises idiosyncratic risk and enhances returns (Grubel, 1968), and recent studies confirm its continued benefits for investors (Kelliher, Hazrachoudhury, and Irving, 2022). Yet, investors persistently overweight domestic (or home) equities in portfolios, a phenomenon known as equity home bias (EHB).[1]

Despite voluminous scholarly and practitioner endeavour, the extant literature (including studies on information asymmetry, hedging motivations, taxation, barriers to international investing, behavioural factors, and time-varying risk aversion) has failed to reconcile this puzzling divergence between investment theory and investor practice (Obstfeld and Rogoff, 2000; Chan, Covrig, and Ng, 2005; Bekaert and Wang, 2009; Mishra, 2015; Wallmeier and Iseli, 2022; Sachdeva and Fotheringham, 2023). Today, there is broad consensus on two observed regularities of EHB. First, EHB is present at high levels across most countries and well above the optimal weights prescribed by theory (Markowitz, 1952). Second, EHB has persisted through time, enduring despite decades of global financial integration (Clark, 2005; Rogoff, 2025).[2] Figure 1.1 illustrates the systematic divergence of actual holdings from theoretical benchmarks, reporting the EHB multiple for the 15 largest markets by capitalisation in 2020.

[1] For more than half a century, the field has documented both the presence and persistence of EHB (Levy and Sarnat, 1970; French and Poterba, 1991; Tesar and Werner, 1995; Lewis, 1999; Balasubramanian and Kumar, 2023). Following the neoclassical finance tradition, rational investors are expected to hold the world market portfolio, diversified across countries according to their relative market capitalisations (Markowitz, 1952; Sharpe, 1964; Solnik, 1974). EHB results in portfolio under-diversification, exposing investors to uncompensated idiosyncratic risk (Sharpe, 1964).

[2] Global financial integration is conceptualised as processes that eliminate barriers that segment markets, including: informational, institutional, legal, regulatory, and, transactional constraints (Obstfeld and Rogoff, 2000; Rogoff, 2025). For financial geographers, such processes are not frictionless and are conditioned by spatio-temporal effects (Clark, 2005; Clark and Monk, 2017; Wójcik, Iliopoulos, Ioannou, Keenan, Migozzi, Monteath, Pažitka, Torrance, and Urban, 2024). These ideas are best summarised by Clark's (2005) observation that, *"money flows like mercury (p.99)"* across the geography of international finance.

Figure 1.1 Equity home bias multiple for the 15 largest countries by market capitalisation (2020)



Notes: Data as at 31 December 2020 (in U.S. dollars). The EHB multiple is the ratio between actual domestic holdings and optimal domestic holdings. See Chapter 3 for empirical specifications, including the Model-based example for Australia (Section 3.5.3.1).
Source: IMF (2022), author calculations.

In the neoclassical finance tradition (Markowitz, 1952; Sharpe, 1964; Solnik, 1974), deviations from *a priori* expectations are classified as anomalies; in this context, EHB levels that exceed theoretical weights constitute such an anomaly. When such anomalies exhibit persistence, as in the case of EHB, they are elevated to the status of a *puzzle* (Obstfeld and Rogoff, 2000). Historically, most anomalies in finance are eventually arbitraged away (Fama, 1970; Ross, 1976).[3] However, despite successive refinements, EHB has been consistently observed and documented for more than fifty years.[4] In Kuhn's (1962) terms, such persistent anomalies may signal the limits of a prevailing paradigm, raising the question of whether EHB should still be treated as a puzzle within the neoclassical finance tradition, or instead as evidence of the need for new perspectives.[5]

[3] Shleifer and Vishny (1997) make the case that 'real-world' limits to arbitrage may explain why such anomalies endure within the neoclassical finance tradition.
[4] For historical context, in the late twentieth century, Lewis (1999) characterised the EHB literature as being in a state of deadlock, where successive empirical refinements improved measurement but failed to resolve the underlying puzzle.
[5] Kuhn's (1962) notion of a *paradigm* is useful here as a diagnostic for moments of disciplinary stasis (as is the case with the EHB literature) where persistent anomalies signal that prevailing research approaches are no longer delivering explanatory progress (Kuhn, 1962). However, what is at stake in labelling an approach a paradigm is not simply a rhetorical claim about novelty; it is a stronger statement about what counts as a legitimate question, what counts as evidence, and which methods are treated as authoritative (Kuhn, 1962). In the social sciences, these boundaries are typically less rigid than in Kuhn's (1962) original account of the natural sciences. Paradigms can, and often do, overlap, coexist, and compete without full replacement, and researchers routinely borrow concepts and methods across traditions. The term *paradigm* is used as a framing device to show how the EHB literature exhibits features of 'science' despite it being a long-running puzzle (Kuhn, 1962).

This study adopts a financial geography perspective, which posits that investing is inherently geographic (Clark, 2005). The production of returns requires the investor to reach out across space and through time, allocating capital to markets characterised by spatial variegation and temporal sequencing (Clark and Monk, 2017). For the financial geographer, investment decisions are embedded within spatial and temporal contexts and evolve through processes of clustering and path dependence, rather than as frictionless abstractions (Arthur, 1989; North, 1990).[6] This conceptual lens provides the foundation for the analyses that follow and motivates a research design capable of addressing the puzzle on multiple fronts.

1.2 Context

Research on EHB has reached a state of stasis. This makes understanding the broader research context critical. The neoclassical finance tradition treats EHB as a puzzle; in contrast, financial geography reframes it as being embedded in space and time.[7] For the financial geographer, context matters. Investment decisions are not abstract or placeless, but are embedded in networks of space and time, as well as institutional practice (Clark and Monk, 2017). For this reason, this study situates EHB within financial geography, laying the foundation for the spatio-temporal perspective developed.[8]

Against the provocations of O'Brien (1992), who foreshadowed a diminished role for space and place in international finance, the production of investment returns still leads to capital being overallocated to home-domiciled equities (Levy, 2017; Huberman, 2001; Mishra, 2015; Clark and Monk, 2017; Sachdeva and Fotheringham, 2023; Wójcik, Iliopoulos,

[6] It is (humbly) observed that there is an expansive nomenclature in the field used to describe the processes of clustering and path dependency. For clarity, this study refers to *clustering* as the spatial process through which countries with similar levels of EHB group together across space and *path dependence* as the temporal process through which these patterns evolve through time (Arthur, 1989; North, 1990; David, 1994; Leyshon and Thrift, 1998; Clark, 1998; Martin, 1999, 2010; Clark, Mansfield, and Tickell, 2001; Martin and Sunley, 2006, 2010; Wójcik, 2012; Coe, Lai, and Wójcik, 2014; Lai, 2020).

[7] A further complication is that what is referred to in this study as the neoclassical finance tradition is itself *heterogeneous*. Under that umbrella sit distinct approaches and empirical practices; ranging from equilibrium asset-pricing and market-efficiency claims, to portfolio-selection frameworks, as well as market microstructure and behavioural predictions (Markowitz, 1952; Sharpe, 1964; Fama, 1970; Solnik, 1974; O'Hara, 1995; Huberman (2001); Barberis and Thaler, 2003). Treating this diversity as a single paradigm risks overstating internal coherence and underplaying the extent to which important disagreements already exist within finance about assumptions, methodologies, and inference. Accordingly, when this study contrasts the neoclassical finance tradition with financial geography, it does so with the awareness that the boundary is not a simple binary. This matters because Kuhn's (1962) idea of paradigms as incommensurable sits uneasily with the reality that finance and geography can share objects of inquiry, partial vocabularies (e.g. financial integration), and even methods, while still differing in how space and time are conceptualised (Kuhn, 1962). That tension is acknowledged here and returned to in the conclusion

[8] To borrow Mark Twain's famous quip, *"the reports of my death are greatly exaggerated,"* it is argued that geography remains very much alive and remains indispensable for gaining new perspectives on the EHB puzzle.

Ioannou, Keenan, Migozzi, Monteath, Pažitka, Torrance, and Urban, 2024). While the dominant narrative across the fields of finance, economics, and geography over the observation period of this study (2001 through 2020) has been one of deepening global financial integration (Bekaert and Harvey, 1995; Obstfeld and Rogoff, 2000; Karolyi and Stulz, 2002; Posen, 2025; Rogoff, 2025; World Economic Forum, 2025), the phenomenon of EHB persists.[9] The persistence of this puzzle suggests that the key assumptions underpinning the neoclassical finance tradition, hypothesised to erode home bias, have proven insufficient, justifying a renewed attention to the spatio-temporal dimensions of investing.

1.2.1 Space

Space, like time, is not a neutral backdrop for investment decisions; it actively structures and shapes the production of financial returns (Clark and Monk, 2017). In the neoclassical finance tradition, space is typically reduced to the domicile of the investor, with each country treated as an independent unit in the world market portfolio (Solnik, 1974). From this perspective, the central spatial distinction is *domestic* versus *foreign*, and interdependencies across locations are largely assumed away (Mishra, 2015).

By contrast, spatio-temporal analysis treats space as relational and structured, emphasising both global association and local neighbourhoods (Moran, 1950; Anselin, 1995; Rey and Anselin, 2010). Global Moran's Index measures clustering across the system as a whole (global), while Local Indicators of Spatial Association (LISA) identify country-specific clusters, outliers, and regimes of interdependence (local). In this framework, space is conceived as a network of neighbours, where proximity (say, geographical, institutional, and/or informational) shapes investor decision making and may amplify persistence (Leyshon and Thrift, 1998; Wójcik, 2011; Clark, Feldman, Gertler, and Wójcik, 2018).

To test for spatio-temporal effects, this study considers multiple spatial layers. At the global level, the study examines whether EHB exhibits global spatial association, consistent with Tobler's (1970) first law, *"near things are more related than distant things (p.236)."* At the local level, neighbourhood structures are specified to detect clusters of similarity (for example, high EHB countries surrounded by high EHB neighbours) and spatial outliers (countries whose behaviour diverges from their region). Two guiding questions frame the

[9] The dynamism of EHB through time has been documented by Fratzscher (2009), Milesi-Ferretti and Tille (2011), and Forbes and Warnock (2012). These studies found that, during the Global Financial Crisis (GFC), investors retreated further to the proximate; their revealed behaviour showed that they preferred to be exposed to a crisis at home rather than abroad.

research design: who is your neighbour?; and, how much does your neighbour matter? Answers to these two questions allow neighbourhood structures to be defined and tested.

1.2.2 Time

Consistent with the discussion of space, the field of financial geography frames time as something more than a neutral sequence of observations (Clark, Feldman, Gertler, and Wójcik, 2018). Returning to the neoclassical finance tradition, time is treated as a homogeneous sequence of intervals (days, months, quarters, or years) within which markets are assumed to seek equilibrium (Engle and Granger, 1987; Johansen, 1991; Hamilton, 1994; Stock and Watson, 2002; Pesaran, 2015). Time-series econometric approaches (such as cointegration or error correction models) are designed to identify causal dynamics, asking whether variables share a long-run relationship or how quickly shocks dissipate (Engle and Granger, 1987). In this framing, persistence is typically reduced to a statistical artefact to be corrected, rather than an object of inquiry (see Chapter 5).

In this study, persistence is not a *nuisance term* but an indicator of how patterns evolve across space and time. Spatio-temporal analysis treats time as a state of the system (Moran, 1950; Cliff and Ord, 1981; Rey, 2001, 2014; Elhorst, 2014). The contribution of Cliff and Ord (1981) on spatial statistics is seminal and provides a fundamental building block for the methodological approach adopted. Here, the trajectory of EHB is not simply a line through homogeneous intervals, but a process conditioned by past states and neighbouring dynamics; local clusters evolve and these transitions are themselves the phenomena of interest (Rey and Anselin, 2010; Rey and Janikas, 2005).

The adoption of such framing in the research design is a non-trivial decision. In Chapters 4 and 5, states are operationalised at multiple temporal scales: annually (level of EHB), annual changes (to detect year-to-year change, or delta, in the level of EHB), in five-year blocks (to consider the impact of economic cycles, crises, and recoveries), over the full twenty-year horizon (to examine clustering across space and path dependence through time), and at the individual country level (using the example of Australia). This multi-layered framing distinguishes transitory noise from meaningful spatio-temporal effects.

1.3 Problem

The presence and persistence of EHB imply that investors systematically forego the well-known gains from international diversification for geographically concentrated portfolios (Grubel, 1968). For the investor, the potential adverse consequences of holding idiosyncratic risk cannot be overstated (Sharpe, 1964). Portfolios exhibiting EHB are more susceptible to geopolitical and economic shocks (Bridgewater Associates, LP, 2019) and liquidity risk (Wójcik, 2011).[10] At the macro-prudential level, investor practice shapes the geography of finance through their role as actors in global financial networks (Wójcik, 2018) and by the spatially variegated nature of their investment arrangements (Urban, 2019). As Clark and Monk (2017) have argued, the production of investment returns is always and everywhere embedded in geography. Framed this way, EHB transcends a micro-level anomaly (or 'quirk') and emerges as a macro-level force structuring global financial geographies.

Building on the previous section, Tobler's (1970) first law provides a useful process framework for examining EHB through neighbourhood dynamics. Although not causal, Tobler's (1970) law highlights the potential informational value of proximity and relatedness. This line of reasoning raises important questions about the validity of research designs that ignore such effects and instead impose aspatial time-series frameworks, thereby jeopardising the reliability of reported results (Leyshon and Thrift, 1998; Martin, 1999; Clark, 1998). Recent work by Pace and Calabrese (2022) has shown the perils of omitting spatio-temporal effects, which can lead to estimation bias in empirical finance.

The field of financial geography brings new insights that show how spatio-temporal effects are mediated through regulatory regimes, institutional environments, and the social, political, and cultural geographies of familiarity, trust, and confidence (Martin and Pollard, 2017; Clark, Feldman, Gertler, and Wójcik, 2018; Sachdeva and Fotheringham, 2023). It is hypothesised that such neighbourhood connectivity is critical for our understanding of the production of returns. In this context, the study tests the hypothesis that spatio-temporal effects are integral to unravelling the EHB puzzle. Recognising the role of such effects leads to the broader relational structures that underpin international finance, with global capital flows emerging as a key variable for this study.

[10] On the issue of investment risk, Bridgewater Associates, LP (2019) has stated that, *"the best way we know to earn consistent returns and preserve wealth is to build portfolios that are as resilient as possible to the range of ways the world could unfold (p.1)".*

Global capital flows weave a network where the foreign equity assets of one country are mirrored by foreign equity liabilities in another. These flows are fundamental to the operation of international finance: they drive cross-border investment, influence market functioning, shape policy choices, and determine how shocks are transmitted (Miranda-Agrippino and Rey, 2020; Coppola, Maggiori, Neiman, and Schreger, 2021). They also embody the interdependencies and asymmetries of global markets, making them central to understanding both the persistence and the geography of EHB. For this study, global capital flows are the *connective tissue* linking micro-level investor choices in the production of returns, with macro-level investment outcomes.

Finally, as the world becomes increasingly integrated, understanding the factors that drive and influence these flows, ranging from investor psychology and geopolitical events to technological advancements and regulatory frameworks, becomes essential for comprehending the complex dynamics of global finance (Davis, Valente, and Van Wincoop, 2021; Ioannou and Wójcik, 2021). These flows, which involve the movement of capital between countries, are central to understanding a range of economic and investment phenomena, and the focus of this study, the puzzling persistence of EHB.

1.4 Objectives

The presence and persistence of EHB is the most enduring puzzle in international finance. As outlined previously, despite more than half a century of research, studies anchored in the neoclassical finance tradition have failed to resolve it, inviting new perspectives (Ardalan, 2019).[11] While earlier sections framed the EHB puzzle, this section provides a conceptual roadmap for each chapter, outlining what is done and why it is done. The study undertakes a systematic treatment of the EHB puzzle through four interrelated research questions. It first asks how EHB should be defined, examining the competing forms by which the puzzle is conceptualised (what is EHB? Chapter 2). It then considers how EHB can be measured, evaluating alternative approaches to estimation (how should EHB be measured? Chapter 3). The third question addresses whether EHB is systematically present across space, with particular attention to clustering within neighbourhood structures (is EHB systematically present across space? Chapter 4). Finally, the study investigates whether these patterns

[11] Kuhn (1970) argues that theories developed under different paradigms may lack a shared basis for comparison. In this study, the key points of contention are competing conceptions of space and time by the neoclassical finance tradition and financial geography as it relates to the EHB puzzle.

persist, consistent with the dynamics of path dependence (does EHB persist across space and time? Chapter 5).

Chapter 2 confronts the problem that the forms of EHB remain contested. Multiple conceptualisations and approaches exist in the literature, but without clarity on what constitutes EHB, the puzzle lacks a stable conceptual foundation. The objective is to undertake a Systematic Literature Review (SLR) of how EHB has been defined and measured, and to establish a coherent basis for subsequent analysis.

Chapter 3 addresses the problem that the statistical properties of competing EHB measures are poorly understood. Although widely used in the extant literature, it is unclear whether the different measures of EHB capture distinct phenomena or whether they behave similarly through time. The objective is to test the statistical similarity of these measures and to evaluate their distributional characteristics, providing clarity on whether the choice of measure affects empirical results.

Chapter 4 takes up the challenge that EHB has yet to be examined through a spatio-temporal structure. Studies from the neoclassical finance tradition treat countries as independent units, overlooking the possibility that EHB clusters into meaningful neighbourhood regimes. The objective is to test for spatio-temporal effects to identify the presence (or otherwise) of global and local patterns of EHB.

Chapter 5 engages with the problem that the dynamics of EHB across space and time have been neglected. Existing studies have not adequately explored how patterns of EHB evolve, nor how results differ when statistically significant (filtered) and statistically naïve (unfiltered) neighbourhoods are compared. The objective is to investigate these dynamics using spatio-temporal approaches, thereby garnering new insights into the persistence and evolution of EHB. It is hoped that by addressing these four problems in sequence: definition; measurement; presence; and, persistence, the study will centre future EHB research on spatio-temporal effects. In doing so, it contributes new insights into both the EHB puzzle and the geography of investor practice.

1.5 Methodology

This study explores the EHB puzzle through a multi-method research design that integrates approaches from the fields of finance, economics, and geography. It is organised around four interrelated problems in the EHB debate: definition; measurement; presence; and, persistence. Each problem is addressed with a corresponding method. Chapter 2 begins by undertaking a

SLR, providing a transparent and replicable protocol to clarify how EHB has been *defined* and *measured* across disciplines (Tranfield, Denyer, and Smart, 2003). Chapter 3 turns to the question of measurement, employing a Quantile Shift Function (QSF) to test the statistical similarity (or otherwise) of competing EHB measures (Wilcox and Erceg-Hurn, 2012). Chapter 4 tests for the presence of spatio-temporal effects by applying Global Moran's Index and LISA to identify spatial association, clustering, and neighbourhood effects in EHB across countries (Moran, 1950; Anselin, 1995). Finally, Chapter 5 addresses persistence by applying Transition LISA and Directional LISA to examine whether EHB evolves over time (Rey and Anselin, 2010; Elhorst, 2014; Rey and Janikas, 2005).

The analytical commitment underpinning this study is that the selected methodology must be aligned with the character of the specific problem across the EHB puzzle. As established, traditional econometric approaches are designed to address questions of causality and equilibrium (Engle and Granger, 1987; Johansen, 1991; Hamilton, 1994; Stock and Watson, 2002; Pesaran, 2015). While such approaches remain valuable, they treat time as uniform and countries as independent units, assumptions that limit their ability to capture potential spatio-temporal effects. By contrast, this study privileges *correlation over causation*, testing whether EHB clusters across space and persists through time (Chapters 4 and 5).

1.6 Data

The empirical analysis in this study draws on multiple, complementary sources of data, each aligned with the four central problems identified in Section 1.4 and the methodological design outlined in Section 1.5. In keeping with the emphasis in Sections 1.2.1 and 1.2.2 on the importance of both space and time, the data are deliberately multi-layered: scholarly studies; international financial benchmarks and holdings; and, geospatial classifications. The combination of global return benchmarks and country-level portfolio holdings provides a comprehensive dataset for analysis.

In Chapter 2, the dataset comprises leading academic studies on EHB. A SLR provides the foundation for clarifying definitions and measures, treating the scholarly record itself as the dataset (Tranfield, Denyer, and Smart, 2003). The SLR establishes the definitional basis of the puzzle and anchors the study in the academic debate.

In Chapter 3, a range of data sources are required to estimate the competing measures of EHB. At the core is the Morgan Stanley Capital International (MSCI) All

Country World Index (ACWI), which provides the global benchmark portfolio. MSCI indices are critical for evaluating the success (or otherwise) of the production of returns process and guide the practice of global investing, including the issuance and governance of investment mandates (Clark, Dixon, and Monk, 2009, 2013; Clark and Monk, 2017; Drew and Walk, 2019). While the MSCI classification has evolved over time, this study follows the 2020 MSCI standard to maintain consistency across the sample period. In this way, the dataset reflects both academic precedent and institutional practice (Table 1.1).

Table 1.1 Country classification (MSCI, 2020)

MSCI ACWI Index					
MSCI World index (23/23) Developed markets			Emerging Markets index (20/27) Emerging markets		
Americas	Europe & Middle East	Pacific	Americas	Europe & Middle East & Africa	Asia
Canada	Austria	Australia	Argentina	Czech Republic	~~China~~[12]
United States	Belgium	Hong Kong	Brazil	Egypt	India
	Denmark	Japan	Chile	Greece	Indonesia
	Finland	New Zealand	Colombia	Hungary	Korea
	France	Singapore	Mexico	~~Kuwait~~	Malaysia
	Germany		~~Peru~~	Poland	Pakistan
	Ireland			~~Qatar~~	Philippines
	Israel			Russia	~~Taiwan~~
	Italy			~~Saudi Arabia~~	Thailand
	Netherlands			South Africa	
	Norway			Turkey	
	Portugal			~~UAE~~	
	Spain				
	Sweden				
	Switzerland				
	United Kingdom				

Notes: The sample contains 43 countries from 2001 through 2020 and follows the classification for MSCI (2020) ACWI. All 23 countries in the MSCI World index (developed markets) are included, and 20 from a total of 27 countries are included from the MSCI Emerging Markets index. China, Kuwait, Peru, Qatar, Saudi Arabia, Taiwan, and, the United Arab Emirates are excluded due to data limitations.
Source: MSCI (2020)

[12] China is excluded from the current analysis due to data limitations, as it was only included in the Coordinated Portfolio Investment Survey (CPIS) database from December 2015 (see Appendix 2).

As reported in Table 1.1, the sample comprises all 23 developed markets in the MSCI World Index and 20 emerging markets from the MSCI Emerging Markets Index, giving a total of 43 countries (accounting for over 85% of the MSCI ACWI index by market capitalisation). Seven emerging markets (China, Kuwait, Peru, Qatar, Saudi Arabia, Taiwan, and the United Arab Emirates) are excluded due to data limitations in the International Monetary Fund's (IMF) Coordinated Portfolio Investment Survey (CPIS) dataset.[13] These exclusions are consistent with prior studies that balance comprehensive global coverage against the availability and reliability of consistent financial data (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015). In short, optimal (benchmark) weights are estimated and then compared with actual portfolio holdings from the IMF CPIS, operationalising the EHB level as the difference between theoretical and observed portfolio allocations.[14]

[13] The empirical analysis in this study draws on the IMF's CPIS, which provides internationally comparable data on cross-border equity positions. These global portfolio positions capture the revealed portfolio preferences of investors *in aggregate*, rather than the characteristics, constraints, or motivations of individual investor types. As such, CPIS data are well suited to analysing broad patterns in international portfolio allocation, including EHB, but they do not permit direct inference about the behaviour of specific investor types. The principal strengths of the CPIS lie in its global coverage, consistent reporting framework, and institutional credibility, which together make it a widely used source for cross-country analysis of international portfolio holdings (Fidora, Fratzscher, and Thimann, 2007; Mishra, 2015, 2017). At the same time, the data are subject to well-known limitations inherent in all survey-based collections. In particular, the CPIS may be affected by underreporting, and reporting practices may differ systematically across jurisdictions. Such geographic variation in reporting quality has the potential to influence measured levels of EHB and therefore warrants caution in cross-country interpretation. For this reason, the results in this study are interpreted as describing patterned regularities in observed portfolio positions. The empirical chapters implement a range of robustness checks designed to assess the sensitivity of the results to alternative data treatments and specifications. While the detailed results of these checks are not discussed in Chapter 1, their inclusion throughout the analysis provides reassurance that the core spatial and temporal patterns identified are not artefacts of a particular data construction or reporting assumption.

[14] The analysis also relies on the MSCI country classification to define the investment universe and benchmark structure used in measuring EHB. For consistency across the sample period, the study applies the 2020 MSCI classification retrospectively to earlier years, rather than adopting a fully time-varying classification that reflects historical changes in country status and classification methodology. This choice involves a trade-off. A dynamic classification would more closely reflect contemporaneous market categorisations at each point in time, while a fixed classification ensures comparability across years and avoids introducing structural breaks driven by changes in classification rather than underlying portfolio decisions. The approach adopted here reflects a deliberate methodological decision aligned with the stated research objectives, which focus on identifying spatial and temporal regularities in EHB over a long horizon. The implications of this choice are therefore acknowledged explicitly, and the results are interpreted with appropriate caution, recognising that alternative classification schemes may yield different absolute levels of measured EHB while leaving the core patterns of clustering and persistence intact. For completeness, in 2000, the set of developed markets included in the MSCI ACWI index was *the same* as in 2020 (N = 23), while the classification of several emerging economies was revised over the period from 2000 to 2020 (for instance, Jordan, Morocco, and Venezuela were part of the index in 2000 and have been replaced by Saudi Arabia, Kuwait, Qatar, and the United Arab Emirates in 2020) (MSCI, 2012, 2020).

In Chapter 4, the analysis turns to the spatial presence of EHB, requiring data that are used as inputs to respond to two questions: who is your neighbour?; and, how much does your neighbour matter? As an exploratory study, neighbourhood structures are specified in two complementary ways. The first approach is distance-based, measuring the distance between the financial centres of the 43 countries in the sample (Z/Yen Group and Long Finance, 2025). Financial centres are pivotal nodes within global financial networks, the very networks that are used daily in the production of investment returns (Gehrig, 2000; Haberly and Wójcik, 2020, 2022; Wójcik, 2020; Ioannou, Wójcik, and Pažitka, 2021; Wójcik, Keenan, Pažitka, Urban, and Wu, 2022). Geographic coordinates are taken from the GeoNames geographical database (GeoNames, 2025), and countries are identified using ISO3 standard codes (International Organization for Standardization, 2020). Spherical distances are calculated using the World Geodetic System (WGS84) (Macomber, 1984), implemented through the geosphere package in R (Hijmans, 2025). From these distances, the k-nearest neighbours (k = 2-5) are selected without distance limitation, and neighbours are weighted using both $1/n$ (equal weighting) and $1/d$ (inverse distance weighting). The second approach applies the MSCI ACWI benchmark classifications (MSCI, 2020), which divide the sample into six boundary categories: (i) Americas, Developed Market (AM_DM); (ii) Europe & Middle East, Developed Market (EME_DM); (iii) Pacific, Developed Market (PAC_DM); (iv) Americas, Emerging Market (AM_EM); (v) Europe & Middle East & Africa, Emerging Market (EMEA_EM); and (vi) Asia, Emerging Market (AS_EM) (as per Table 1.1). Within each boundary, neighbour sets are constructed based on the total number of countries, again weighted by both $1/n$ and $1/d$. In this way, the study combines continuous spatial distance with institutional boundary classifications, ensuring that the analysis reflects both geographical contiguity and the structures that organise the production of returns.[15]

In Chapter 5, the data take the form of the LISA clusters themselves (in this sense, the LISA classifications from Chapter 4 become the input to Chapter 5). The Transition LISA (Spatial Markov chain) and directional LISA require a panel of local classifications across the twenty-year study period, enabling the analysis of persistence and spatio-temporal effects (Rey and Anselin, 2010; Elhorst, 2014; Rey and Janikas, 2005).

[15] This approach is consistent with the broader literature on spatial dependence, which has defined neighbours by countries (Darmofal, 2015), equal weighting (Baller, Anselin, Messner, Deane, and Hawkins, 2001; Cliff and Ord, 1981; Anselin, 1988), distance (Cliff and Ord, 1981; Anselin, 1995), boundary classifications (LeSage and Pace, 2009), trade channels (Beck, Gleditsch, and Beardsley, 2006), or social and geographic proximity (Tolnay, Deane, and Beck, 1996). More recently, spatial statistics such as LISA have also been applied as tools for case selection and research design (Ingram and Harbers, 2020).

1.7 Findings

The findings presented in this study address the EHB puzzle through four research questions of definition, measurement, presence, and persistence. The SLR undertaken in Chapter 2 shows that definitions of EHB are fragmented across model-based, data-based, and hybrid forms, but all remain anchored in the neoclassical finance tradition (Lewis, 1999; Coeurdacier and Rey, 2013). Definitional ambiguity has constrained progress, while prevailing measures are overwhelmingly aspatial and static, overlooking clustering and persistence effects central to financial geography (Clark and Wójcik, 2007; Wójcik, 2011).

Using a QSF approach, Chapter 3 finds that model-based, data-based, and hybrid measures are highly correlated and *statistically indistinguishable*, rendering decades of debate over the 'best' measure largely inconsequential (French and Poterba, 1991; Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015). More significantly, it reveals widening cross-national heterogeneity: some countries have declined to near-zero EHB, while others remain chronically high. These descriptive findings suggest both the presence and persistence of spatio-temporal effects.

The key contribution of Chapter 4 is that it establishes that EHB is not randomly distributed, but clustered across space in a given state (year), as evidenced by significant Global Moran's Index and LISA test statistics (Moran, 1950; Anselin, 1995). Persistent neighbourhood structures classified as Low-Low clusters (that is, holding low EHB at home as well as their prescribed neighbours) dominate European developed markets, while High-High clusters (high levels of EHB at home and among neighbours) are concentrated in Asian emerging markets, revealing a dual-regime structure. Benchmark-defined neighbourhood structures (using MSCI ACWI) yield stronger and more stable clustering than purely geographic definitions, demonstrating the boundary-setting power of benchmarks in international finance (Wójcik, 2020).

To trace the dynamics of neighbourhood structures, Chapter 5 employs both transition and directional LISA methodologies, finding strong path dependence: countries in High-High, High-Low, Low-Low, and Low-High regimes overwhelmingly remain locked in place. The evidence shows predictable trajectories, rather than random movements, reflecting path dependence in the production of returns (North, 1990; Clark and Monk, 2017). These results contradict the predictions of the neoclassical finance tradition that anomalies should dissipate from arbitrage (Fama, 1970; Obstfeld and Rogoff, 2000), demonstrating instead that EHB is self-reinforcing and embedded by enduring spatio-temporal effects.

Finally, the analysis shows that, regardless of benchmark-defined neighbourhood structure, investors have systematically lowered EHB levels over all blocks of time, but the rate of decline has been markedly different across countries and regions, particularly post the GFC.

1.8 Conclusion

This study advances the claim that the EHB puzzle is best understood as a spatio-temporal phenomenon embedded in global financial geographies (Clark and Wójcik, 2007; Wójcik, 2020; Haberly and Wójcik, 2022). The presence and persistence of EHB is not artefacts of definition or measurement, but rather the patterned outcome of clustering and path dependence (Arthur, 1989; North, 1990; David, 1994; Leyshon and Thrift, 1998; Clark, 1998; Martin, 1999, 2010; Clark, Mansfield, and Tickell, 2001; Martin and Sunley, 2006, 2010; Wójcik, 2012; Coe, Lai, and Wójcik, 2014; Lai, 2020). In summary, the study makes four contributions: conceptually, it resolves definitional ambiguities in the field (French and Poterba, 1991; Lewis, 1999); methodologically, it shows that competing measurement approaches to EHB yield similar results (Mishra, 2015) and that tests for spatio-temporal effects are essential tools for capturing its dynamics (Moran, 1950; Anselin, 1988; Rey, 2001, 2004); empirically, it reveals how neighbours and benchmark logics shape the presence and persistence of EHB (Wójcik, Iliopoulos, Ioannou, Keenan, Migozzi, Monteath, Pažitka, Torrance, and Urban, 2024); and theoretically, it challenges the assumption that anomalies necessarily dissipate under arbitrage (Clark and Monk, 2017).

The implications of this perspective extend beyond academe. For investors and their fiduciaries, diversification must be evaluated in spatio-temporal terms (French and Poterba, 1991; Coeurdacier and Rey, 2013). Portfolio construction is not solely a function of individual portfolio allocations but is conditioned by neighbourhood clustering and persistence (Anselin, 1995; Rey and Le Gallo, 2009). Fiduciaries must therefore ask not only whether portfolios are globally diversified, but also whether they are embedded in regimes that systematically amplify or mitigate risk (Clark and Monk, 2017; Drew and Walk, 2019). In this regard, the EHB puzzle should not be reduced to a transient anomaly that the neoclassical finance tradition assumes arbitrage will inevitably eliminate (Fama, 1970). Rather, it is best understood as a structural feature of international finance, an enduring outcome of the ways in which global capital flows move across space and through time.

2. On the Definition of Equity Home Bias

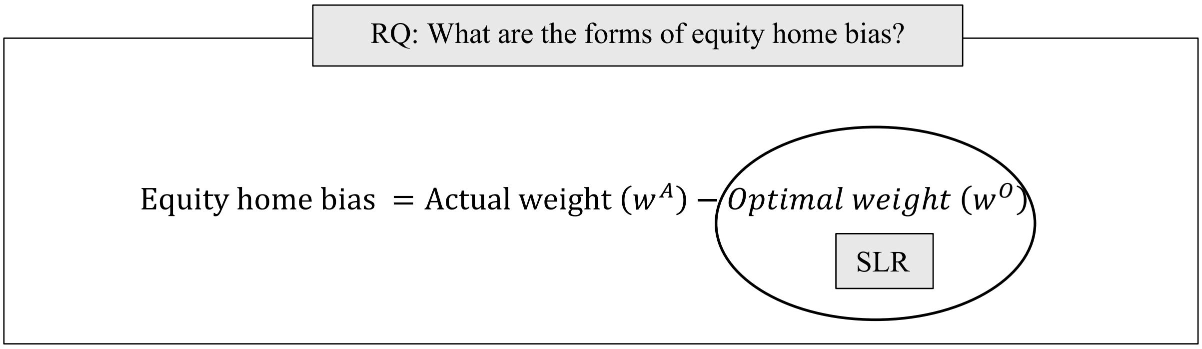
2.1 Introduction

Chapter 1 established that the foundational challenge in the equity home bias (EHB) debate is definitional, since without conceptual clarity subsequent analysis of measurement (Chapter 3), presence (Chapter 4), and persistence (Chapter 5) risks incoherence. Despite more than half a century of research, there is no single agreed conception of what constitutes EHB (Lewis, 1999; Sercu and Vanpée, 2012; Ardalan, 2019). Different studies adopt competing forms of EHB, leading to inconsistencies in how the puzzle is operationalised and interpreted (French and Poterba, 1991; Baele, Pungulescu, and Ter Horst, 2007; Levy and Levy, 2014; Mishra, 2015). A lack of definitional clarity hinders reliable comparison across studies using competing definitions of optimal portfolio diversification. It is argued that the EHB puzzle has endured for over fifty years, not only because of its presence and persistence, but also because of its conceptual instability (Obstfeld and Rogoff, 2000).

The purpose of this chapter is to conduct a SLR of how EHB has been *measured* in the academic literature. The review is therefore explicitly focused on the construction, interpretation, and comparability of EHB measures, rather than on providing a comprehensive review of the full range of theoretical explanations proposed for the phenomenon. This focus reflects the central role that measurement plays in shaping empirical claims about the presence and persistence of EHB. The scope of the review has important implications. By concentrating on measurement, the review necessarily places less emphasis on other strands of the EHB literature, including (but not limited to) behavioural explanations, sectoral composition, and ownership structures. These topics are not dismissed as unimportant; rather, they fall outside the primary objectives of the systematic review as defined here. The resulting synthesis should therefore be read as a foundation for understanding the empirical strategies used to quantify EHB, rather than as an exhaustive account of all theoretical explanations or causal mechanisms proposed in the literature (such as dimension reduction techniques employed by Mishra, 2015). Clarifying these methodological and definitional issues is particularly important, as it resolves ambiguities surrounding the construction of EHB measures and ensures that subsequent chapters can systematically examine the presence, and persistence of EHB without conflating measurement differences with substantive explanations.

The most challenging task facing researchers in estimating EHB is the identification of *optimal* weights (Markowitz, 1952; Merton, 1972; Solnik, 1974).[16] While there is consensus regarding the measurement of *actual* weights, the literature is not settled on the 'best' characterisation of optimal (or benchmark) weights (see Figure 2.1).[17] The chapter undertakes a Systematic Literature Review (SLR) of how EHB has been measured. The purpose of the review is twofold. First, it consolidates the competing forms of EHB (model-based, data-based, and hybrid) each distinguished by how the optimal benchmark weight for international equity investment is specified (Markowitz, 1952; Sharpe, 1964; Solnik, 1974). Second, it evaluates the methodological assumptions underpinning these forms, demonstrating that while they differ in emphasis, all share a common foundation in the neoclassical finance tradition (Fama, 1970; Ross, 1976; Stulz, 1981).

Figure 2.1 Conceptual framework



Note: The SLR centres on the literature related to the optimal weight computation. The definition of weights is as follows: actual foreign equity holdings in the total equity portfolio of investors (actual weight (w^A)); and, the optimal foreign holding or benchmark share (optimal weight (w^o)).

A key finding to emerge from this review is not only the contested nature of EHB definitions, but also the absence of spatio-temporal perspectives. Across the three dominant forms of EHB (model-, data-, and hybrid-based), space is treated merely as the domicile of the investor and time as a homogeneous sequence of intervals, a common assumption of

[16] In this study, optimal weights refer to the mean-variance efficient portfolio allocation held by a rational investor. Optimal weight estimation in portfolio selection was first considered by Markowitz (1952), extended by Merton (1972) to intertemporal settings, and by Solnik (1974) and Sercu (1980) in the development of international versions of the Capital Asset Pricing Model (I-CAPM). In this case, optimal weights are used as a benchmark against which investor holdings can be evaluated (Cooper and Kaplanis, 1994; Jeske, 2001).
[17] As noted by Baele, Pungulescu, and Ter Horst (2007), *"any meaningful explanation of the equity home bias requires a correct characterisation of the benchmark weights, i.e., those to which actual holdings can be compared (p. 607)."*

time-series approaches (Engle and Granger, 1987).[18] This silence is striking given the insights of financial geography, which emphasises that investment is inherently embedded in networks of space and time (Leyshon and Thrift, 1998; Clark, 1998; Clark and Monk, 2017; Clark, Feldman, Gertler, and Wójcik, 2018). Studies that ignore such interdependencies risk estimation bias (Pace and Calabrese, 2022). They may also overlook the patterned ways in which EHB evolves across markets, reflecting systemic and structured dynamics rather than a jumble of random observations (Moran, 1950; Rey, 2001, 2014). Thus, the systematic review not only consolidates the received forms of EHB but also reveals a profound gap: the failure of existing measures to recognise spatio-temporal effects.

A systematic approach is used to identify and address these gaps. Prior reviews of EHB have been anchored narrowly within the disciplines of finance and/ or economics (Lewis, 1999; Ardalan, 2019). The SLR methodology, by contrast, applies a transparent and replicable protocol designed to minimise subjectivity and to integrate perspectives across finance, economics, *and* geography (Mulrow, 1994; Tranfield, Denyer, and Smart, 2003; Denyer and Tranfield, 2009; Xiao and Watson, 2019).[19] This enables the development of a coherent conceptual foundation for the analyses undertaken in Chapters 3 through 5.

The chapter makes four contributions. First, it documents and classifies the received forms of EHB (model-based, data-based, and hybrid) together with their associated measures. Second, it evaluates their methodological assumptions, highlighting both strengths and limitations. Third, it identifies the silence on spatio-temporal effects, positioning this as the central gap that motivates the study's empirical turn. Fourth, it shows that existing studies overwhelmingly pursue causal inference within time-series econometric frameworks (Engle and Granger, 1987; Johansen, 1991; Stock and Watson, 2002; Pesaran, 2015), thereby neglecting correlation-based approaches that capture clustering and path dependence across space and time (Moran, 1950; Anselin, 1995; Rey and Anselin, 2010). Taken together, these contributions bridge the definitional ambiguity of EHB with the broader research agenda of financial geography, preparing the ground for consideration of the puzzle.

[18] The work of Engle and Granger (1987) is seminal as it formally considered time as a substantive dimension in the field of economics. That insight underlines the critique advanced in this study, specifically, while EHB research relies heavily on time-series econometrics, it has generally treated time as homogeneous intervals rather than as structurally significant sequences (Rey and Anselin, 2010; Rey and Janikas, 2005).

[19] The SLR methodology was first applied to synthesise medical research (Mulrow, 1994) and adapted for the social sciences by Tranfield, Denyer, and Smart (2003). The main advantage of conducting a SLR is that it has a clear stated purpose, a question, and a defined search approach (with stated inclusion and exclusion criteria) to provide a qualitative appraisal of articles (Jesson, Matheson, and Lacey, 2011).

The remainder of the chapter is organised as follows. Section 2.2 sets out the SLR methodology, including database selection, keyword strategy, and screening procedures. Section 2.3 classifies the received forms of EHB and Section 2.4 summarises the forms under their disciplinary basis. Section 2.5 discusses the findings in light of the broader EHB puzzle, highlighting limitations and gaps. Section 2.6 concludes by drawing out implications for this study, bridging the definitional ambiguity of EHB with the broader research agenda of financial geography and preparing the ground for a re-interpretation of the puzzle through the lens of spatio-temporal effects. Chapter 3 then builds directly on this foundation by testing whether these competing measures exhibit convergence or divergence in their statistical properties.

2.2 Methodology

Given the persistence of the EHB puzzle, the literature review design must be able to cope with a variety and richness of research designs and findings (that is, not just from the fields of finance and economics, but also geography). Chapter 2 adopts a mix of quantitative and qualitative scoping, focusing on received research methodologies on EHB measures (Tranfield, Denyer, and Smart, 2003). More specifically, evidence from qualitative studies is descriptively summarised in the systematic review report.[20] The SLR approach of Tranfield, Denyer, and Smart (2003) provides a methodology to realise a consistent study that investigates the forms of EHB (and their accompanying measures). A systematic approach to undertaking a critical literature review strives to be bias-free using rigorous protocols (Jadad, Cook, and Browman, 1997; Rowley and Slack, 2004; Petticrew and Roberts, 2008; Saunders, Lewis, and Thornhill, 2009). As part of such protocols, published studies were identified through searches of Web of Science core collection, Google Scholar, and Scopus for the period from 1900 through 2023. The three databases are chosen because of their

[20] Literature reviews can take five categories based on the purpose: (1) descriptive; (2) test; (3) extend; (4) critique; and, (5) hybrid reviews (Xiao and Watson, 2019). Types of descriptive reviews include narrative reviews, textual narrative synthesis, meta-summary, and meta-narrative and scoping review (Kitzmueller and Shimshack, 2012; Wójcik, 2022). A testing review looks to answer a question about the literature or test a specific hypothesis. A testing review can be broken into subcategories based on the type of literature being analysed. Testing reviews on quantitative literature involve statistical analysis, whereas qualitative testing reviews look at results in various contexts to determine generalisability (Lovell, 1973; Pawson, Greenhalgh, Harvey, and Walshe, 2005). An extending review attempts to build upon the literature to create new, higher order constructs and is often conducted through qualitative or mixed literature because of its theory building nature (Dixon-Woods, 2011). A critical review involves comparing a set of literature against an established set of criteria (Paré, Trudel, Jaana, and Kitsiou, 2015). Finally, hybrid reviews involve a combined review of all methodologies discussed above (Moffitt, 1992).

multidisciplinary nature and reduced bias regarding publishers, and current relevance. The SLR in this chapter follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) family of protocols as a guiding framework for transparency and replicability (Mulrow, 1994). PRISMA principles are used to structure the review process by making explicit how studies are identified, screened, assessed for eligibility, and included in the final review sample.

2.2.1 Search terms

EHB is considered to consist of two elements (that is, equity *and* home bias) and is cross-disciplinary, straddling the fields of finance, economics, and geography. To ensure that all aspects are fully captured by the keywords, three search strings were included (Table 2.1). The first string is finance-related terms and included keywords such as "*equity home bias*" or "*incomplete diversification.*" The second search string contained economics-related keywords such as "*cross border investment*" or "*investor diversification.*" The third search string considered geography-related keywords such as "*proximity bias*", or "*familiarity*", or "*geography of finance*". The keywords were chosen based on previous literature reviews on similar topics, the author's own research and practitioner experience, and expert views from fellow academics and practitioners. These terms were used in search fields of abstract, publication title, and subjects.

Table 2.1 The search string and keyword assembly

Subject discipline	Keyword(s)/ Search string
Finance-related keywords	("equity home bias") OR ("incomplete diversification")
Economics-related keywords	("cross border investment") OR ("investor diversification")
Geography-related keywords	("proximity bias") OR ("familiarity") OR ("geography of finance")

2.2.2 Search results

A five-step approach to identify the papers for the systematic literature review was followed. First, using the Web of Science core collection, Google Scholar, and Scopus databases, a collection of journal articles, books, chapters of books, working papers (conference papers were excluded) and industry articles for the defined search terms with an open starting time to include as many publications as possible up to 2023 was curated.

The initial search attempts identified 8,882 titles (1,577 from Web of Science core collection; 5,613 titles from Google Scholar; and, 1,692 from the Scopus database). The search results were stored in CSV format to include all the essential paper information such as paper title, authors' names and affiliations, abstract, keywords (author keywords), and references. Duplicate records were removed from the dataset. After eliminating duplicates, a total of 6,702 papers remained. Second, non-English and conference proceedings, dissertations, and low-rated journals were excluded, resulting in 3,577 papers selected for the next round (Table 2.2, Panel A: Initial screening).[21]

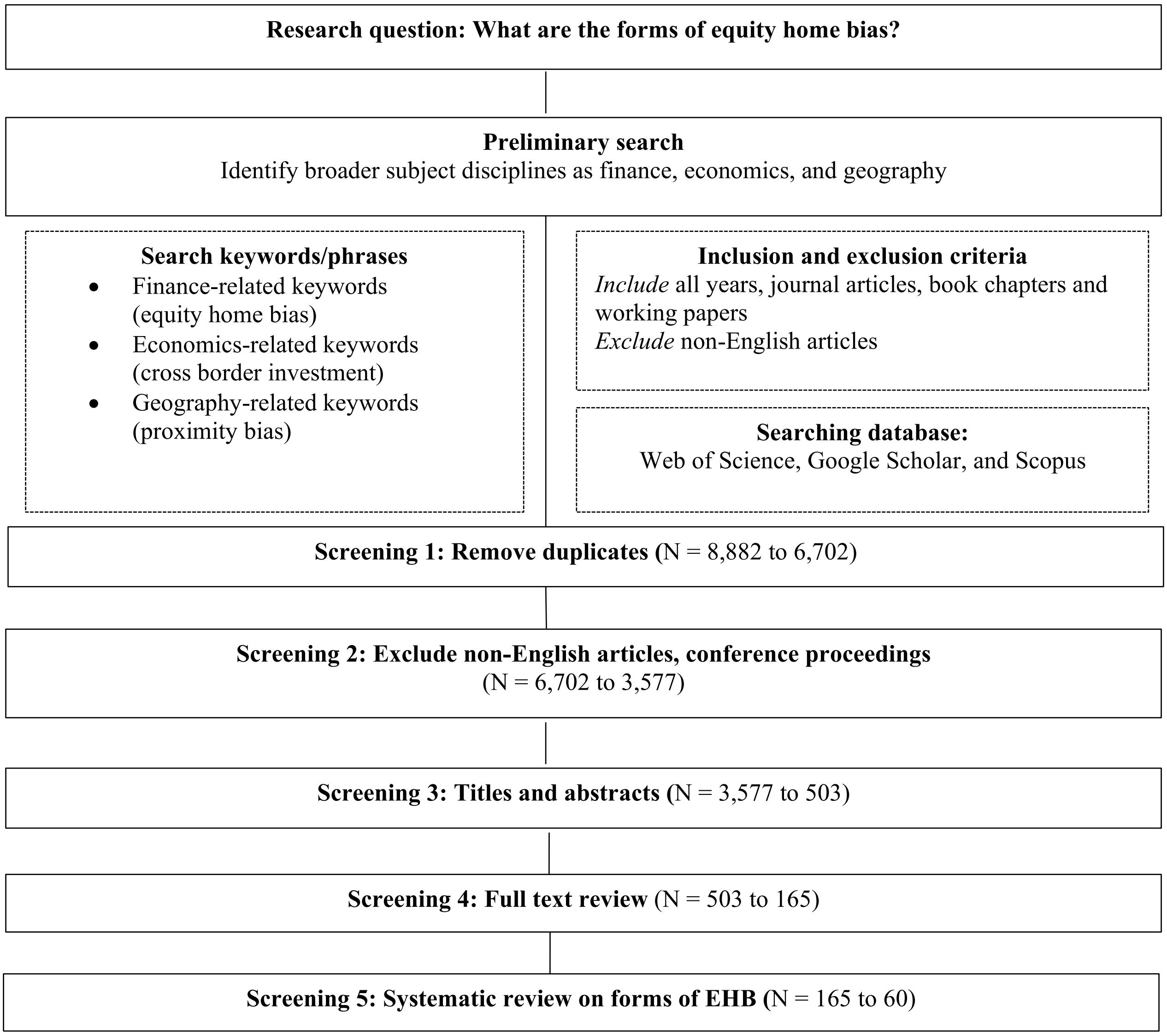
Table 2.2 Inclusion and exclusion criteria in the refinement

Inclusion criteria	Exclusion criteria
Panel A: Initial screening	
All years, Journal articles, Books / book chapters, Working papers	Non-English language journals, Conference proceedings, dissertation, Journal ranking (ABDC (equivalent) C or below)
Panel B: Advanced screening	
Papers post initial screening	Papers discuss a home bias form (measure) or not?

Third, the papers were screened by titles and abstracts. Some 503 records were selected for the fourth round of selection. The fourth step included a review of the full text of these papers and identified 165 articles. All 165 papers were then coded thoroughly using a range of dimensions to prepare them for the final analysis phase. Papers were excluded when: they mainly focused on cross-border investment, trade barriers, and international diversification, but superficially touched on EHB; or, they focused on other asset classes or asset owners (such as bonds, mutual funds, and pension funds) and only cursorily considered equity allocation. Fifth, in final screening (Table 2.2, Panel B: Advanced screening), an additional screening criterion was applied, specifically, whether the selected articles discuss an EHB form (and accompanying measure(s)). This additional criterion distinguished conceptual articles (without empirical frameworks) from studies that propose and/ or apply specific EHB measures. For the systematic review, 60 studies out of 165 which discuss various forms of measures of EHB were formally reviewed. The summarised process for refining the literature search is presented in Figure 2.2.

[21] Low-rated journals were denoted as those ranked (equivalent) C or below by the Australian Business Deans Council (ABDC). Published rankings are available at https://abdc.edu.au/research/abdc-journal-quality-list/.

Figure 2.2 Framework of systematic literature review

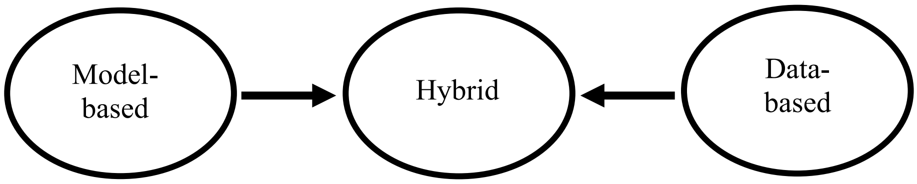


It is important to note that this SLR is not exempt from limitations. The keywords were selected according to the definition of EHB and the related literature and, as such, may not be exhaustive. Some papers that fit the inclusion and exclusion criteria were omitted because they discussed home bias in other asset classes (such as the study by Krebbers, Marshall, McColgan, and Neupane, 2023 on European corporate bonds). In addition, a different set of search terms could generate a different sample to review, resulting in different interpretations for the field. Expanding the keywords to include more geographical keywords such as patriotism, regional blocks, flight-to-home, and so on, or the inclusion of other related disciplines, could result in a much broader review of the field and result in a much broader scope of papers studying the EHB puzzle. Moreover, the grouping of articles into different subject disciplines and grouping of measures into different forms was also subjective.[22]

2.3 Forms of Equity Home Bias

As opposed to various definitions of EHB research discussed in the 165 articles (Screening 4), only 60 studies discussed how to measure this phenomenon, and were therefore included in the SLR (refer Appendix 1 for a detailed listing of the reviewed papers for the SLR).

Figure 2.3 Received forms of equity home bias



Note: The received forms of calculating EHB are; model-based, data-based, and hybrid.

As presented in Figure 2.3, the findings of the SLR shed light on the three received forms of estimating optimal weight in the EHB equation (French and Poterba, 1991; Lewis, 1999; Pástor, 2000; Jeske, 2001; Baele, Pungulescu, and Ter Horst, 2007; Xing and Li, 2011; Levy and Levy, 2014; Mishra, 2015; Pungulescu, 2015, among others). These forms of EHB are well founded in the neoclassical finance tradition, with model-based estimates derived from the Capital Asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965) and data-based estimates framed by modern portfolio theory (Markowitz, 1952).[23] The existence of these two home bias forms is supported by Lewis (1999), who observed that, *"studies of the pricing relationships have taken at least two (non-mutually exclusive) forms (p.597)."*

[22] A sensitivity analysis was undertaken to examine the distribution of keywords. It was found that 77% of the articles chosen for the final stage to be included in the SLR contains the search string "equity home bias", whereas 6% of the articles contain the term "investor diversification." For completeness, the other results were: familiarity (3%); cross border investment (3%); more than one search string (3%); "incomplete diversification" (2%); proximity bias (2%); and, "geography of finance" (0%). This confirms the output (reviewed papers) are reflected by the chosen search terms.

[23] The I-CAPM was introduced by Solnik (1974), Sercu (1980), Stulz (1981), and Adler and Dumas (1983). As noted by Mishra (2015), *"The international asset pricing model of Solnik (1974) and Sercu (1980) takes into account exchange rates. Cooper and Kaplanis (1986) treat the world market as just a mixture of national portfolios, reflecting a mixture of costs faced by various investors from different environments (p. 297)."*

An alternative to model-based and data-based forms of EHB is the incorporation of some degree of mistrust in the model of equilibrium (i.e., the Hybrid form). Leading contributions in the field of Bayesian portfolio selection frameworks have been made by Pástor (2000), Pástor and Stambaugh (2000), Garlappi, Uppal, and Wang (2007), and Mishra (2015). The inclusion of some level of mistrust in the equilibrium model provides different sets of optimal portfolio weights and alternative estimates of home bias. As the degree of scepticism about the model grows, the resulting optimal weights shift away from those implied by the model-based approach to those obtained from the data-based approach (Mishra, 2015). As will be illustrated in the summary below (Table 2.3), it is important to note that all three forms of EHB are derived from the same neoclassical finance tradition (and underlying assumptions). All EHB measures face the joint hypothesis problem, meaning that any observed bias reflects not only investor behaviour but also the equilibrium model assumptions under which it is tested (Fama, 1970). Thus, model-based and data-based forms are inseparable from their assumed equilibrium frameworks, while hybrid forms substitute a parametrised mistrust in those same assumptions.

Table 2.3 SLR summary table

Form of measure	Equilibrium model	Key studies from the SLR	Critique
Model-based	▪ The I-CAPM approach of Solnik (1974) and Sercu (1980) predicts that an investor should hold equities from a country as per that country's share of the world market capitalisation. ▪ The I-CAPM suggests that there is a positive, linear relationship between the risk premium on a domestic portfolio and the expected excess return on the world market benchmark (Lewis, 1999; Schoenmaker and Bosch, 2008). ▪ Two key assumptions of the I-CAPM are: (1) that the I-CAPM is valid in a perfectly integrated world, where the law-of-one price holds universally; and, (2) that markets clear (total wealth is equal to the total value of securities).	▪ The SLR identified many studies that used the model-based form of EHB (Lewis, 1999; Amadi, 2004; Asgharian and Hansson, 2006; Baele, Pungulescu, and Ter Horst, 2007; Sørensen, Wu, Yosha, and Zhu, 2007; Morse and Shive, 2011; Bekaert and Wang, 2009; Mishra, 2008, 2011, 2015; and, Xing and Li, 2011). ▪ Several authors use the I-CAPM benchmark as a baseline and derive various measures to capture different dynamics of the economy (Bekaert and Wang, 2016; Coval and Moskowitz, 1999; Cai and Warnock, 2006). ▪ Most of the papers in the field anchor their analysis in the traditional, model-based form (Baele, Pungulescu, and Ter Horst, 2007; Asgharian and Hansson, 2006; and, Mishra, 2015).[24]	▪ I-CAPM estimates have been criticised on three grounds: (1) exchange rate risk; (2) lack of incorporation of positive correlation of income and domestic stock market performance; and, (3) the dynamism of correlation through time (Morse and Shive, 2011). These observations have led Morse and Shive (2011) to hypothesise that, "*the gains from diversification are overstated in the CAPM (p. 418).*" ▪ A further objection relates to the inability to observe the actual wealth of investors, therefore, using market capitalisation as a proxy for a country's total wealth may be incomplete. Benchmarks should include items such as human capital which can be hard to obtain and quantify (Sercu and Vanpée, 2012).

[24] Mishra (2008) and Mishra and Ratti (2013) derive a measure using the I-CAPM framework that compares the float-adjusted portfolio for countries against a float-adjusted world market portfolio. Another example is the Coval and Moskowitz (1999) study that uses CAPM as the benchmark and computes distance-adjusted portfolio weights against actual portfolio weights. Furthermore, several studies have calculated optimal weights of the EHB as the proportion of the portfolio weight of country *i* in the portfolio of U.S. investors, with the portfolio weight of country *i* in the world market portfolio (Warnock, 2002; Kho, Stulz, and Warnock, 2009).

Form of measure	Equilibrium model	Key studies from the SLR	Critique
Data-based	▪ Data-based measures are derived from the mean-variance portfolio theory proposed by Markowitz (1952). ▪ The seminal work of Cooper and Kaplanis (1994) showed that this approach seeks to capture the difference between the covariance risks of a particular asset in the portfolios chosen by the foreign and local investors.[25]	▪ The SLR highlighted numerous studies that adopt the data-based form of EHB (Lewis, 1999; Cooper and Kaplanis, 1994; Baele, Pungulescu, and Ter Horst, 2007; Jeske, 2001; Boyle, Garlappi, Uppal, and Wang, 2012; Levy and Levy, 2014; Mishra, 2015, 2017; Asgharian and Hansson, 2006; Lindblom, Mavruk, and Sjögren, 2017; Lundtofte, 2009; Wu and Gau, 2017; Levy, 2017). ▪ Data-based estimates are based on the mean-variance utility function and use different optimal weights to optimise the required (optimal) allocation. ▪ The most common two estimation methods of the data-based form of EHB are: (1) mean-variance optimised weights; and, (2) minimum-variance optimised weights (Baele, Pungulescu, and Ter Horst, 2007; Pungulescu, 2015; Mishra, 2015).	▪ As noted, data-based optimal weights are calculated in a standard mean-variance framework (utility function), using the sample moments of the return data. However, the sample mean and variance of asset returns are notoriously unreliable estimates of the true expected returns and variance (see Merton, 1972, 1980; Britten-Jones, 1999; Jeske, 2001). ▪ Data-based methods typically ignore the inherent time-series properties in financial time-series (such as stationarity and structural breaks). The resulting optimal weights from data-based methods may incorporate extreme and/or volatile values, of little use as optimal investment benchmarks. ▪ Accordingly, data-based approaches persist partly because of limited consensus on an alternative approach.

[25] Studies using data-based measures consider whether investors adjust their expected returns of foreign assets downwards to reflect market frictions such as transaction costs, information asymmetries, and/ or controls on international capital flows (Glassman and Riddick, 1994, 2001; French and Poterba, 1991; Cooper and Kaplanis, 1994, 2000; Sercu and Vanpée, 2007, 2008). It can be hypothesised that subtracting the costs of investing in foreign assets from the expected returns of these assets results in EHB.

Form of measure	Equilibrium model	Key studies from the SLR	Critique
Hybrid	▪ The hybrid form is a derivative of model-based and data-based approaches (Pástor, 2000). This approach incorporates some degree of mistrust in the model of equilibrium. ▪ The hybrid approach is a two-step procedure: (1) the prior distribution uses the I-CAPM approach in calculating model mistrust (by way of standard error of the I-CAPM intercept term); and, (2) the optimal weights are then computed using the mean-variance portfolio theory based on the posterior distribution. ▪ This method allows for the continuous updating of initial beliefs with incoming data, even when those initial beliefs are naïve or uninformed. It enables data-driven distributional assumptions of the inputs, resulting in a probabilistic outcome.	▪ The SLR found a collection of studies that employed hybrid EHB measures (Pástor, 2000; Uppal and Wang, 2003; Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015, 2017; Asgharian and Hansson, 2006; Pungulescu, 2015; Wu and Gau, 2017; Mukherjee, Paul, and Shankar, 2018). ▪ Pástor (2000) investigates to what extent optimal portfolio weights vary with various degrees of mistrust in the asset pricing model. In this Bayesian framework, the investor is neither forced to unconditionally accept the pricing relationship, nor to discard it completely in favour of the data.[26]	▪ The hybrid approach utilises both modern portfolio theory and an asset pricing model to estimate optimal portfolio weights. The hybrid form is subjected to all the assumptions and limitations applicable to model-based and data-based forms. ▪ Moreover, the hybrid approach requires assumptions to be made regarding the distributional parameters from which model mistrust is drawn. The calculation of the posterior distribution requires assumptions to be made regarding the conjugate priors depending on the estimation technique. A common approach is to use normal density and Gamma distributions (Mishra, 2015). ▪ As such, the validity of the hybrid estimates is largely dependent on whether model mistrust reflects the imposed parametric distribution.

[26] Garlappi, Uppal, and Wang (2007) adopt a multi-prior approach to address the optimal weights volatility problem. They limit estimation risk by restricting expected asset returns in the standard mean-variance framework to lie within a specified confidence interval around its estimated value.

2.4 Discipline-based analysis

The previous analysis identified the most recurrent EHB forms (and accompanying measures). After reviewing the 60 studies in detail, home bias definitions were categorised into three disciplinary categories (finance, economics, or geography). The information collected under each subject disciplinary category was then coded. The first group looked at whether the definition was to create a measure in the finance context. This group of studies considered whether the measure discussed over (or under) allocation in foreign assets thereby leading a country to be less (or more) home biased (French and Poterba, 1991). These types of measures compute optimal (or benchmark) weights and actual weights to derive an estimate of EHB (see Jeske, 2001; Baele, Pungulescu, and Ter Horst, 2007; Xing and Li, 2011; Levy and Levy, 2014; Mishra, 2015).

The second group looked at an economics-related definition such that they offer explanations of EHB associated with the existence of national boundaries. These types of measures often account for cross-border trading barriers (political and monetary boundaries, exchange rate fluctuation, variations in regulation, culture, taxation differences, and sovereign risk), and the role of corporate finance and asymmetric information in quantifying EHB (see Cooper and Kaplanis, 1994; Obstfeld and Rogoff, 2000; Warnock, 2002; Foad, 2012; Pungulescu, 2015).

The third group looks at geography-related aspects of the EHB measures, that is, those measures that consider home bias using proxies such as proximity bias, local bias, and familiarity bias (with important contributions by Coval and Moskowitz, 1999; Van Wincoop and Warnock, 2010; Huberman, 2001; Foad, 2011; Baltzer, Stolper, and Walter, 2013).27 As mentioned in Coval and Moskowitz (1999), this group of studies document that investors may prefer geographically proximate investments, "… *investors may simply feel more comfortable about local companies, or firms they hear a lot about, or they may have a psychological desire to invest in the local community (p. 2046).*"[28] Moreover, due to the interrelatedness of the subject disciplines, a study could belong to more than one group. For instance, the work of Lewis (1999) incorporates both finance and economic theories to explain EHB in equities and consumption, while Coval and Moskowitz (1999) and Huberman

[27] While EHB can be clearly defined (that is, investors disproportionately allocating to domestic over international equities), it is important to note that proximity bias is a broader phenomenon. The work of Boschma (2005) provides a typology of proximity bias that includes: geographic; cognitive; social; organisational; and, institutional dimensions.

[28] This is supported by the important work of Huberman (2001) on familiarity and the production of returns.

(2001) consider finance and geography explanations of local preferences. The breakdown of reviewed articles can be framed as overlapping circles of a Venn diagram. Specifically, the three main subject disciplines (finance, economics, geography), the intersection of sub-disciplines (finance, economics; finance, geography; economics, geography), and the overlap of all disciplines (finance, economics, geography). This is presented in Table 2.4.

Table 2.4 Breakdown of subject discipline of the reviewed studies (N = 60)

Subject discipline	Number of studies
Finance	30
Economics	0
Geography	1
Finance, Economics	15
Finance, Geography	6
Economics, Geography	1
Finance, Economics, Geography	7
Total number of articles	60

Note: The count of studies is reported for each subject discipline.

Table 2.4 shows that 50% (N = 30) of the articles are in the finance discipline, 25% (N = 15) are from financial economics, with 10% (N = 6) of the studies from financial geography. Only 2% (N = 1) are geography related and 12% (N = 7) of the 60 studies belong to all three subject disciplines. For completeness, Table 2.5 (below) links the EHB definition categories with its form: model-based; data-based; and, hybrid.

Table 2.5 Linking theoretical subject discipline with equity home bias forms (N = 60)

Subject discipline	Model-based	Data-based	Hybrid
Finance	23	9	6
Economics	0		
Geography	0		
Finance, Economics	11	4	
Finance, Geography	4		
Economics, Geography	1		
Finance, Economics and Geography	6	2	1

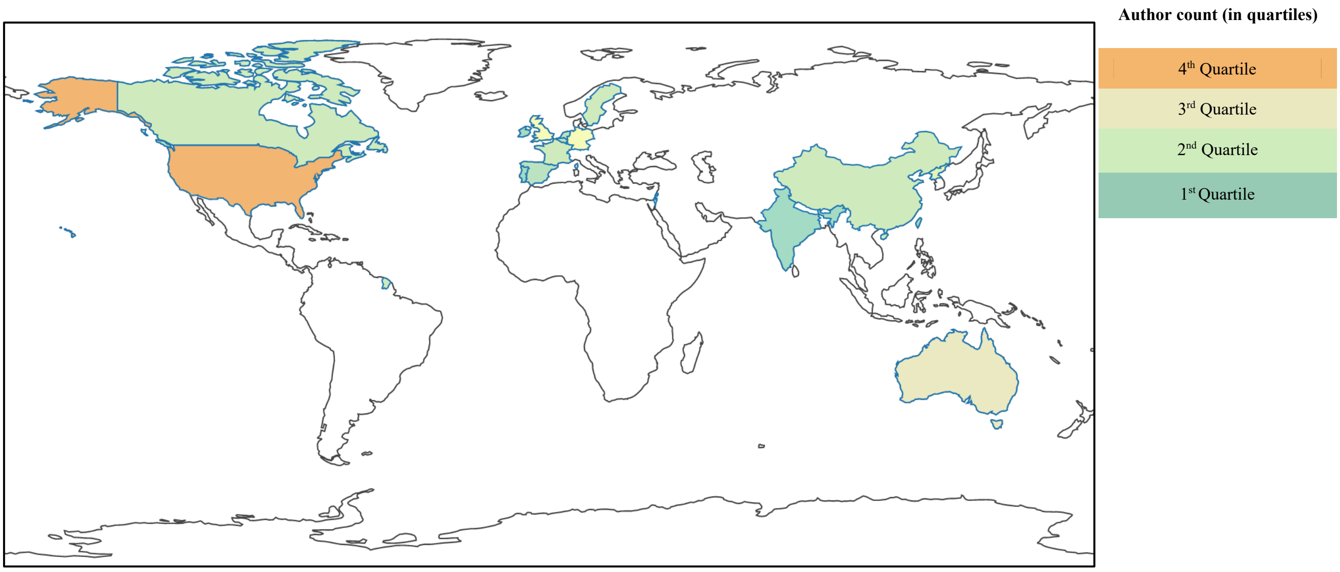
Note: The count of articles is reported, noting that some studies belong to multiple subject disciplines.

It is evident that empirical estimations of EHB are popular among empirical fields such as finance and its intersection with economics (finance, economics). This outcome is perhaps owed to the lack of reliable data on cross-border holdings and possible barriers to international investment (Ahearne, Griever, and Warnock*,* 2004).[29] Moreover, the possibility of anchoring the estimation of EHB into well-developed methodological frameworks such as mean-variance optimisation of Markowitz (1952), and/ or the CAPM of Sharpe (1964) and Lintner (1965), is another plausible reason that has driven the popularity of the empirical disciplines. It is against this backdrop that finance scholars have developed the dominant forms (and measures) of EHB that have become received in the field.[30]

A notable outcome of the SLR is the very limited engagement with the geography of finance in the EHB literature (finance, geography). Out of the 60 studies reviewed, only 15 engaged with geographical perspectives in some form. Where this occurs, the findings highlight that investment behaviour is spatially and institutionally embedded, drawing attention to proximity, clustering, and path dependence (Leyshon and Thrift, 1998; Clark, 2005; Clark and Wójcik, 2007; Wójcik, 2011, 2012, 2018). Yet, this engagement is strikingly asymmetric: the geographical literature routinely cites financial economics, but the financial economics literature does not reciprocate, underscoring a disciplinary imbalance. Such limited interdisciplinary engagement has potentially important implications for the future trajectory of EHB research. One possible explanation lies in the dominance of U.S.-domiciled first authors. Figure 2.4 depicts the geographic bias of the reviewed studies, showing that 45% of first authors are based in the U.S., followed by Australia (12%), and the U.K. (8%).

[29] Refer to Warnock (2002) for a study on the implication of underestimated international holdings for the home bias and high turnover puzzle.
[30] The SLR also finds several other one-off assessments of EHB. These include: Obstfeld and Rogoff's (2000) work that considered trade costs; Grote and Umber's (2006) research where EHB is presented as partial proximity for M&A transactions; Georgopoulos and Hejazi (2009) work on correlation between domestic savings and investment (Feldstein-Horioka puzzle, suggesting that these correlations reduces the EHB somewhere between 45% and 90%); Bekaert, Harvey, Kiguel, and Wang (2016) who partially considered the I-CAPM framework and assessed co-movement measures reacting to globalization with several controls for geography; and, Chen, Huang, Xiao, and Zhao (2020) which takes the form of a subsidiary location study with control variables.

Figure 2.4 Geographic distribution of author (first) affiliation



Note: Global distribution of publications by author (first) affiliation. Maps were produced by R 3.6.1.

First-author concentration clearly reflects the dominance of U.S. business schools in the debate. This is perhaps reinforced by the global weight of U.S. equity markets, which account for more than half of world market capitalisation during much of the review period (French and Poterba, 1991; Fidora, Fratzscher, and Thimann, 2007; MSCI, 2020). A further contributing factor may be the incentive structure of finance as a discipline, which rewards technical econometric innovation over interdisciplinary exchange (Granger, 2005). Collectively, these dynamics have created what Martin (2018) describe as a form of disciplinary, *"lock-in (p. 857)."* As a result, geography's insights into clustering and path dependence remain marginal to the mainstream EHB literature (Arthur, 1989; North, 1990; David, 1994; Clark, 1998; Martin, 1999, 2010; Martin and Sunley, 2006, 2010).

Most studies reduce space to the country of domicile and treat time as a simple sequence of annual observations, regardless of whether measures are model-based, data-based, or hybrid. This abstraction is surprising given longstanding arguments that financial phenomena are embedded in spatial and temporal contexts (Clark, 2005; Clark and Wójcik, 2007; Wójcik, 2011, 2012, 2018; Clark and Monk, 2017). By overlooking the possibility of structural relations across space and through time, existing research may miss patterns of clustering and path dependence that are central to understanding the EHB puzzle.

2.5 Discussion

The interrelated nature of the three forms of EHB (and their measures) is important to the debate and cannot be understated. Model-based measures (and the I-CAPM developed by Solnik, 1974; Sercu, 1980; Stulz, 1981; Adler and Dumas, 1983) have developed from the seminal contribution of Sharpe (1964) regarding the role of systematic risk in modern portfolio theory (Markowitz, 1952). Likewise, data-based measures are operationalised within the mean-variance optimisation approach of Markowitz (1952). Both modern portfolio theory and the CAPM are built on the neoclassical finance tradition.[31] As discussed previously, model-based and data-based estimates of EHB rely on some model of equilibrium.

In more recent years, challenges to modern portfolio theory (and accompanying asset pricing models) have resulted in the development of Bayesian approaches where the investor has prior views about the mean and variance of returns and updates these views through time (Lai, Xing, and Chen, 2011; Bauder, Bodnar, Parolya, and Schmid, 2020). This has led researchers to incorporate a degree of mistrust in the model of equilibrium (that is, hybrid measures) (Wu and Gau, 2017; Mukherjee, Paul, and Shankar, 2018). However, hybrid measures (of all stripes) are themselves a derivative of both model-based and data-based measures. By way of example, hybrid measures account for the standard errors of, say, the I-CAPM asset pricing model by assuming the same underlying parametric distribution (for example, a Student-t and/ or Gaussian distribution) of model-based estimates.

All forms of EHB (and their accompanying estimates) are derived from a single theoretical framework (specifically, the neoclassical finance tradition) with their respective estimation approaches operationalised using common underlying assumptions. Interestingly, many papers in the field report estimates from all three forms of EHB. The work of Mishra (2015), for instance, reported quantitatively (very) similar EHB results regardless of the form used in the estimation.[32] In fact, Mishra (2015) uses the high correlation across different estimates of EHB as a rationale for extracting a common measure (principal component) in

[31] See the seminal contribution of Ross (2009) that considers the central tenets of the neoclassical finance tradition, including: frictionless markets; completeness of the arbitrage function; investors holding homogeneous expectations regarding risk and reward; agents as rational, self-seeking, and risk-averse; informationally efficient markets; and, asset price fluctuations being driven by changes in fundamental value.
[32] Baele, Pungulescu, and Ter Horst (2007), state that *"two alternative home bias measures (were) calculated using, respectively, the data-based and Bayesian weights as benchmarks ... we obtain qualitatively similar results as for the I-CAPM home bias (p. 625)."* Likewise, Mishra (2015) reports that, *"I find slightly lower values of Bayesian home bias measures compared with I-CAPM for several countries in our sample. I also find that for a few countries there is not much change in home bias measures using the various models (p. 304)."*

subsequent calculations. However, the issue of group comparison across the estimates (say, a group of EHB model-based estimates at a point in time versus a group of data-based estimates for the same period) for similarity has not been formally considered by the field to date. Again, this opens another potential path for future work on the matter of group differences across the competing measures (and the associated distributional properties) of EHB (with measurement of EHB the key consideration in Chapter 3).

2.6 Conclusion

This chapter addresses the challenge that definitional clarity is a prerequisite for coherent measurement, presence, and persistence of EHB. The SLR methodology uncovers how EHB has been defined and measured across the literature (Mulrow, 1994; Tranfield, Denyer, and Smart, 2003; Denyer and Tranfield, 2009; Xiao and Watson, 2019). From an initial pool of 8,882 titles, 60 studies were identified as directly engaging with the forms and measures of EHB. These contributions have been classified into three received forms (model-based, data-based, and hybrid) and each was grounded in the neoclassical finance tradition (Markowitz, 1952; Sharpe, 1964; Fama, 1970; Ross, 1976; Stulz, 1981; Adler and Dumas, 1983).

The conclusions from the systematic review are fourfold. First, the three dominant definitions of EHB were consolidated, showing how each specifies 'optimal' portfolio weights differently while sharing common assumptions. Second, the review revealed a paucity of studies engaging with the geography of finance; existing measures are overwhelmingly aspatial and static, overlooking potential spatio-temporal effects (Leyshon and Thrift, 1998; Wójcik, 2011, 2012, 2018). Third, the literature is silent on whether these competing measures converge or diverge in their statistical properties, and little is known about the distributional behaviour of EHB across space and time (Mishra, 2015). Fourth, the field is methodologically dominated by time-series econometric approaches designed for causal inference (Engle and Granger, 1987; Johansen, 1991; Stock and Watson, 2002; Pesaran, 2015). In this paradigm, time is treated as a homogeneous sequence of intervals and countries as independent units, leaving little scope for analysing clustering and path dependence (Moran, 1950; Anselin, 1995; Rey and Anselin, 2010).

These findings highlight the limits of what Kuhn (1970) would term a *paradigm* that has structured and constrained the EHB debate for over half a century. Within the neoclassical finance tradition, geography is largely rendered moot, and investor behaviour is reduced to equilibrium abstractions. As reported, the field of finance and its intersection with economics (finance, economics) has led the research agenda on EHB for the past fifty years. The seminal work of Markowitz (1952) assumes that capital is allocated strictly to those opportunities offering the 'best' (or efficient) risk, reward, and correlation characteristics for a risk-averse investor. Under such assumptions, O'Brien (1992) famously hypothesised that, *"the need to base decisions on geography will alter and diminish (p. 2),"* envisioning a world where the forces of globalisation would render space irrelevant and arbitrage would function perfectly (Ross, 2009). Yet, as Kuhn (1970) reminds us, paradigms persist despite mounting anomalies. The presence and persistence of EHB, widely documented in the literature, have been mounting for over half a century (Huberman, 2001; Mishra, 2015; Jagannathan, Jiao, and Karolyi, 2022).

By limiting (or, less charitably, by ignoring) the potential impacts of geography on investor decision-making, manifest in bounded information-processing capacities, institutional environments, and the unevenness of global capital flows, the prevailing paradigm has constrained the explanatory power of EHB research (Wójcik, 2011). This review, therefore, highlights the need for a more critical framework; one attuned to the patterned realities of clustering and path dependence in international finance (Clark, Feldman, Gertler, and Wójcik, 2018). It is posited that progress requires moving beyond the search for causality to uncovering correlation and interdependence across space and time.

In conclusion, this chapter has demonstrated that definitional ambiguity, a methodological orientation aligned to the neoclassical finance tradition, and disciplinary silences, combine to leave the EHB puzzle only partially understood. By bridging the definitional challenge identified in Chapter 1 with the neglected role of spatio-temporal effects, the SLR has prepared the ground for a re-interpretation of the puzzle that foregrounds correlation and interdependence. Having clarified the definitional foundations of EHB and documented the limitations of existing measures, Chapter 3 now addresses the next challenge: whether these competing measures exhibit statistical convergence or divergence and, in doing so, tests the robustness of the puzzle's measurement foundations.

3. On the Measurement of Equity Home Bias

3.1 Introduction

Despite the ongoing integration of global financial markets, investors continue to exhibit a strong preference for domestic equities, foregoing the diversification benefits of international investment. As shown in Chapter 2, the three forms of equity home bias (EHB) (model-based, data-based, and hybrid) converge on a common task: estimating the optimal portfolio weights prescribed by the neoclassical finance tradition. When actual portfolio weights are compared against these optimal benchmarks, however, investors consistently under-allocate to international equities. It is precisely this divergence between the theoretical optimum and observed practice that generates EHB. Moreover, the evidence overwhelmingly documents not only the presence of EHB, but its persistence internationally (Ahearne, Griever, and Warnock, 2004; Baele, Pungulescu, and Ter Horst, 2007; Fidora, Fratzscher, and Thimann, 2007; Sørensen, Wu, Yosha, and Zhu, 2007; Coeurdacier and Rey, 2013; Levy and Levy, 2014; Mishra, 2015; Solnik and Zuo, 2017; Hu, 2023).

This chapter takes up the second of the four research questions introduced in Chapter 1, specifically, the measurement of EHB. Building on the definitional clarity established in Chapter 2, it asks whether competing measures of EHB behave differently in practice or simply capture the same underlying phenomenon. The analysis also investigates whether the distributional characteristics of the reported EHB estimates reveal systematic departures from standard statistical assumptions that may themselves signal spatio-temporal effects. These findings provide a bridge to Chapter 4, which formally tests for the presence of spatio-temporal effects, and to Chapter 5, which examines its clustering and path dependence over time.

In financial geography, as in finance, measurement is pivotal: it shapes how the EHB puzzle is framed and how subsequent empirical analysis is interpreted. While prior work has focused on quantifying EHB using a particular form (and measure), no study has systematically tested the rationale for maintaining multiple EHB measures if their empirical behaviour is indistinguishable. Moreover, existing studies have been largely silent on the distributional properties of EHB (for instance, normality, skewness, and possible multimodality), particularly when estimates are embedded within the context of space and time. Accordingly, two lines of inquiry are pursued in this chapter. The first is a formal hypothesis test of whether competing measures of EHB are statistically similar through time.

The second is an exploratory analysis of the distributional properties of EHB measures across both space and time, recognising that departures from Gaussian assumptions (such as skewness and multimodality) may themselves be anecdotal evidence of spatio-temporal effects.

To address these concerns, this chapter opens by computing a full panel (for 43 countries over the period 2001 through 2020) of EHB levels across the three forms and their associated measures. First, the model-based measure employs the International Capital Asset Pricing Model (I-CAPM) framework (Solnik, 1974; Sercu, 1980; Stulz, 1981; Adler and Dumas, 1983). Next, there are two data-based measures, mean-variance (Markowitz, 1952) and minimum-variance (min-variance) (Baele, Pungulescu, and Ter Horst, 2007). Finally, the hybrid measure uses a Bayesian approach, where the investor has prior information about means and variances of returns and updates these views through time (Pástor, 2000). Understanding the competing nature of the four measures is important to the research debate and cannot be understated. However, the literature to date is not settled on whether these competing measures of EHB are indeed similar, and, it is unclear how the differences in forms relate to differences in EHB estimation (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015).[33] This gap foreshadows the first line of inquiry in this chapter.

Following a short comparative analysis of the full panel of EHB estimates resulting from the four measures, a Quantile Shift Function (QSF) methodology is used to test for the statistical similarity (or otherwise) among these estimates through time.[34] The advantage of this methodology is that, instead of simply testing the difference at the mean level (which reduces complexity), it tests differences across entire distributions (deciles), potentially identifying rich patterns, and does not impose a parametric distribution on the data (Rousselet, Pernet, and Wilcox, 2017; Wilcox and Erceg-Hurn, 2012; Wilcox, Erceg-Hurn, Clark, and Carlson, 2014).[35]

The novel finding from the QSF analysis is the non-rejection of the null hypothesis, that is, the received measures of EHB are *statistically indistinguishable* across time. Statistically, the estimates of EHB are highly correlated and cannot be separated at the 5% level of confidence. The EHB puzzle is not an artefact of how it is measured, whether

[33] For instance, due to the high correlation of EHB results from eight competing measures, Mishra (2015) advocates for using a dimension reduction technique (principal component analysis) to find a common factor in explaining EHB.
[34] The hypothesis is designed to conduct a pair-wise comparison of all combinations of the four EHB measures over the observation period.
[35] In short, the QSF methodology enables the detection of distributional differences across deciles without imposing normality assumptions.

through model-based, data-based, or hybrid approaches, the conclusion remains the same. The results suggest that the decades of debate over which measure is 'best' may be less consequential than previously assumed, since all forms of estimation arise from the neoclassical finance tradition and ultimately describe the same phenomenon. From a research design perspective, the results justify proceeding with a single measure of EHB without loss of generality.

The findings reported in Chapter 3 are consistent with prior literature on the puzzle, indicating that estimates are observed to be persistently and significantly non-zero and that EHB has generally exhibited only a modest downward trajectory (Ahearne, Griever, and Warnock, 2004; Baele, Pungulescu, and Ter Horst, 2007; Fidora, Fratzscher, and Thimann, 2007; Sørensen, Wu, Yosha, and Zhu, 2007; Coeurdacier and Rey, 2013; Levy and Levy, 2014; Mishra, 2015; Solnik and Zuo, 2017). However, a closer inspection (using a Sankey diagram) suggests that these aggregate inferences may mask the underlying spatial and temporal dynamics of the puzzle, raising the possibility that conclusions drawn from mean values risk suffering from the flaw-of-averages (Savage and Markowitz, 2009). This motivates an exploratory analysis of the distributional properties of EHB estimates, particularly whether the empirical distribution departs from normality in ways that may signal spatio-temporal effects.

The contribution of Chapter 3 is twofold. First, it addresses the gap on whether multiple measures of EHB are necessary if all yield statistically indistinguishable results. It is argued that the EHB literature is incremental and hinders the ability of truly understanding the underlying structure of the data. Second, it addresses the lack of attention to the distributional assumptions underpinning EHB estimation by characterising the empirical properties of the estimates. This constitutes the first, albeit anecdotal, attempt to consider the spatially variegated and temporally uneven nature of the EHB puzzle.

The remainder of the chapter is organised as follows. Section 3.2 reviews the relevant literature. Section 3.3 outlines the methods used in empirical estimation. Section 3.4 describes the data. Section 3.5 presents the analysis, consisting of two main subsections aligned with the formal hypothesis and the exploratory objective. Section 3.6 concludes by discussing the findings and motivation to test for spatio-temporal effects.

3.2 Literature review

Despite well-theorised and documented gains from international diversification, the EHB puzzle persists (French and Poterba, 1991; Mishra, 2017). For some fifty years, voluminous studies have attempted to provide explanations for not only the existence, but the persistence, of investors holding geographically proximate portfolios. The main lines of interest of scholarly inquiry have centred on transaction costs, such as fees, commissions, and higher spreads (Tesar and Werner, 1995; Glassman and Riddick, 2001; Sercu and Vanpée, 2008; Warnock, 2002), direct barriers to international investment (Black, 1974; Stulz, 1981; Errunza and Losq, 1985), differences in the amount and quality of information between domestic and foreign stocks (Gehrig, 1993; Brennan and Cao, 1997; Van Nieuwerburgh and Veldkamp, 2006), and, research on psychological or behavioural factors (Huberman, 2001; Coval and Moskowitz, 1999). However, these competing explanations, both individually and in aggregate, have not been able to satisfactorily account for the observed EHB in international finance (Ahearne, Griever, and Warnock, 2004; Mishra, 2015).

The literature on the EHB puzzle continues its causal search for the 'right' set of covariates (both rational and behavioural) and estimation techniques that can 'best' capture the phenomenon (Baele, Pungulescu, and Ter Horst, 2007; Schoenmaker and Bosch, 2008; Baltzer, Stolper, and Walter, 2013; Mishra, 2015; Solnik and Zuo, 2017; Cooper, Sercu, and Vanpée, 2018). One possible shortcoming of most previous studies is that the focus has been on the aggregate level of the puzzle. This study claims that any meaningful explanation of EHB first requires a correct characterisation and understanding of the structure of the puzzle. This important dynamism is surprisingly overlooked in the literature. This observation can be explicitly linked to Savage and Markowitz's (2009) concept of the 'flaw-of-averages', which highlights the limitations of relying solely on the first moment of the distribution (the mean) to draw inferences. This study contributes by examining EHB while relaxing parametric distributional assumptions, looking beyond the mean, and exploring the constructs of space and time.

3.3 Estimating Equity Home Bias

This section presents the equations used to estimate EHB. EHB is calculated as per Eq. [1] and is present when the actual weight is less than the optimal weight (Baele, Pungulescu, and Ter Horst, 2007; Pungulescu, 2015; Mishra, 2015).[36,37] The EHB of country i in time t ($EHB_{i,t}$) takes the value zero when the assets have been optimally allocated, and equals a value of one when investors hold only domestic assets.

$$EHB_{i,t} = 1 - \frac{w_{i,t}^{A}}{w_{i,t}^{o}} \qquad [1]$$

where $EHB_{i,t}$ is the EHB of country i in time t. $w_{i,t}^{A}$ is the actual weight or holdings of country i in time t, and $w_{i,t}^{o}$ is the optimal weight of country i in time t. This method results in annual measures of EHB for the 43 countries for 20 years, across four estimation techniques (43 countries x 20 years x 4 measures = 3,440 EHB estimates).

3.3.1 Actual weight calculation

The actual foreign holding (actual weight: $w_{i,t}^{A}$) is the ratio of foreign equity holdings of a country and total equity holdings (Eq. [2]). The total equity holding comprises both foreign and domestic holdings. The domestic equity holding is the difference between the country's total market capitalisation and foreign equity liabilities (Baele, Pungulescu, and Ter Horst, 2007; Pungulescu, 2015; Mishra, 2015; Coppola, Maggiori, Neiman, and Schreger, 2021). The calculation of actual weight of country i in time t is given in Eq. [2];

$$w_{i,t}^{A} = \frac{FEA_{i,t}}{FEA_{i,t} + mc_{i,t} - FEL_{i,t}} \qquad [2]$$

[36] In cases where actual foreign weight is greater than optimal portfolio weight, this chapter uses the adjusted equation as suggested by Eq. [13] in Baele, Pungulescu, and Ter Horst (2007, p. 613).
[37] Other scaling approaches of EHB calculations are found in Kho, Stulz, and Warnock (2009) and Sercu and Vanpée (2012).

where $FEA_{i,t}$ is foreign equity assets of country i in time t. $FEL_{i,t}$ is foreign equity liabilities of country i in time t, and $mc_{i,t}$ is the market capitalisation of country i in time t. This method results in 860 annual actual weights (43 countries x 20 years = 860 actual weights).

3.3.2 Optimal weight calculation

In each of the received forms of EHB, the calculation of *optimal* weights involves specifying the share of domestic versus foreign equities that an investor should hold under a given estimation approach. Following the findings in Chapter 2, it is important to recall that all forms (model-based, data-based, hybrid) calculate optimal weights using methodologies derived from the neoclassical finance tradition. The following sections formalise each of the forms (model-based, data-based, and hybrid) in turn. Collectively, these respective approaches result in 3,440 annual optimal weights (43 countries x 20 years x 4 measures).

3.3.2.1 Model-based optimal weight calculation

According to this form of EHB optimal weight calculation, in an international setting, the optimal investment weights of a country are given by the relative shares of domestic and foreign equities in the world market capitalisation (that is, the I-CAPM benchmark). In the model-based approach, the optimal weight of foreign holdings is shown in Eq. [3];

$$\omega^*_{model,i,t} = 1 - \frac{mc_{i,t}}{wmc_t} \qquad [3]$$

where $mc_{i,t}$ is the market capitalisation of country i in time t and wmc_t is the world market capitalisation in time t. Since this form of measure uses the I-CAPM model as the benchmark, it is important to assess the validity of the I-CAPM benchmark allocation. The standard I-CAPM model can be written as in Eq. [4];

$$R_D - R_F = \beta + \beta_D(R_W - R_F) + \varepsilon \quad [4]$$

where R_D is the return on the domestic market portfolio, R_F is the risk-free rate, R_W is the return on the world market portfolio, β_D is world beta of the domestic market, β is the intercept (the risk premium for the domestic market for an asset uncorrelated with the world market portfolio) and ε is the error term.

3.3.2.2 Data-based optimal weight calculation

Two proxies for the data-based optimal weight calculation are estimated, specifically: mean-variance optimised weights and minimum-variance optimised weights.

3.3.2.2.a Mean-variance optimised weights

The availability of returns data enables the study to use the sample moments as estimates of the true parameters (Mishra, 2015). The common starting point is the mean-variance framework of Markowitz (1952) where an investor is assumed to select a portfolio that maximises their expected utility as shown in Eq. [5];

$$\max \omega'\mu - \frac{\gamma}{2}\omega'\Sigma\omega \quad [5]$$

where ω is the vector of N portfolio weights allocated to N assets, that is, domestic and foreign equity holdings ($N = 2$), μ is N-vector of expected returns, Σ is the $N \times N$ variance-covariance matrix of returns, and γ is the coefficient of relative risk aversion (Glassman and Riddick, 2001; Mishra, 2015).[38] Under the assumptions that $\omega' I = 1$ (I is an N-dimensional vector of ones that ensures the sum of the allocated weights to all assets in a portfolio sums to one), and the risk-free rate is chosen as the zero-beta portfolio (Mishra, 2015), the portfolio choice solution (fully invested normalised tangency-portfolio) in the mean-variance

[38] As with Glassman and Riddick (2001) and Mishra (2015), the study assumes relative risk aversion $\gamma = 3$.

framework, when short sales are allowed, can be presented as Eq. [6] (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015);

$$\omega^*_{data,mean-variance} = \frac{\Sigma^{-1}\mu_e}{I'\Sigma^{-1}\mu_e} \quad [6]$$

where μ_e is the vector of the expected excess returns (over the risk-free rate) and, as discussed, I is an N-dimensional vector of ones. This solution involves the true (unobserved) expected returns and variance-covariance matrix of the returns.

3.3.2.2.b Minimum-variance optimised weights

The global minimum variance portfolio is the leftmost portfolio of the mean-variance efficient frontier and is unique in that security weights are independent of expected returns on individual securities (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015). For N assets having a variance-covariance matrix Σ and if the vector of expectations is μ, I is an N-dimensional vector of ones, the minimum variance portfolio weight as per Merton (1972) is;

$$\omega^*_{data,min-variance} = \frac{\Sigma^{-1}I}{I'\Sigma^{-1}I} \quad [7]$$

3.3.2.3 Hybrid optimal weight calculation

The important work of Pástor (2000) approaches portfolio selection using a Bayesian framework that incorporates a prior belief in an I-CAPM. Pástor and Stambaugh (2000) investigate the portfolio choices of mean-variance-optimising investors who use sample evidence to update prior beliefs concerning either risk-based or characteristic-based pricing models. The degree of trust can be captured by *t*-statistics of the intercept β (Mishra, 2015).

A statistically insignificant intercept β allows a strong belief that the I-CAPM model is valid and that optimal portfolio weights are close to those of I-CAPM (Solnik, 1974; Mishra, 2015). A higher value of *t*-statistics of the intercept β generates less trust in the model-based I-CAPM approach, and portfolio weights are closer to the data-based mean variance approach (Mishra, 2015). Hybrid optimal weights consider employing different degrees of mistrust in the I-CAPM by employing different standard errors of the intercept.

The prior: In the Bayesian analysis, there is prior (non-data) belief in the model: that is, belief in a zero intercept and no mispricing (Pástor, 2000; Mishra, 2015). The prior is updated using returns data to a certain extent, depending on the chosen degree of mistrust in the model. The sample mispricing β is shrunk towards the prior mean of β to obtain the posterior mean of β. Following Pástor (2000) and applied in Mishra (2015), this study uses a natural conjugate prior;

$$p(\beta, h) = p(\beta)p(h) \tag{8}$$

where $p(\beta, h)$ is a Normal density and $p(h)$ is a Gamma density.

$$p(\beta) = \frac{1}{(2\pi)^{\frac{k}{2}}}\left|\underline{V}\right|^{-\frac{1}{2}} exp\left[-\frac{1}{2}\left(\beta - \underline{\beta}\right)' \underline{V}^{-1}(\beta - \underline{\beta})\right] \tag{9}$$

$$p(h) = C_G^{-1} h^{\frac{\underline{v}-2}{2}} exp\left(\frac{-h\underline{v}}{2\underline{s}^{-2}}\right) \tag{10}$$

where $\underline{V}$ is a $k \times k$ positive definite prior covariance matrix, $\underline{v}$ is degrees of freedom, $\underline{s}^2$ is square of standard error, error precision $h = \sigma^{-2}$ and C_G is the integrating constant for the Gamma probability density function (Pástor, 2000 and, again, applied in Mishra, 2015).

The posterior: Based on the prior distribution above and the likelihood function (see Mishra, 2015) the posterior distribution can be written as;

$$p(\beta, h|y) \propto \exp\left\{\left[-\frac{1}{2}\left\{h(y - X\beta)'(y - X\beta) + \left(\beta - \underline{\beta}\right)' \underline{V}^{-1}(\beta - \underline{\beta})\right\}\right]\right\} h^{\frac{N+\underline{v}-2}{2}} \exp\left[\frac{-h\underline{v}}{2\underline{s}^{-2}}\right] \tag{11}$$

A posterior simulator, called the Gibbs sampler, uses conditional posteriors to produce random draws, $\beta^{(s)}$ and $h^{(s)}$ for $s = 1,2, \ldots . S$, which are used to study posterior properties (Pástor, 2000).

The Gibbs sampler: Let θ be a P-vector of parameters and $p(y|\theta), p(\theta)$ and $p(\theta|y)$, are the likelihood, prior and posterior, respectively (Pástor, 2000; Mishra, 2015). The Gibbs sampler involves the following steps:

Step 1: Choose a starting value, $\theta^{(0)}$.

For $s = 1, \ldots . S$:

Step 2: Take a random draw $\theta_{(1)}^{(s)}$ from $p(\theta_{(1)}|y, \theta_{(2)}^{(s-1)}, \theta_{(3)}^{(s-1)}, \ldots \ldots \ldots . \theta_{(B)}^{(s-1)})$

Step 3: Take a random draw $\theta_{(2)}^{(s)}$ from $p(\theta_{(2)}|y, \theta_{(1)}^{(s)}, \theta_{(3)}^{(s-1)}, \ldots \ldots \ldots . \theta_{(B)}^{(s-1)})$

Step 4: Take a random draw $\theta_{(3)}^{(s)}$ from $p(\theta_{(3)}|y, \theta_{(1)}^{(s)}, \theta_{(2)}^{(s)}, \theta_{(4)}^{(s-1)} \ldots \ldots \ldots . \theta_{(B)}^{(s-1)})$

Step 5: Take a random draw $\theta_{(B)}^{(s)}$ from $p(\theta_{(B)}|y, \theta_{(1)}^{(s)}, \theta_{(2)}^{(s)}, \theta_{(4)}^{(s)} \ldots \ldots \ldots . \theta_{(B-1)}^{(s)})$

Following these steps will yield a set of *S* draws, $\theta^{(s)}$ for $s = 1, \ldots . S$. Drop the first S_0 of these to eliminate the effect of $\theta^{(0)}$and average the remaining draws S_1 to create estimates of posterior features of interest (Mishra, 2015). In the empirical estimation, the study discards an initial $S_o = 1{,}000$ burn-in replications and includes $S_1 = 1{,}000$ replications (Pástor, 2000; Mishra, 2015).

$$\mu = \frac{1}{S_1} \sum_{s=S_0+1}^{S} \theta^{(s)} \qquad [12]$$

$$cov(\theta|y) = \frac{1}{S_1 - 1} \sum_{s=S_0+1}^{S} (\theta^{(s)} - \mu)(\theta^{(s)} - \mu)' \qquad [13]$$

Prediction and optimal weights: The predictive density is calculated as;

$$p(y^*|y) = \iint p(y^*|y, \beta, h)\, p(\beta, h|y) d\beta\, dh \quad [14]$$

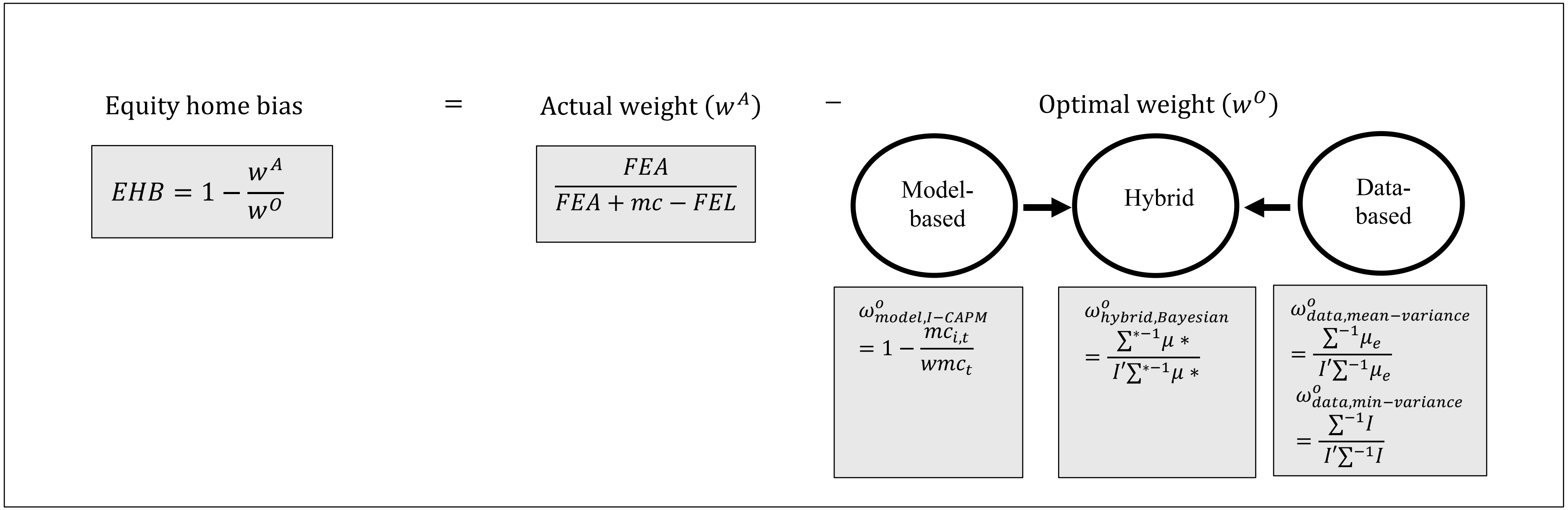
The Bayesian mean-variance optimal weights are as follows (Pástor, 2000; Pástor and Stambaugh, 2000; Mishra, 2015):

$$\omega^* = \frac{\sum^{*-1} \mu^*}{I' \sum^{*-1} \mu^*} \quad [15]$$

where μ^* is the predictive mean and $\sum^*$ is the predictive variance-covariance matrix obtained from the Bayesian approach and, again, I is an N-dimensional vector of ones.[39] Figure 3.1 summarises the four EHB approaches undertaken in this study.

[39] This framework is also discussed in Pástor (2000), Baele, Pungulescu, and Ter Horst, (2007), and Mishra (2015).

Figure 3.1 Summary of equity home bias estimation



Note: The forms of EHB are: model-based, data-based, and hybrid. The $FEA_{i,t}$ is foreign equity assets of country i in time $t.$ $FEL_{i,t}$ is foreign equity liabilities of country i in time t, and $mc_{i,t}$ is the market capitalisation of country i in time t. wmc_t is the world market capitalisation in time $t.$ μ_e is the vector of the expected excess returns (over the risk-free rate). $\sum$ is the $N \times N$ variance-covariance matrix of returns. μ^* is the predictive mean and $\sum^*$ is the predictive variance-covariance matrix obtained from the Bayesian approach. I is an N-dimensional vector of ones.

3.4 Data

It is important to acknowledge that the robustness of the empirical results reported in this study is not only a function of the models applied (Chapter 2), but also of the quality and construction of the underlying data. This section describes the data used in the study. The study sample contains 43 countries for the period 2001 through 2020 as captured by the standard MSCI ACWI index classification (MSCI, 2020) (Table 3.1).

Table 3.1 Country classification (MSCI, 2020)

MSCI ACWI Index					
MSCI World index (23/23) Developed markets			**Emerging Markets index (20/27) Emerging markets**		
Americas	**Europe & Middle East**	**Pacific**	**Americas**	**Europe & Middle East & Africa**	**Asia**
Canada	Austria	Australia	Argentina	Czech Republic	~~China~~
United States	Belgium	Hong Kong	Brazil	Egypt	India
	Denmark	Japan	Chile	Greece	Indonesia
	Finland	New Zealand	Colombia	Hungary	Korea
	France	Singapore	Mexico	~~Kuwait~~	Malaysia
	Germany		~~Peru~~	Poland	Pakistan
	Ireland			~~Qatar~~	Philippines
	Israel			Russia	~~Taiwan~~
	Italy			~~Saudi Arabia~~	Thailand
	Netherlands			South Africa	
	Norway			Turkey	
	Portugal			~~UAE~~	
	Spain				
	Sweden				
	Switzerland				
	United Kingdom				

Notes: The sample contains 43 countries from 2001 through 2020 and follows the standard classification for the MSCI (2020). All 23 countries in the MSCI World index (developed markets) are included in the analysis and 20 from a total of 27 countries are included from the MSCI Emerging Markets index. China (for completeness, EHB results from China for 2015 through 2020 are reported in Appendix 2), Kuwait, Peru, Qatar, Saudi Arabia, Taiwan, and, the United Arab Emirates are excluded due to data limitations (crossed out countries).
Source: MSCI (2020)

Following Baele, Pungulescu, and Ter Horst (2007), weekly MSCI U.S. $ denominated returns for the 43 countries and the world market (proxied by MSCI ACWI index) for the period from January 1996 to December 2020 are used.[40,41] The weekly risk-

[40] EHB estimates are calculated for the period 2001 through 2020. However, the study collects data from January 1996 to December 2020 for the Hybrid, Bayesian prior estimation.
[41] For the optimal weight calculations using data-based mean-variance and minimum variance estimations, 1,040 return observations are used for a single country (52 weeks for a year for 20-year period).

free rate is the one-month treasury bill rate from Ibbotson and Associates.[42] Market capitalisations for the model-based figures are obtained from Bloomberg L.P. (2022) and World Bank (2022). Actual portfolio weights are based on the foreign portfolio assets and liabilities reported in the International Monetary Fund's (IMF) Coordinated Portfolio Investment Survey (CPIS) dataset.[43,44] The CPIS dataset collects foreign portfolio assets and liabilities on a country-of-domicile basis, which may diverge from the operational headquarters of the ultimate investor (Coppola, Maggiori, Neiman, and Schreger, 2021). This distinction is non-trivial in jurisdictions such as Ireland and Luxembourg, where fund domiciliation (for example, the Undertakings for Collective Investment in Transferable Securities (UCITS) in Ireland) significantly exceeds domestic market size (Irish Funds, 2023; Association of the Luxembourg Fund Industry, 2022; Wójcik, 2011, 2018). Specific to this study, the CPIS captures cross-border flows into funds legally domiciled in Ireland, even where investment decisions are executed by managers located elsewhere. This creates potential measurement biases and complicates the interpretation of observed EHB values (Lane and Milesi-Ferretti, 2008; Coppola, Maggiori, Neiman, and Schreger, 2021). The specific EHB results for Ireland, where the interaction between fund domicile and domestic financial structures is particularly pronounced, are taken up later in this chapter.

3.5 Analysis

This section consists of four subsections: (1) estimates of EHB; (2) testing the statistical similarity (or otherwise) of EHB estimates; (3) model-based estimation and its generalisability; and, (4) testing the distributional properties of EHB estimates and providing some initial perspectives regarding the results across space and through time.

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[42] One-month weekly T-Bill rate by Ibbotson and Associates Inc.
Retrieved from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[43] CPIS All economies' derived tables.
Retrieved from https://data.imf.org/?sk=B981B4E3-4E58-467E-9B90-9DE0C3367363&sId=1424963554286.
[44] In 1997, the IMF conducted the first CPIS, in which 29 countries participated. CPIS reports data (in U.S. dollar) terms on foreign portfolio asset holdings (divided into equity, long term debt, and short-term debt) by the residence of the holder. CPIS collects bilateral data among participating and other countries, which enables them to improve their statistics on the non-resident holdings of their portfolio investment liabilities and associated financial flows and investment income data. In 2001, IMF conducted a second CPIS; after that, it was provided annually. The CPIS data are a comprehensive source for international portfolio holdings and have been an excellent resource in estimating EHB, yet, CPIS data suffer from some caveats (refer to Mishra (2015, p. 301) for discussion on IMF's CPIS database). As of 25 August 2025, the last record of CPIS data is up to December 2023. Therefore, the decision was made not to consider a partial block, with the final block ending in December 2020.

3.5.1 Estimates of Equity Home Bias

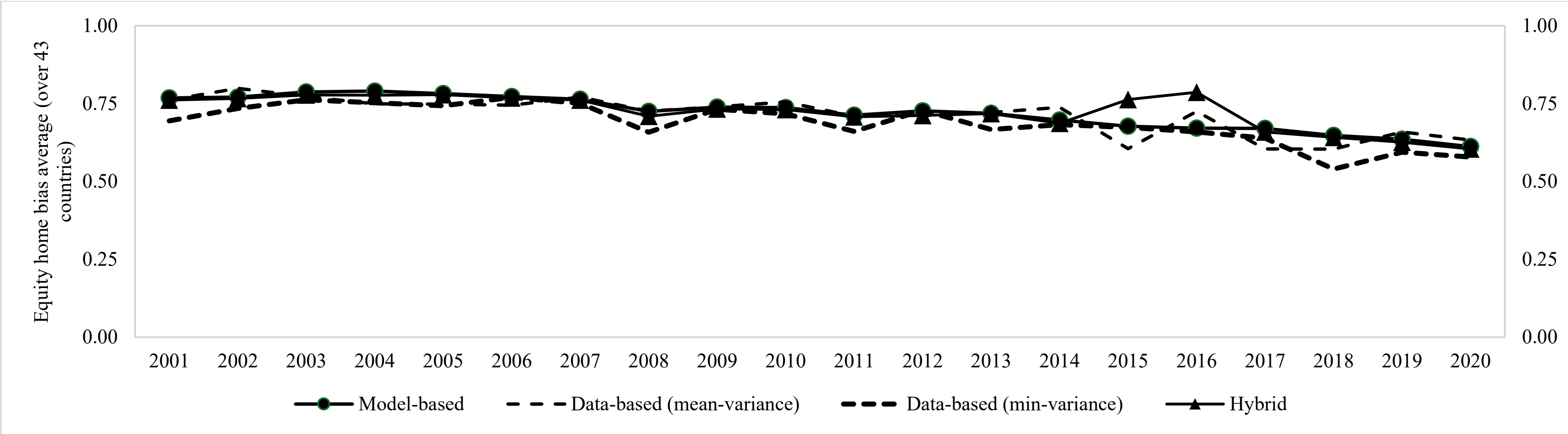
This section presents estimates of EHB derived from: (1) model-based; (2) data-based mean-variance; (3) data-based minimum-variance; and, (4) hybrid estimation measures of EHB over the observation period, 2001 through 2020. The aggregate estimates of EHB are reported under the three forms (using the four estimation methods).[45,46] The results suggest that, regardless of the estimation method, the EHB puzzle is alive and well. Figure 3.2 presents two striking patterns of the puzzle.

Firstly, the superimposed nature of the four lines provides visual insights on the matter of statistical similarity of the competing measures of EHB. This result corroborates the findings of past scholars who find quantitatively similar EHB values regardless of the form they used to estimate EHB (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015). To support this visual finding, the estimates garnered from all three EHB forms exhibit a remarkably high correlation with each other (the average correlation between data-based and model-based approach is 0.86 (average of data-based mean-variance and data-based minimum-variance with model-based approaches), the average correlation between data-based and hybrid approach is 0.75 and, the correlation between hybrid and model-based approach is 0.81. The observed similarity, together with high correlation, provides a pathway to the first hypothesis on testing the statistical similarity of the competing measures.

The second striking observation from Figure 3.2 is the observed downward trend over the sample period. On the matter of trend, the results corroborate the work of Ahearne, Griever, and Warnock (2004), Baele, Pungulescu, and Ter Horst (2007), Levy and Levy (2014), and Mishra (2015) in reporting a modest downward trend in the general level of EHB over time. On the significance (or otherwise) of the aggregate downward trend in the estimates, the work of Baele, Pungulescu, and Ter Horst (2007) concludes that EHB, *"has not decreased sizeably (p.64)"* through time.[47]

[45] The actual portfolio weights are presented in Appendix 3. This chapter reports the EHB estimates (individual country results) from each estimation method from 2001 through 2020 in Appendix 4.
[46] Model-based EHB measures rely on the validity of the I-CAPM benchmark to set optimal weights (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015). The regression analysis undertaken suggests that the I-CAPM model is valid, with optimal portfolio weights close to the theoretical I-CAPM allocations (see Appendix 5).
[47] Using a sample of 25 countries for the period (and similar methodological approaches from the early 1990s through to 2004), Baele, Pungulescu, and Ter Horst (2007) concluded that, *"the puzzle is eroding at a global level (p.608)."*

Figure 3.2 Average equity home bias estimates (2001 through 2020)



	Average of equity home bias estimation results from 2001 through 2020																			
	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
Model-based	**0.768**	0.771	0.787	0.79	**0.782**	0.772	0.763	0.724	0.739	**0.737**	0.712	0.726	0.719	0.697	**0.677**	0.671	0.67	0.647	0.636	**0.612**
Data-based (mean-variance)	**0.762**	0.799	0.773	0.749	**0.748**	0.745	0.77	0.725	0.739	**0.755**	0.709	0.711	0.721	0.738	**0.605**	0.724	0.604	0.604	0.659	**0.633**
Data-based (min-variance)	**0.694**	0.734	0.762	0.752	**0.743**	0.77	0.75	0.658	0.732	**0.717**	0.661	0.729	0.667	0.682	**0.673**	0.659	0.639	0.54	0.594	**0.578**
Hybrid	**0.761**	0.766	0.777	0.777	**0.778**	0.768	0.761	0.709	0.732	**0.730**	0.708	0.711	0.718	0.687	**0.763**	0.786	0.659	0.642	0.626	**0.604**

Note: The four estimates are computed using model-based, data-based mean-variance, data-based min-variance, and hybrid. The lines represent the average over 43 countries in the sample from 2001 through 2020. All four lines exhibit a marginal downward trend. The absolute drops in EHB between 2001 and 2020 are 0.16, 0.13, 0.12, and 0.16 for model-based, data-based mean-variance, data-based min-variance and hybrid EHB, respectively.

3.5.2 Testing the similarity of Equity Home Bias estimates

This section addresses the first major line of inquiry in this study. Chapter 3 tests the hypothesis that the received measures of EHB are statistically indistinguishable across time, using a QSF methodology (Wilcox and Erceg-Hurn, 2012; Wilcox, Erceg-Hurn, Clark and Carlson, 2014).

3.5.2.1 Quantile shift function methods

In comparing the received forms, an approach that is not restricted by placing some distributional assumption on the sample is required. A prerequisite for testing the mean difference in two groups is to assume a normal and/or other similar form of symmetric distribution (for example, a Student *t*-distribution). A standard, Gaussian procedure makes (very) strong assumptions, including that distributions differ only in central tendency. Under these conditions, the typical observation in each distribution can be summarised by the mean, with a *t*-test sufficient to detect changes in location. However, in general terms, *t*-tests on means may not always be robust (Posten, 1984).[48]

Due to limitations on standard practice of testing mean differences using a *t*-test, a family of tools is considered that allow a comparison of entire distributions, or shift functions (Wilcox and Erceg-Hurn, 2012; Wilcox, Erceg-Hurn, Clark, and Carlson, 2014). The shift function allows researchers to understand and quantify how two distributions differ. In practical terms, the shift function describes how one distribution should be rearranged to match the other one and it estimates how (and by how much one distribution must be shifted). The power of the test is that it moves from simply testing differences in a single measure of central tendency, to differences across entire distributions.[49]

[48] In addition, there is no reason *a priori* to assume that two distributions differ only in the location of the bulk of the observations. Effects can occur in the tails of the distributions as well (Posten, 1984).

[49] A systematic method for characterising how two independent distributions differ was first proposed by Doksum (1974) and further developed in subsequent work (Doksum and Sievers, 1976; Doksum, 1977). These studies introduced the idea of plotting quantile differences between two distributions as a function of the quantiles of one group. Wilcox (1995) later proposed an alternative technique that offered better probability coverage and potentially more statistical power than the original approach, although it was limited to decile computations, fixed at a 0.05 significance level, and applicable only to paired outcomes. More recently, this framework has been advanced through the development of a new shift function based on a percentile bootstrap (Wilcox and Erceg-Hurn, 2012; Wilcox, Erceg-Hurn, Clark, and Carlson, 2014). This latter version, which addresses many of the limitations of earlier techniques, is employed in this study.

The Wilcox, Erceg-Hurn, Clark, and Carlson (2014) shift function approach uses the Harrell-Davis quantile estimator to estimate the deciles of two distributions (Harrell and Davis, 1982)[50]; it then computes 95% confidence intervals of the decile differences with a bootstrap estimation of the deciles' standard error and controls for multiple comparisons so that the type I error rate remains around 5% across the nine confidence intervals. In formal terms, the goal is to test:

$$H_0\colon \theta_{q1} = \theta_{q2,} \qquad [16]$$

where θ_{qj} is the qth quantile corresponding to the jth group ($j = 1{,}2$).

To describe the details of the proposed test of Wilcox, Erceg-Hurn, Clark, and, Carlson (2014), let X_{ij} be a random sample from the jth group ($i = 1,2, \ldots . nj$). First, we generate a bootstrap sample from the j^{th} group by resampling with replacement nj observations from group j. Let $\widehat{\theta_j^*}$ be the estimate of the qth quantile for group j based on this bootstrap sample. Let $d_j^* = \widehat{\theta_1^*} - \widehat{\theta_2^*}$ (Wilcox, Erceg-Hurn, Clark, and, Carlson, 2005). Next, repeat this process B times yielding d_b^*, $b = 1, \ldots . B$. Here, $B = 2000$ is used. Let $l = \alpha B/2$, rounded to the nearest integer, and let $u = B - l$. Letting $d_{(1)}^* \leq \cdots \leq d_{(B)}^*$ represent the B bootstrap estimates written in ascending order, an approximate $1 - \alpha$ confidence interval for $\theta_1 - \theta_2$ is:

$$(d_{(l+1)}^*, d_{(u)}^*) \qquad [17]$$

Let A denote the number of times d^* is less than zero and let C be the number of times $d^* = 0$ (Wilcox, Erceg-Hurn, Clark, and, Carlson, 2014). Letting;

$$\widehat{p^*} = \frac{A+0.5C}{B}, \qquad [18]$$

a (generalised) p-value is $2min(\widehat{p^*}, 1 - \widehat{p^*})$.

[50] The one method that performed well in simulations was based, in part, on the estimator derived by Harrell and Davis (1982). The Harrell and Davis (1982) estimate of the qth quantile uses a weighted average of all the order statistics. Harrell-Davis estimator generally competes well with alternative estimators that again use a weighted average of all the order statistics (Wilcox, Erceg-Hurn, Clark, and Carlson, 2014).

3.5.2.2 Quantile shift function results

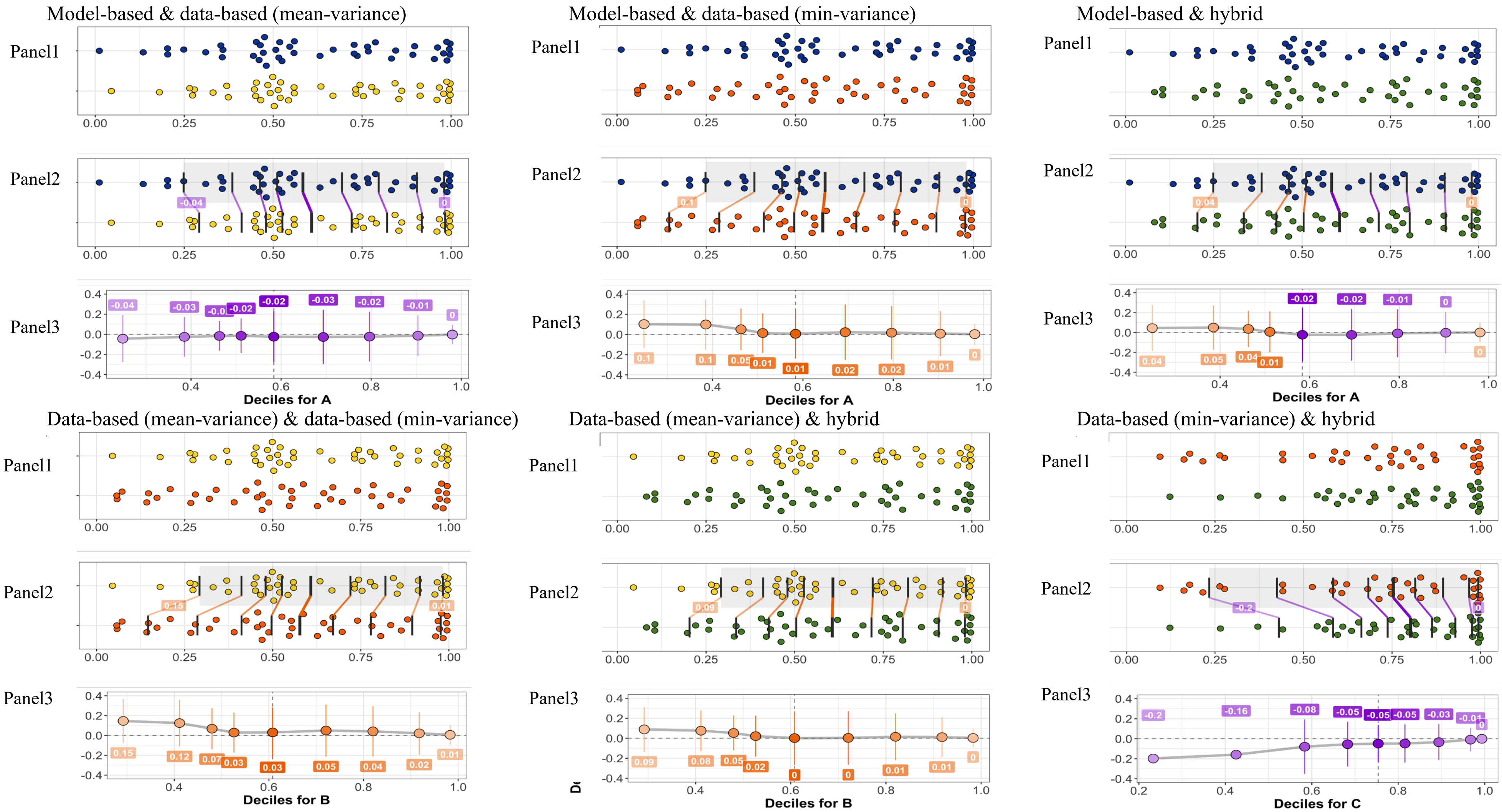
The QSF methodology allows an evaluation of comparability across the competing EHB measures in six pair-wise combinations, labelled as: (1) model-based & data-based (mean-variance); (2) model-based & data-based (min-variance); (3) model-based & hybrid; (4) data-based (mean-variance) & data-based (min-variance); (5) data-based (mean-variance) & hybrid; and, (6) data-based (min-variance) & hybrid. As discussed, the QSF is a non-parametric method that allows differences between two distributions to be examined across their quantiles, rather than relying on global tests of equality (Doksum and Sievers, 1976; Wilcox, Erceg-Hurn, Clark, and Carlson, 2014). By considering quantile-by-quantile comparison, the QSF can detect potential heterogeneity that may be masked by mean-based measures. Given the sheer volume of analysis (six pair-wise combinations tested annually for 20 years), the full results from 2001 to 2020 are reported in Appendix 6. For completeness, Table 3.2 and Figure 3.3 present the findings for all six pair-wise combinations in 2020, allowing for detailed consideration.

Prior to considering specific results, the QSF analysis shows that across all six pair-wise comparisons of EHB measures, the bootstrapped confidence intervals always included zero for every decile *and* every year (2001 through 2020).[51] This means that the null hypothesis cannot be rejected. In practical terms, it is found that all measures, regardless of form, produce statistically indistinguishable results annually and the selection of EHB measure does *not* change the ranking of countries or the shape of the distribution of EHB.

[51] Again, it is important to note that in interpreting the QSF results, statistical significance is assessed by whether the 95% bootstrap confidence interval around the quantile difference includes zero, rather than by whether the point estimate lies between the lower and upper bounds (which it necessarily does by construction; Tibshirani and Efron, 1993; Davison and Hinkley, 1997).

Turning to the specific matter of both the magnitude and direction of shifts, it is observed that the quantile shifts are economically small. For instance, in the comparison of model-based and data-based (mean-variance) measures, the largest shift is -0.044 at the first decile, with a confidence interval spanning -0.278 to 0.190 (bolded in Table 3.2). Across other comparisons, shifts remain within -0.05 to +0.15. Another feature of the reported results is the consistency across measures. The results hold regardless of the measure selected over the sample period, indicating convergence in distributional properties. In the upper deciles (0.7 to 0.9), the shift functions flatten, suggesting stability in spread and harmonisation between measures (Rousselet, Pernet, and Wilcox, 2017). Notably, countries consistently appear in the same decile ranges across measures *and* across the full 2001 through 2020 period, implying that rankings of EHB levels are not sensitive to methodological specification (Mishra, 2015). The consistency of decile ranking through both space (countries) and time (years) reinforces the robustness of the findings. It suggests that the presence and persistence of EHB is not contingent on how it is measured, but rather a structural feature of the production of returns (Clark and Monk, 2017).

Figure 3.3 Quantile shift function analysis to compare the equity home bias measures in 2020



Note: A stands for model-based measures, B stands for data-based-mean-variance measure, C stands for data-based-min-variance measure, D stands for hybrid measure. Black vertical bars overlaying each distribution indicate the 0.1, 0.2, 0.3, 0.4 0.5, 0.6, 0.7, 0.8, and 0.9 deciles. Quantile shifts are indicated by connecting lines denoting shifts. For each difference, the vertical line indicates its 95% bootstrap confidence interval. Dots are colour coded to indicate the size of the shift. The size of the quantile shift is denoted in colour boxes above or below the coloured dots.

Table 3.2 Differences in quantiles and the bootstrapped confidence intervals for the equity home bias comparison in 2020

Model-based (A) & data-based (mean-variance: B)

Quantile	A	B	A-B	CI lower	CI upper
0.1	0.248	0.292	-0.044	**-0.278**	**0.190**
0.2	0.385	0.411	-0.026	-0.223	0.171
0.3	0.463	0.480	-0.017	-0.164	0.131
0.4	0.511	0.526	-0.015	-0.188	0.158
0.5	0.584	0.608	-0.024	-0.277	0.229
0.6	0.694	0.721	-0.027	-0.298	0.244
0.7	0.796	0.820	-0.024	-0.271	0.224
0.8	0.904	0.918	-0.014	-0.216	0.188
0.9	0.980	0.983	-0.003	-0.097	0.092

Model-based (A) & data-based (min-variance: C)

Quantile	A	C	A-C	CI lower	CI upper
0.1	0.248	0.146	0.102	-0.130	0.335
0.2	0.385	0.286	0.099	-0.157	0.355
0.3	0.463	0.412	0.051	-0.153	0.256
0.4	0.511	0.497	0.014	-0.178	0.206
0.5	0.584	0.577	0.007	-0.233	0.246
0.6	0.694	0.671	0.022	-0.250	0.295
0.7	0.796	0.779	0.018	-0.245	0.28
0.8	0.904	0.896	0.008	-0.207	0.223
0.9	0.980	0.977	0.004	-0.099	0.106

Model-based (A)& hybrid (D)

Quantile	A	D	A-D	CI lower	CI upper
0.1	0.248	0.203	0.045	-0.189	0.279
0.2	0.385	0.335	0.050	-0.171	0.272
0.3	0.463	0.427	0.036	-0.144	0.216
0.4	0.511	0.505	0.007	-0.199	0.212
0.5	0.584	0.606	-0.022	-0.288	0.243
0.6	0.694	0.717	-0.023	-0.283	0.237
0.7	0.796	0.805	-0.009	-0.250	0.232
0.8	0.904	0.906	-0.002	-0.213	0.208
0.9	0.980	0.980	0.000	-0.094	0.095

Data-based (mean-variance: B) & data-based (min-variance: C)

Quantile	B	C	B-C	CI lower	CI upper
0.1	0.292	0.146	0.146	-0.076	0.368
0.2	0.411	0.286	0.125	-0.111	0.361
0.3	0.480	0.412	0.068	-0.138	0.274
0.4	0.526	0.497	0.029	-0.173	0.231
0.5	0.608	0.577	0.031	-0.221	0.283
0.6	0.721	0.671	0.049	-0.212	0.311
0.7	0.820	0.779	0.041	-0.212	0.295
0.8	0.918	0.896	0.022	-0.193	0.237
0.9	0.983	0.977	0.006	-0.091	0.104

Data-based (mean-variance: B) & hybrid (D)

Quantile	B	D	B-D	CI lower	CI upper
0.1	0.292	0.203	0.089	-0.135	0.313
0.2	0.411	0.335	0.076	-0.128	0.281
0.3	0.480	0.427	0.053	-0.123	0.228
0.4	0.526	0.505	0.022	-0.184	0.227
0.5	0.608	0.606	0.002	-0.267	0.270
0.6	0.721	0.717	0.004	-0.265	0.272
0.7	0.820	0.805	0.015	-0.220	0.250
0.8	0.918	0.906	0.011	-0.187	0.210
0.9	0.983	0.98	0.003	-0.088	0.094

Data-based (min-variance: C) & hybrid (D)

Quantile	C	D	C-D	CI lower	CI upper
0.1	0.146	0.203	-0.057	-0.277	0.162
0.2	0.286	0.335	-0.049	-0.301	0.204
0.3	0.412	0.427	-0.015	-0.256	0.225
0.4	0.497	0.505	-0.008	-0.237	0.222
0.5	0.577	0.606	-0.029	-0.292	0.233
0.6	0.671	0.717	-0.046	-0.310	0.219
0.7	0.779	0.805	-0.026	-0.285	0.232
0.8	0.896	0.906	-0.010	-0.228	0.207
0.9	0.977	0.980	-0.003	-0.100	0.093

Note: The letter A stands for model-based measures, B stands for data-based-mean-variance measure, and so on. A-B is the model-based (A) minus data-based (mean-variance: B) at each decile and is represented in Panel 3 (Figure 3.3). CI lower and CI upper indicates the bootstrapped confidence bands for the lower and upper levels respectively. 2,000 non-parametric bootstrap replications are performed. When a confidence interval includes zero, the difference is considered non-significant, with an alpha threshold of 0.05.

The results reported for 2020 provide a useful case study given the heightened volatility in global equity markets that year associated with the COVID-19 pandemic (IMF, 2020; OECD, 2024). Figure 3.3 presents the six pair-wise QSF comparisons for this year, with Table 3.2 reporting the corresponding quantile differences and bootstrapped confidence intervals. Each plot in Figure 3.3 contains three panels. Panel 1 presents the empirical distributions of two EHB measures side by side, with countries plotted as scatter points positioned according to local density. Panel 2 overlays the deciles of the distribution as vertical lines (thin lines for deciles, thick line for the median), while coloured connectors join matching deciles across the two distributions: orange lines for positive differences and purple lines for negative differences. Labels indicate the size of the shift at the first and ninth deciles. Panel 3 displays the quantile shift function directly, plotting the size of the decile differences against the quantiles of the benchmark distribution, with vertical bars showing 95% bootstrap confidence intervals (Wilcox, Erceg-Hurn, Clark, and Carlson, 2014).

Across all comparisons in 2020, the quantile shift functions remain close to zero, and in every case the 95% confidence intervals span zero (Table 3.2).[52] For instance, when comparing the model-based and data-based (mean-variance) measures, estimated quantile differences range from -0.044 at the 0.1 quantile to -0.003 at the 0.9 quantile, with wide confidence bands (-0.278 to 0.190 at the lower decile). In the comparison of data-based (mean-variance) and data-based (min-variance) measures, the differences are slightly positive (0.146 at the 0.1 quantile) but remain statistically indistinguishable from zero. One of the features of the 2020 result is the flattening of the QSF lines in the upper deciles (0.7 to 0.9) across all six comparisons, indicating stability in the spread of distributions at higher quantiles. Consistent across all time periods (see Appendix 6), high-EHB or low-EHB deciles under one measure are located in the *same* decile ranges under the competing measures. In short, the 2020 analysis corroborates the broader finding of the QSF over all time periods: EHB estimates derived from different measures do not materially alter the distribution of estimates across countries. The robustness of this result, even during a period of severe financial stress (2020), provides support to more formally test for spatio-temporal effects.

[52] By way of illustration, consider the 0.1 quantile for the first pair-wise combination, (1) model-based & data-based (mean-variance), in 2020. The confidence interval bounds are reported as -0.278 (lower) and 0.190 (upper), are in **bold** (Table 3.2). The test is whether the interval includes zero. In this case, yes, $-0.278 < 0 < 0.190$, hence the null is not rejected at the 5% level (Tibshirani and Efron, 1993; Davison and Hinkley, 1997). This non-rejection is found for each pair-wise combination annually for 20 years, regardless of measure.

3.5.3 Model-based estimation and its generalisability

Following the QSF analysis of the three forms of EHB (model-based, data-based, and hybrid), the results demonstrate that the received measures are statistically indistinguishable. Given this similarity, it is necessary to select a preferred form for subsequent analysis. It is not surprising that the four estimates derived from these forms are practically the same as they are all derived from the same theoretical framework (that is, modern portfolio theory and the CAPM) and, importantly, use the same set of empirical assumptions (normality and linearity).

To advance the field's understanding of the EHB puzzle, a preferred form (and accompanying estimation approach) is needed. The case is made for defaulting to an approach that prioritises simplicity, practicality, and parsimony with regard to global capital flows. Reflecting Clark's (2005) observation that, *"money flows like mercury (p.99),"* the study moves forward with the form of EHB that draws directly on global capital flows in its estimation approach, that is, the model-based form.

Several arguments are made to support this decision. Most importantly, the inputs to model-based estimates of EHB - actual weight (global capital flows) *and* optimal weight components (market capitalisation benchmarks) - are not subject to the same degree of modelling assumptions or estimation error as in other approaches. The use of market capitalisation benchmarks at the country level (and then compared with bilateral capital flows at the country level in computing weights) reflects *actual* global capital flows. That said, it is acknowledged that market capitalisation indices are themselves constructed by index providers, and while widely adopted, they are not free of methodological choices.

Furthermore, model-based measures are justifiable both theoretically (the model-based form assumes that investors are mean-variance efficient and hold equities from a country as per that country's share of world market capitalisation) and practically (the optimal allocations are computed using standard market capitalisation indices as the benchmark which informs the investment policy and practice of investors around the world, a view supported by Clark and Monk, 2017). In data-based and hybrid measures, to maximise the expected utility and arriving at optimised weights, it requires several constraints and/ or assumptions to be addressed: such as the budget constraint, the availability of a risk-free rate, and allowing for short-selling (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015). Finally, it must be stated that no form of EHB estimate is without its limitations, either theoretically or empirically. The decision to move forward with model-based estimates allows consideration of the actual decisions made by investors around the world and thereby incorporating the *"spatial and temporal logic of global capital flows (p.99)"* (Clark, 2005).

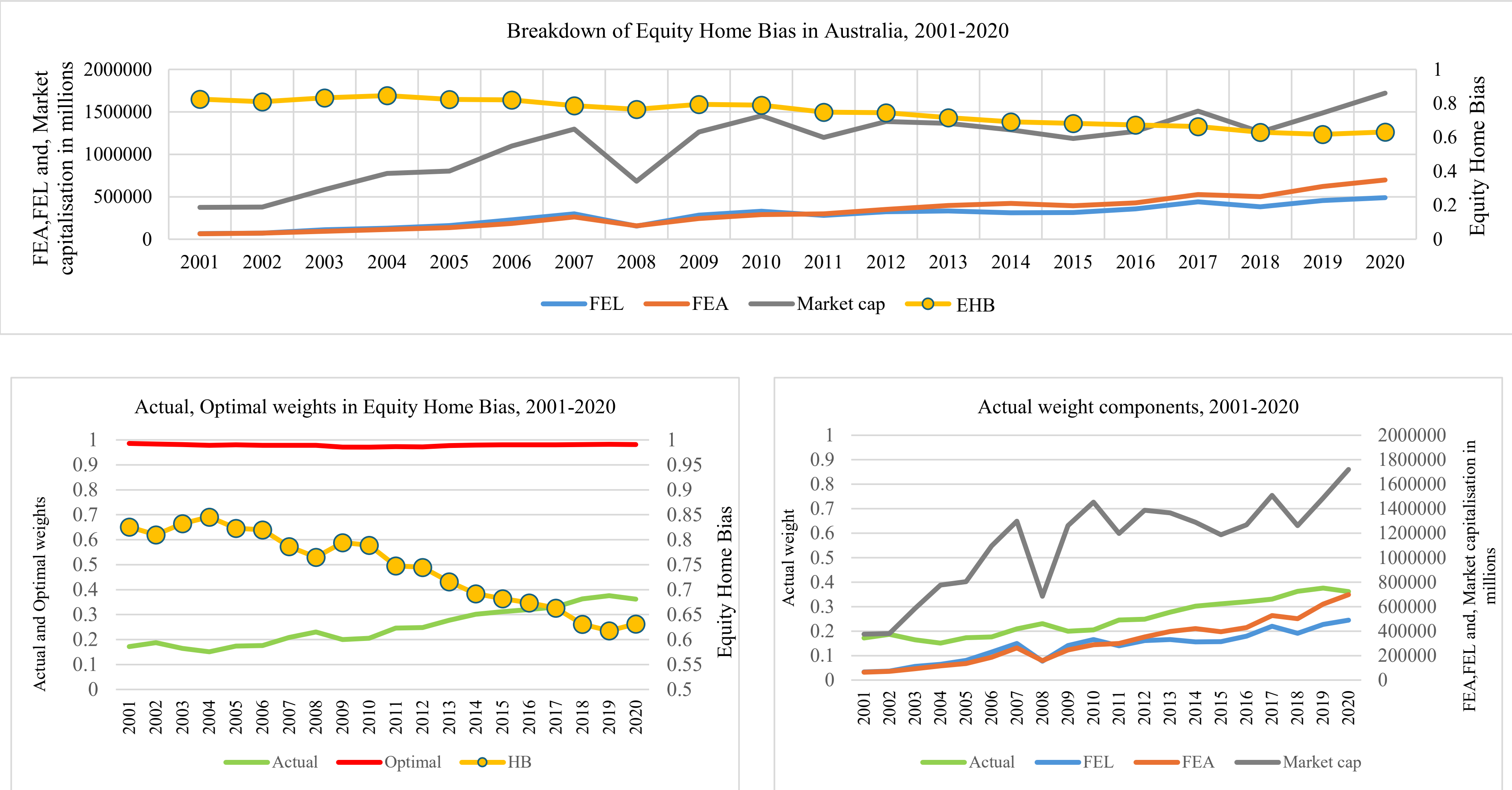
3.5.3.1 Model-based estimation example (Australia)

To illustrate the process of estimating EHB using the model-based method, this section presents an example for Australia. As outlined, the estimation proceeds in two steps. First, actual EHB is calculated as the deviation between an aggregate Australian investor's realised foreign equity holdings (from IMF CPIS data) and the global market-capitalisation benchmark (MSCI ACWI weights). Second, the model-based optimal benchmark is specified. The resulting EHB measure reflects the proportionate underweighting of foreign equities once the optimal portfolio share is accounted for.

Figure 3.4 (below) shows Australia's EHB level for the period 2001 through 2020, showing persistently high EHB despite gradual convergence from 0.825 in 2001 to 0.631 in 2020. The 2020 EHB result for Australia is bolded to reconcile Australia's EHB multiple reported as 34.8x in Figure 1.1 *Equity home bias multiple for the 15 largest countries by market capitalisation (2020)* in Chapter 1. In short, the actual foreign holding share is calculated as $W_{i,t}^{A} = 0.362$, obtained by dividing foreign equity assets by the total of foreign equity assets, plus Australia's market capitalisation (less foreign equity liabilities). This implies actual domestic holdings of 63.82%. The optimal domestic holding is determined by Australia's market capitalisation relative to the world market capitalisation, equal to 1.83%. Consequently, Australia's EHB multiple is calculated as the ratio of actual to optimal domestic holdings: $EHB\ multiple = \frac{63.8\%}{1.8\%} \approx 34.8$x.

Figure 3.4 Model-based estimation example (Australia)

Country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	**2020**
Australia	0.825	0.809	0.832	0.845	0.823	0.820	0.786	0.765	0.794	0.789	0.747	0.744	0.716	0.692	0.682	0.673	0.663	0.630	0.617	**0.631**



3.5.4 Exploring the distributional properties of equity home bias estimates

This section considers whether EHB estimates follow a normal distribution. Testing the distributional properties provides confidence in their statistical generalisability using the well-known central tendency statistics across both the dimensions of space and time. The use of spatial and temporal directions is informed by the visual inspection of the annual quantile shift analysis, which is summarised in a Sankey diagram (Figure 3.5, below). The Sankey diagram reports model-based estimates converted to deciles at five arbitrary time points within, specifically, the start (2001) and the end of the observation period (2020), by country. The five-year block size is chosen to summarise the two-decade observation period, as economic conditions typically evolve in cycles, including periods of expansion, recession, and recovery. This timeframe allows for capturing these cyclical patterns, providing a clearer understanding of how economic shifts impact EHB. Additionally, significant policy changes, market reforms, or global events (for example, the GFC, COVID-19) often unfold over several years. While yearly data provide detailed insights (see next section for annual distributional analysis), it may be too granular for identifying broader trends, whereas larger time spans may overlook recent developments. Five-year blocks strike a balance, providing sufficient granularity to detect patterns without losing sight of the larger context.[53]

The results presented in Figure 3.5 corroborate previous results in the literature that EHB has a downward trend in aggregate (black line) (Ahearne, Griever, and Warnock, 2004; Baele, Pungulescu, and Ter Horst, 2007; Heathcote and Perri, 2013; Levy and Levy, 2014; Mishra, 2015; Solnik and Zuo, 2017). However, this aggregate pattern conceals substantial spatial and temporal variation. Instead, the annual within-measure variation is widening asymmetrically. This is shown in the decline of the lower decile cut-off, which fell by nearly half (54%) compared to the beginning of the study, whereas the upper decile cut-off recorded only a marginal reduction (1%).[54] Recalling that a level of EHB that approaches one results in no holdings of the world portfolio (and a value of zero meaning an investor holds the optimal weight of international equities), the visual inspection of country-level estimates highlights the uneven contours of EHB across countries through time.

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[53] Chapter 5 tests across 20- and five-year blocks for spatio-temporal effects.

[54] Further pointing to the potential limitations of using central tendency statistics when analysing the distribution of EHB estimates, the difference between the mean and median is not consistent through time.

As presented by the Sankey diagram, some countries exhibited extreme levels of EHB (EHB_i) at the start and the end of the sample (such as Philippines, India, Turkey, Pakistan, and Indonesia $EHB_i = 0.9991$). Others started the period with below average levels of EHB and ended the period with negligible levels (Netherlands $EHBi = 0.0113$, as well as Norway and Belgium). Ten countries (Czech Republic, Finland, France, Spain, Chile, Portugal, Hungary, Israel, Argentina, and U.S.) had above average EHB levels at the start of the period (2001) and below average at the end (2020), and one country, Ireland, mirrored that result (below- to above-average, $EHB_i = 0.1603$ in 2001 to $EHB_i = 0.7276$ in 2020). [55] Finally, while the maximum of the estimates of EHB were similar at the start and the end of the period, the minimum of the estimates more than halved, resulting in a marked increase in the range of EHB estimates through time. Accordingly, the aggregate downward trend is not uniformly supported, and intra-measure variation has widened asymmetrically over the sample period.

The results presented in the Sankey diagram (Figure 3.5) point to the importance of understanding distributional properties of EHB measures. Specifically, it confirms the need to look beyond the central tendency values when making inferences of a dataset whose values are collected in space (domicile) through time (annually). Understanding the variation around the mean in each sample via space and time is important as it is a prerequisite to making inferences regarding the aggregate downward trend of EHB (Curran-Everett and Benos, 2007).[56] These results pose some challenging questions for the neoclassical finance tradition and its embedded assumptions regarding normality and the homogeneity of investors, while highlighting the potentially uneven spatial and temporal dynamics of EHB.

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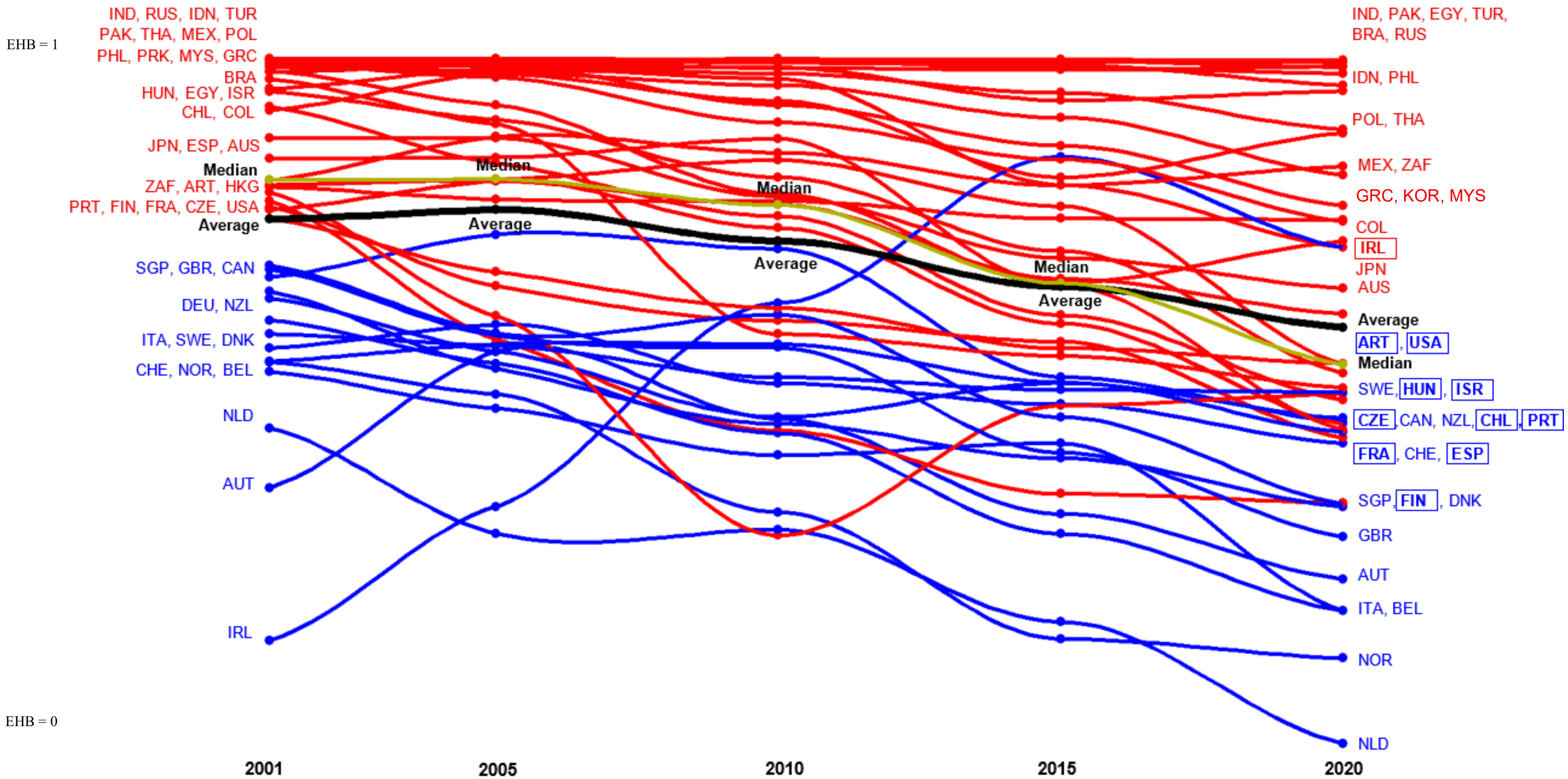
[55] Ireland foreign equity liabilities exceeded its market capitalisation, resulting in a negative actual weight calculation. This may reflect the 'dual role' of Ireland's financial system: first, Ireland has emerged since the 1990s as one of the world's largest domiciles for UCITS, funnelling global capital through Dublin's International Financial Services Centre (Wójcik, 2011; Irish Funds, 2023); second, the collapse of the domestic banking sector during the GFC left Irish banks more domestically constrained in their equity exposures (Honohan, 2009; Hardiman and Dellepiane, 2011). The duality of Ireland's global role as a fund domicile with the localisation of domestic banks may help explain why EHB increased rather than declined, but this finding remains underexplored (Wójcik, 2018; Heckemeyer and Hemmerich, 2020; Wójcik, Iliopoulos, Ioannou, Keenan, Migozzi, Monteath, Pažitka, Torrance, and Urban, 2024). Future research could disentangle whether Ireland's rising EHB reflects structural features of its fund-domicile model or statistical artefacts of CPIS reporting (Lane and Milesi-Ferretti, 2008; Coppola, Maggiori, Neiman, and Schreger, 2021).

[56] In a received Gaussian framework, the mean, median and mode overlaps and the tails of the distribution are symmetrical around the central tendency statistics (Curran-Everett and Benos, 2007). The Shapiro-Wilk test for normality (that is, testing whether the sample data have the skewness and kurtosis matching a normal distribution) is used to test the assumption of normality at 5% level of significance.

Figure 3.5 Five-year summary of EHB through space and time



Year	Minimum	10%	20%	30%	40%	50% (Median)	60%	70%	80%	90%	Maximum	Average	Median-average gap
2001	0.160	0.562	0.635	0.699	0.793	0.825	0.926	0.975	0.993	0.997	0.999	0.768	0.057
2005	0.315	0.554	0.587	0.611	0.736	0.826	0.891	0.976	0.988	0.996	0.999	0.782	0.044
2010	0.312	0.460	0.502	0.597	0.646	0.789	0.834	0.918	0.976	0.996	0.999	0.737	0.052
2015	0.162	0.382	0.489	0.533	0.590	0.676	0.773	0.839	0.930	0.990	0.998	0.671	0.005
2020	0.011	0.261	0.393	0.469	0.514	0.559	0.728	0.775	0.895	0.986	0.997	0.612	-0.053
Change since 2001 in % terms	**-93%**	**-54%**	**-38%**	**-33%**	**-35%**	**-32%**	**-21%**	**-20%**	**-10%**	**-1%**	**-0.2%**	**-20%**	

Note: Sankey diagram prepared using R 3.6.1 shows average EHB with black line and median with yellow lines. Countries (lines) are colour coded as blue (below-average) or red (above-average) at the start of the sample (2001). The country labels are colour coded as blue (below average) or red (above average) for start (2001) and end (2020) of the sample.

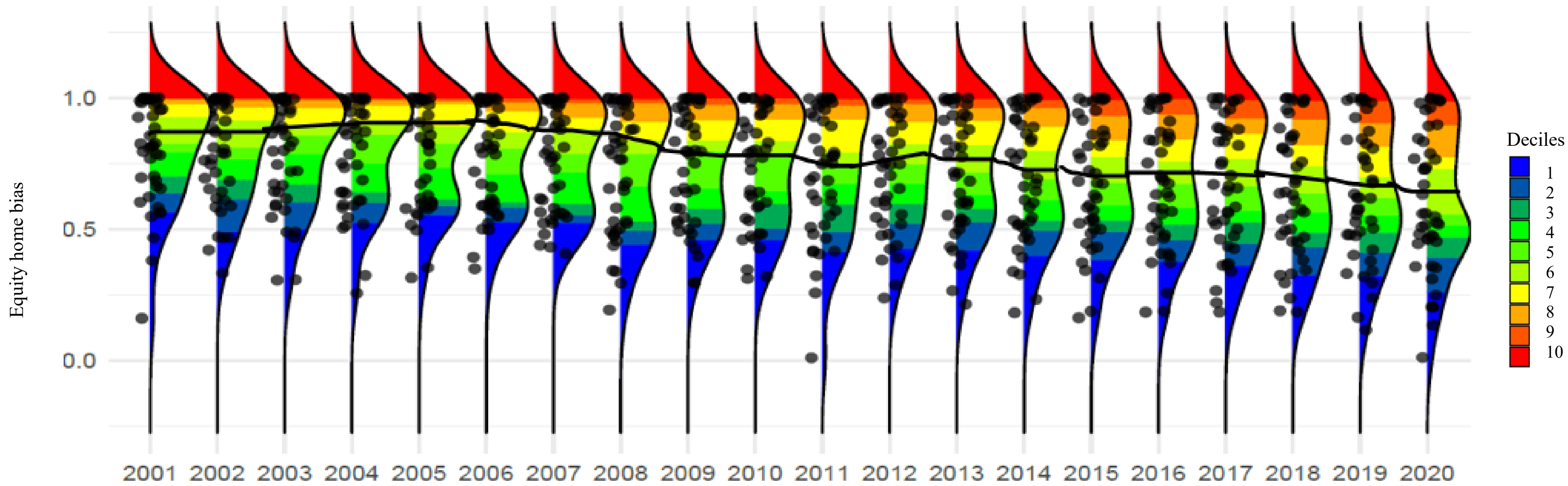
3.5.4.1 Annual analysis

The next step in the analysis formally tests whether the estimates of EHB follow a normal distribution by year for the study sample (Figure 3.6). All years from 2001 to 2020 reject the normality assumption using the Shapiro-Wilk test at the 5% level of significance. The majority of yearly distributions are negatively skewed, with kurtosis less than three, indicating a platykurtic distribution. Moreover, the year-wise analysis on the tails of the distribution hints that the downward trajectory of EHB through time is greatly informed by the lower tail of the distribution. While there is marked stability in the right tail of the distribution, the annual skewness results suggest growing instability in the left tail, and the spread of outcomes (standard deviation) has generally increased through time. This is due to the very high EHB estimates being close to one (on average, $EHB_i > 0.99$), while the minimum values decline more than ten times during the 20 years ($EHB_i = 0.16$ in 2001 to $EHB_i = 0.01$ in 2020).

The findings suggest that there is no single, consistent trajectory (or pattern) of EHB through time. Over the past two decades, it appears that some investors are increasingly globalised in their allocation to global equities, to the point where the very notion of EHB becomes irrelevant. Moreover, there has been increasing dynamism in holding mean-variance efficient portfolios (Markowitz, 1952), particularly post the GFC. Another group of investors are lowering home allocations to equities in a staged manner, albeit accelerating post the GFC; others are exclusively invested in their home market, chronically home biased, and anchored to the geographically proximate.

The way the EHB distribution has changed since 2001 through 2020, with its characteristics of unimodal to bimodal distributions, provides insights on different levels of convergence trends. This mode emerges in the high-EHB group first and gradually moves towards a low-EHB group. Further, not uniformly so, a second mode emerging in 2003 corresponds to an increase in members of the low-EHB group, many of whom are escapees from the high-EHB group.

Figure 3.6 Probability density plots through time (aggregated over space (countries))



Year	**2001**	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
Mean	**0.768**	0.771	0.788	0.791	**0.782**	0.775	0.766	0.726	0.741	**0.737**	0.715	0.729	0.722	0.699	**0.671**	0.673	0.672	0.649	0.637	**0.612**
Std dev.	**0.200**	0.197	0.205	0.206	**0.202**	0.199	0.200	0.239	0.221	**0.222**	0.248	0.225	0.229	0.24	**0.238**	0.244	0.246	0.253	0.256	**0.272**
Skewness	**-0.89**	-0.46	-0.75	-0.77	**-0.55**	-0.40	-0.29	-0.46	-0.40	**-0.39**	-0.70	-0.43	-0.41	-0.33	**-0.29**	-0.24	-0.23	-0.14	-0.12	**-0.16**
Max	**0.999**	0.999	0.999	0.999	**0.999**	0.999	0.999	0.999	0.999	**0.999**	0.999	0.999	0.998	0.998	**0.998**	0.998	0.998	0.998	0.998	**0.997**
Min	**0.160**	0.332	0.305	0.256	**0.315**	0.348	0.407	0.191	0.295	**0.312**	0.010	0.237	0.213	0.181	**0.162**	0.183	0.184	0.184	0.115	**0.011**
Max-Q3 (Upper tail)	**0.015**	0.019	0.014	0.023	**0.019**	0.025	0.028	0.041	0.045	**0.049**	0.052	0.059	0.067	0.081	**0.132**	0.133	0.118	0.143	0.157	**0.159**
Q1-Min (Lower tail)	**0.514**	0.315	0.337	0.366	**0.283**	0.241	0.155	0.320	0.241	**0.250**	0.523	0.312	0.323	0.336	**0.349**	0.301	0.303	0.277	0.361	**0.445**
Kurtosis	**3.797**	2.117	2.554	2.688	**2.107**	1.802	1.563	1.951	1.867	**1.829**	2.970	2.059	2.060	1.978	**2.171**	1.993	1.864	1.845	1.996	**2.119**
Shapiro-Wilk normality test	**0.91***	0.92*	0.89*	0.88*	**0.88***	0.89*	0.89*	0.91*	0.91*	**0.91***	0.92*	0.93*	0.93*	0.93*	**0.95***	0.94*	0.94*	0.94*	0.95*	**0.95***

Note: The probability density plots, by year, present the dispersion of the model-based EHB around the average. The black line presents the downward trend in the average annual model-based EHB estimates from 2001 through 2020. Summary statistics are for the model-based EHB measure by time. The Shapiro-Wilk test is a goodness-of-fit test that determines whether sample data have skewness and kurtosis that matches a normal distribution,* denotes the 5% level of significance, and the *p*-value < 0.05 implies that the distribution of the data is significantly different from a normal distribution. The deciles are colour coded from blue (values below the first decile) and red (values above the ninth decile).

3.5.4.2 Country-level analysis

As canvassed by the I-CAPM prediction, investors are expected to hold listed equities from around the world in proportion to each country's share of global market capitalisation, a result based on the key assumptions, such as the absence of barriers to international investment (Mishkin, 2006). In practice, however, investing in geographically extensive listed equities markets is a non-trivial decision. By definition, investors have a home and must design an investment strategy for listed equities that extends their reach in space and time to garner the benefits of diversification in the production of returns. In the following sections, patterns in EHB estimates are considered by country of domicile. Investors are always and everywhere embedded in geography.[57]

For the purposes of this study, country-level analysis (that is, the sum of institutional and individual investor decisions and resultant global capital flows into listed equities) is conducted to report on spatial distributions of EHB estimates. Figure 3.7 reports the probability density plots by space (country) to gain initial insights regarding the patterns of EHB. The descriptive statistics by country for the model-based EHB measures are reported in Figure 3.7. Around two thirds of the countries (n = 27, or 63% of the sample) reject the normality assumption using the Shapiro-Wilk test for normality, at the 5% level of significance. The remaining one-third (n = 16, or 37% of the sample) did not reject the normality assumption. Interestingly, most countries which failed to reject the normality assumption (Brazil, Egypt, India, Indonesia, Pakistan, Philippines, Russia, Thailand, and, Turkey) are scattered around very high EHB values (with an average $EHB_i > \sim 0.99$).

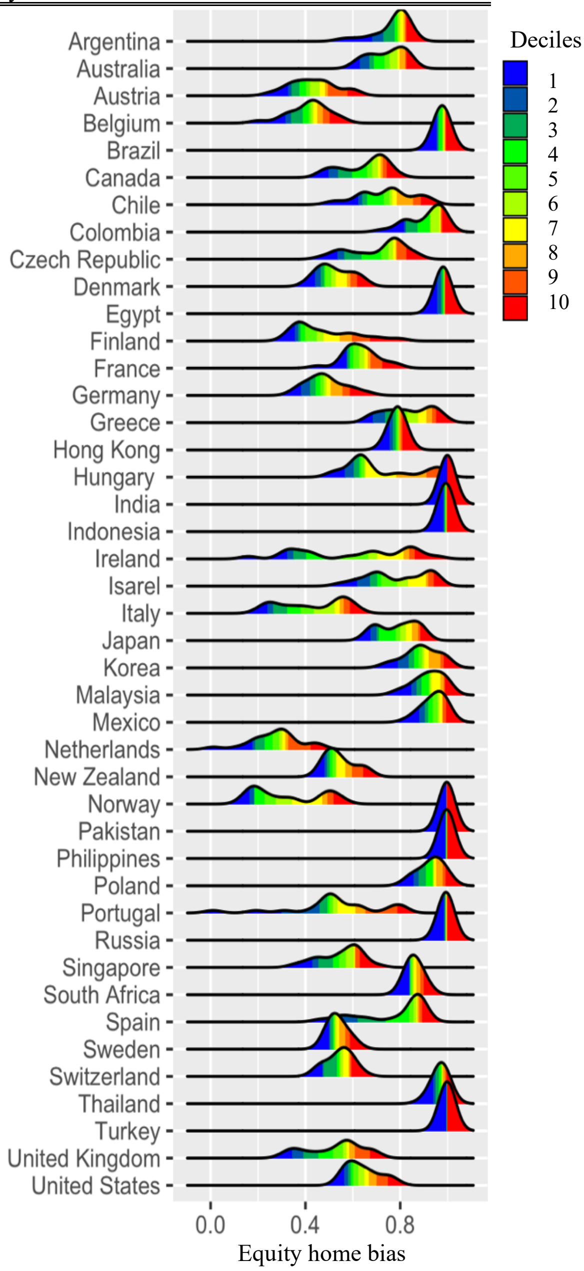
Considerable spatial heterogeneity is observed across countries. For instance, excluding Singapore, Hong Kong, and, Japan, all other Asian countries show high levels of EHB ($EHB_i > \sim 0.90$). Capital-restricted countries in the Asian region (such as India, Indonesia, Pakistan, and, Philippines) have, as expected, reported high levels of EHB. In Europe, considerable heterogeneity is reported within the region, a finding consistent with the work of Lane and Milesi-Ferretti (2005), Schoenmaker and Bosch (2008), and Floreani and Habib (2018). Evidence for the emergence of bi-modal distributions (observed in Figure 3.6)

[57] And it is important to acknowledge that there isn't just 'one' homogeneous investor. Some investors may have predefined limitations on how much foreign exposure is permitted in their portfolio, set perhaps by regulation, policy statements, and/ or to maintain competitiveness within a peer group (Philips, Kinniry, and Donaldson, 2012; Drew and Walk, 2019). Similarly, global diversification may be impractical for investors with a clearly defined domestic liability (Campbell and Viceira, 2002; Cairns, Blake, and Dowd, 2008). Others may be constrained by capital controls that limit cross-border investment (Eichengreen and Mody, 2000).

is confirmed by the country-level analysis; the mode towards the high EHB group countries faces the middle-income trap, limiting their movement towards a lower number, resulting in an acute peak towards the high EHB region.

Figure 3.7 Probability density plots of countries (aggregated over time)

Country	Mean	Std dev.	Skewness	Kurtosis	Max	Min	Shapiro-Wilk normality test
Argentina	0.770	0.075	-1.67	5.451	0.853	0.558	0.808*
Australia	0.745	0.076	-0.34	1.671	0.845	0.617	0.917*
Austria	0.431	0.099	0.17	2.511	0.617	0.248	0.981*
Belgium	0.414	0.085	-0.63	3.677	0.547	0.203	0.962*
Brazil	0.976	0.017	-0.71	2.226	0.993	0.939	0.879
Canada	0.648	0.099	-0.60	1.963	0.787	0.475	0.894*
Chile	0.741	0.117	-0.18	2.442	0.930	0.507	0.967
Colombia	0.908	0.081	-0.83	2.410	0.981	0.727	0.822*
Czech Rep.	0.705	0.120	-0.57	2.019	0.864	0.472	0.905*
Denmark	0.523	0.071	0.29	1.843	0.641	0.418	0.934*
Egypt	0.983	0.009	-1.84	6.123	0.991	0.956	0.756
Finland	0.482	0.136	0.88	2.867	0.795	0.324	0.903*
France	0.632	0.075	0.01	4.016	0.786	0.452	0.955*
Germany	0.485	0.083	0.48	2.770	0.663	0.352	0.969*
Greece	0.833	0.101	-0.13	1.653	0.982	0.676	0.930*
Hong Kong	0.787	0.020	-0.70	2.548	0.814	0.746	0.923
Hungary	0.701	0.147	0.86	2.411	0.970	0.515	0.849*
India	0.999	0.001	0.12	3.283	0.999	0.997	0.938
Indonesia	0.992	0.006	-0.86	2.643	0.999	0.978	0.893
Ireland	0.603	0.243	-0.23	1.618	0.956	0.160	0.920
Israel	0.786	0.130	-0.17	1.691	0.952	0.546	0.916
Italy	0.427	0.142	-0.20	1.434	0.622	0.203	0.904*
Japan	0.789	0.081	-0.23	1.445	0.888	0.668	0.883*
Korea	0.890	0.074	-0.37	2.601	0.992	0.736	0.953*
Malaysia	0.920	0.062	-0.60	2.591	0.994	0.787	0.921
Mexico	0.936	0.046	-0.75	2.769	0.995	0.832	0.924*
Netherlands	0.274	0.108	-0.40	3.806	0.466	0.011	0.966
New Zealand	0.544	0.062	0.79	2.267	0.654	0.477	0.860*
Norway	0.322	0.151	0.35	1.374	0.562	0.134	0.863*
Pakistan	0.996	0.002	-1.80	8.007	0.998	0.991	0.854
Philippines	0.996	0.003	-0.85	2.933	0.999	0.987	0.908
Poland	0.929	0.052	-0.53	2.264	0.994	0.829	0.919*
Portugal	0.526	0.197	-0.83	4.431	0.807	0.010	0.914*
Russia	0.992	0.009	-2.48	11.133	0.999	0.962	0.742
Singapore	0.548	0.091	-0.57	2.572	0.701	0.357	0.936*
South Africa	0.859	0.027	0.62	2.501	0.912	0.817	0.926
Spain	0.777	0.145	-1.05	2.555	0.906	0.463	0.784*
Sweden	0.536	0.036	0.80	2.503	0.605	0.491	0.896*
Switzerland	0.544	0.053	-0.32	2.342	0.642	0.452	0.933*
Thailand	0.968	0.026	-1.25	4.550	0.997	0.897	0.888
Turkey	0.998	0.001	-0.82	2.851	0.999	0.995	0.911
U.K.	0.521	0.121	-0.36	1.966	0.695	0.310	0.934*
U.S.	0.641	0.070	0.65	2.179	0.768	0.559	0.898*



Note: The countries are in alphabetical order. Summary statistics are for the model-based EHB measure by country. The Shapiro-Wilk test is a goodness-of-fit test that determines whether sample data have skewness and kurtosis that match a normal distribution, * denotes the 5% level of significance, and again the p-value < 0.05 implies that the distribution of the data is significantly different from a normal distribution. The deciles are colour coded from blue (values below the first decile) and red (values above ninth decile).

Acknowledging the anecdotal nature of results presented in this section, this analysis points to the potential pitfalls of making sweeping inferences about the EHB puzzle based solely on averages (Savage and Markowitz, 2009). While the forms of EHB are largely similar, EHB estimates seem to exhibit a degree of dispersion over space and time that may be masked at the aggregate level, hence they are far from being statistically generalisable using central tendency values alone.

Many questions arise from this simple analysis. Why do investors in some countries remain chronically home biased (for example, India) through time, while others do not? Does being a neighbour (however defined) hold information content regarding the home country's EHB? As evident in Figure 3.6, emerging market countries such as Argentina, Brazil, and Chile (one possible geographical neighbour set); or India and Pakistan, seem to show similar levels of EHB, however, geographical neighbour sets (based solely on distance) such as Australia, Indonesia, and New Zealand; or the United States, Canada, and Mexico, with a mix of developed and emerging markets, hold varying levels of EHB regardless of their geographic proximity. Why is it that some countries seemingly hold little EHB at all (for instance, the Netherlands and Norway)? Do geographical neighbour sets in developed markets (say, Europe) exhibit co-movement through time? And, why have some countries seen an increase in EHB over the observation period (such as Ireland)?

3.6 Conclusion

The first empirical section of the study tested the statistical similarity of the received measures of EHB estimates for a sample of 43 countries for the period of 2001 through 2020. It was reported that the various estimates of EHB have produced remarkably similar results. On reflection, this was perhaps an unremarkable result, as all empirical measures are derived from the same neoclassical finance tradition (modern portfolio theory and the capital asset pricing model) and supporting assumptions. Conducting a QSF analysis, the results showed that all three forms are statistically indistinguishable at the 5% level of significance. As such, the case for moving forward using traditional, model-based measures of EHB was made.

In light of this novel finding, the next step was to advance the field's understanding of the EHB puzzle. In taking a preliminary step forward, the distributional properties of EHB estimates were tested using a Gaussian framework. By relaxing the standard Gaussian distributional assumption, Chapter 3 has provided a *glimpse* into the uneven contours of EHB estimates. This basic mapping provided a first look at both the role of space (proxied by country) and time (proxied by year) and highlighted the potential perils of inference based on annual averages. In practical terms, investors encounter the global investment landscape as it is, rather than how the assumptions of the neoclassical finance tradition would like it to be. Investors must develop investment routines that, *"deal with a world best understood as a patchwork of heterogeneous expectations, rules, and regulations (p. 2)"* (Clark and Monk, 2017). The asset class under consideration in this study, listed equities, is the single largest component of the investment risk budget (Asimit, Chong, Tunaru, and Zhou, 2025) for investors. Therefore, understanding the EHB puzzle is not only a worthy pursuit for the field, but may also inform future investor and fiduciary practice. The results of Chapter 3 open a range of promising directions for further inquiry. Formal hypothesis testing for spatio-temporal effects in both the presence (Chapter 4) and persistence (Chapter 5) of EHB follows.

4. On the Presence of Equity Home Bias

4.1 Introduction

Chapter 4 seeks to explore why the map of equity home bias (EHB) looks the way it does through time. This chapter tests for the presence of spatio-temporal effects, specifically asking whether the observed geography of EHB reflects structured patterns of clustering and association across countries (and years), or whether it is due to random variation. While Chapter 2 clarified definitional ambiguity and Chapter 3 showed that received measures are statistically indistinguishable, a critical question remains unanswered: does EHB exhibit the presence of global and/ or local structures shaped by space and time? Having established that EHB can be consistently defined and measured, the next task is to determine whether it is present in coherent spatial and temporal patterns, or whether it appears only as country-specific departures.[58]

As has been established, space and time are not neutral backdrops for investment; they actively structure the production of financial returns (Clark and Monk, 2017; Clark, Feldman, Gertler, and Wójcik, 2018). In this spirit, Tobler's (1970) first law of geography, *"everything is related to everything else, but near things are more related than distant things (p. 236)"* provides a conceptual anchor to this study. If proximity shapes information, behaviour, and capital flows, then the observed geography of EHB may be partly explained by spatial dependence and clustering. Ignoring these effects risks model misspecification and biased inference (Florax and Nijkamp, 2003; Abdallah, Dabbou, Gallali, and Hathroubi, 2025). Financial geography has long emphasised that international investment is embedded within networks of clustering and path dependency (Arthur, 1989; North, 1990; David, 1994; Leyshon and Thrift, 1998; Clark, 1998; Martin, 1999, 2010; Clark, Mansfield, and Tickell, 2001; Martin and Sunley, 2006, 2010; Wójcik, 2012; Coe, Lai, and Wójcik, 2014; Lai, 2020; Wójcik, Iliopoulos, Ioannou, Keenan, Migozzi, Monteath, Pažitka, Torrance, and Urban, 2024), making it essential to test for spatio-temporal effects explicitly.

The field of financial geography has emphasised that spatio-temporal effects may not be confined to purely geographic nearest-neighbour relationships (Clark and Wójcik,

[58] A recurrent critique of patterns of EHB estimates is that they are uneven across space and time. Although an examination of year-on-year EHB estimates suggests a downward trajectory in EHB worldwide over the past two decades (Ahearne, Griever, and Warnock, 2004; Baele, Pungulescu, and Ter Horst, 2007; Fidora, Fratzscher, and Thimann, 2007; Sørensen, Wu, Yosha, and Zhu, 2007; Coeurdacier and Rey, 2013; Levy and Levy, 2014; Mishra, 2015; Solnik and Zuo, 2017), there are still considerable differences in the levels of EHB between countries across time.

2007; Florax and Nijkamp, 2003). For instance, common law fiduciary obligations, a distinctive institutional feature shaping the production of returns, are shared by many countries globally (Coffee, 1999; Gordon and Roe, 2004; Clark and Monk, 2017). It could be argued that countries that hold common law traditions and fiduciary obligations may be expected to display declining trajectories of EHB, reflecting similarities in governance, investor protection, and portfolio regulation (Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1998; Stulz and Williamson, 2003; Drew and Walk, 2019). Likewise, global financial centres create functional neighbourhoods that transcend geography. For centuries, London has acted as an intermediary time-zone platform linking Asian and U.S. markets, while Sydney has played a similar role between U.S. and European markets (O'Neill and McGuirk, 2005; Coe, Lai, and Wójcik, 2014; Haberly and Wójcik, 2020, 2022; Wójcik, 2020; Ioannou, Wójcik, and Pažitka, 2021). Such considerations suggest that while the analysis undertaken in Chapter 4 is anchored in geographic and benchmark-based (specifically, MSCI ACWI) neighbourhood definitions, there may also be *a priori* clustering patterns that reflect shared legal traditions, institutional arrangements, and trading platforms (Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1998; Clark, Feldman, Gertler, and Wójcik, 2018). This broader framing ensures that the interpretation of results is not limited to geographical proximity alone.[59]

To address gaps in existing research, this study proposes an exploratory spatio-temporal perspective on the presence of EHB. The methodological framework adopted here explicitly accounts for spatio-temporal effects by examining the following dimensions: spatial dependence and spatial heterogeneity (analysed in Chapter 4); and joint space-time interactions and dynamic spatial heterogeneity (considered in Chapter 5).[60] The framework is implemented using the model-based EHB measure for 43 MSCI ACWI countries over the period 2001 through 2020. In this chapter, time is operationalised as a sequence of independent states, with each year from 2001 to 2020 treated as a discrete observation of the global EHB system. Consistent with the field, the analysis proceeds in two steps. First, *spatial dependence* is tested using Global Moran's Index (Moran, 1950), which measures whether EHB values are more similar among neighbours than would be expected under randomness. Second, *spatial heterogeneity* is assessed through Local Indicators of Spatial

[59] This is consistent with the important work of Boschma (2005) on proximity bias. For this study, EHB may arise not only from geographic distance but also from shared institutions, norms, and/ or cognitive frames, supporting the rationale to test for spatio-temporal effects (Boschma, 2005).
[60] See Figure 4.1 Framework for testing spatial effects.

Association (LISA) (Anselin, 1995), which decompose global association into country-specific clusters and spatial outliers. Together, these methods provide complementary perspectives: Global Moran's Index captures overall (global) spatial autocorrelation, while LISA reveals localised clustering. This aligns with broader developments in testing for spatio-temporal effects, where global and local statistics are combined to capture complex dependence structures that are inherent in geographically referenced data (Florax and Nijkamp, 2003; Baltagi, Bresson, and Pirotte, 2007).[61]

Neighbourhood specification is central to this inquiry. Two guiding questions frame the analysis: *who is your neighbour?*; and, *how much does your neighbour matter?* Neighbours can be defined by contiguity (Anselin, 1988), geographic distance (Cliff and Ord, 1981), or fixed *k*-nearest rules (Getis and Aldstadt, 2004), and weighted equally (such as rook or queen contiguity, Cliff and Ord, 1981) or by distance decay (Tiefelsdorf and Boots, 1995). The selection of a particular specification often depends on the research question at hand. In this study, ten neighbourhood structures are examined, encompassing both distance-based and boundary-based (MSCI ACWI) definitions, with weights specified as either equal ($1/n$) or inverse distance ($1/d$). This dual approach ensures that both geographic and institutional classifications, each central to global investment practice, are reflected in the analysis (Gehrig, 2000; Haberly and Wójcik, 2020; Wójcik, 2020; Wójcik, Keenan, Pažitka, Urban, and Wu, 2022). This also reflects the importance of considering regional integration and financial contagion channels, as documented in cross-market dependence studies (Forbes and Rigobon, 2002).

Preliminary results reject the null hypothesis of no global spatial autocorrelation. Across all states (years), Global Moran's Index is significantly positive, indicating that EHB is not randomly distributed but clustered, that is, countries with high (low) EHB tend to be located near other high (low) EHB countries. The presence of global spatial dependence implies that supra-national factors: cultural similarity (Campos and Kim, 2017); financial integration (Coeurdacier, 2009; Pungulescu, 2009); shared legal systems (Oto-Peralías and Romero-Ávila, 2014); and/ or experience-driven familiarity (Malmendier, Pouzo, and Vanasco, 2020) may shape the geography of EHB. The findings challenge the methodological approach of previous studies in finance and economics (see Chapter 2) that

[61] Spatio-temporal effects include spatial dependence and spatial heterogeneity (Florax and Nijkamp, 2003). Spatial heterogeneity refers to structural relations that vary over space, either in a discrete or categorical fashion (for instance, developed countries vs. emerging countries, or according to a classified hierarchy), or in a continuous manner (such as on a trend surface) (Florax and Nijkamp, 2003). Spatial dependence points to systematic spatial variation that results in observable clusters or a systematic spatial pattern.

assume independence across countries, where ignoring spatial structure may lead to inferences regarding the EHB puzzle being derived from biased and inefficient estimates (Florax and Nijkamp, 2003; LeSage and Pace, 2009).[62]

Given the consistent presence of global spatial dependence in EHB estimates across each state, the analysis proceeds by applying the Local Indicators of Spatial Association (LISA) introduced by Anselin (1995). In this study, LISA is implemented across ten alternative neighbourhood structures, combining distance-based and boundary-based specifications with both equal and inverse-distance weighting schemes. In the first step, LISA classifies each country into one of four categories:

- High-High clusters, where a high-EHB country is surrounded by high-EHB neighbours;
- Low-Low clusters, where a low-EHB country is surrounded by low-EHB neighbours;
- High-Low clusters, where a high-EHB country is surrounded by low-EHB neighbours; and
- Low-High clusters, where a low-EHB country is surrounded by high-EHB neighbours.

In the second step, the statistical significance of these classifications is tested using permutation methods, where the null hypothesis of spatial randomness is rejected if the observed cluster is unlikely to have arisen by chance. Building on this two-stage procedure, the results reveal spatial heterogeneity across regions, with some clusters persisting consistently through time while others fluctuate, highlighting the uneven geography of EHB. In particular, two broad patterns emerge: Low-Low clustering in Europe & Middle East, Developed Market (MSCI ACWI classification), consistent with relatively integrated markets and lower levels of EHB (Sørensen, Wu, Yosha, and Zhu, 2007; Coeurdacier and Rey, 2013), and High-High clustering in Asia Emerging Markets, where persistent EHB is linked to capital controls, information asymmetries, and institutional frictions (Ahearne, Griever, and Warnock, 2004; Mishra, 2015). This two-regime pattern foreshadows the empirical results of

[62] A series of spatially dependent observations therefore contains less information (Florax and Nijkamp, 2003). This is similar to the situation in time-series analysis, wherein a forecast with respect to the future can be partly inferred from what happened in the past.

this chapter and underscores the importance of testing for both global and local spatio-temporal effects (Anselin, 1995; Rey and Anselin, 2010; Elhorst, 2014).

The contribution of Chapter 4 lies in formally establishing the presence of spatial dependence (Global Moran's Index) and spatial heterogeneity (LISA) in EHB, addressing a key limitation of prior research, which treated countries as independent units (Mishra, 2015) and time as an ordinal sequence of observations (Engle and Granger, 1987; Hamilton, 1994). By adopting an explicitly spatio-temporal framework, this chapter demonstrates that the geography of EHB is patterned, clustered, and uneven, providing the empirical foundation for analysis of persistence and dynamics in Chapter 5. The remainder of this chapter is organised as follows. Section 4.2 reviews the relevant literature, situating this study in relation to existing EHB and spatio-temporal research. Section 4.3 describes the data sources and spatial weights. Section 4.4 outlines the methodological framework, including tests for spatial dependence and spatial heterogeneity. Section 4.5 presents the empirical analysis and findings, structured around the two central tests. Finally, Section 4.6 concludes by summarising the key contributions and outlining the rationale for testing for joint space-time interactions and dynamic spatial heterogeneity in Chapter 5.

4.2 Literature review

The traditional literature on EHB has been largely reluctant to consider spatio-temporal effects as having explanatory power for the dynamics of the puzzle (Chapter 2). In most cases, space has been treated merely as a geographic backdrop or a proxy for distance-related frictions (such as countries or regions), while time has been treated as a simple ordinal sequence of years. The number of studies on the topic has expanded significantly, particularly in documenting the aggregate downward trend in EHB through time (Ahearne, Griever, and Warnock, 2004; Baele, Pungulescu, and Ter Horst, 2007; Fidora, Fratzscher, and Thimann, 2007; Sørensen, Wu, Yosha, and Zhu, 2007; Coeurdacier and Rey, 2013; Levy and Levy, 2014; Mishra, 2015; Solnik and Zuo, 2017). More recent contributions have provided evidence that has corroborated this trend while highlighting potential regional asymmetries (Jagannathan, Jiao, and Karolyi, 2022; Sachdeva and Fotheringham, 2023). However, while much of this work emphasises temporal trends, the spatial dimension may be even more fundamental in shaping the structure and persistence of EHB. This gap in the literature has been identified but remains largely unaddressed (Lewis, 1999; Wójcik, 2011).

An emerging strand of the literature has focused on new modelling approaches to the analysis of EHB (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015). Given the potential richness of spatial and temporal dynamics in empirical data, there is a need for computationally based inferential methods that can capture how space and time jointly shape investment outcomes. A central shortcoming of earlier studies is their reliance on aspatial models of equilibrium, overlooking the possibility that neighbourhood effects condition temporal trajectories (Obstfeld and Rogoff, 2000; Abdallah, Dabbou, Gallali, and Hathroubi, 2025). In other words, spatio-temporal dynamics through which geographical neighbours exert influence on a country's EHB are not incorporated adequately. Recent methodological advancements have incorporated these dynamics (Rey, 2001, 2004); with applications across various domains, including physics, meteorology, economics, and environmental studies (Le Gallo, 2004; Rey and Sastré Gutiérrez, 2010; Sastré Gutiérrez and Rey, 2013). The work of Rey and Janikas (2006) and Rey and Ye (2010) extended these approaches to explicitly spatio-temporal contexts, while applications to financial contagion and market integration continue to emerge (Kohler, 2022).

International finance can be better understood as a network, held together by expanding flows of goods, services, people, capital, and, crucially, information (Castells, 1996; Coe, Lai, and Wójcik, 2014; Haberly and Wójcik, 2022). This perspective resonates with financial geography, which emphasises that capital flows are embedded in uneven geographies of regulation, knowledge, and institutional practice (Clark and Monk, 2017; Wójcik, 2011; Clark, Feldman, Gertler, and Wójcik, 2018). Moreover, there is an increased awareness of the relevance of spatio-temporal effects in research design (Paelinck and Klaassen, 1979; Cliff and Ord, 1981; LeSage and Pace, 2009). Such approaches explicitly incorporate space and time effects, and the multidimensionality of spatio-temporal effects calls for misspecification tests and estimators that are notably different from techniques designed for analysis of aspatial time-series data (Florax and Nijkamp, 2003; Anselin, 2010; Rey and Anselin, 2010; Elhorst, 2014; Bivand, Hauke, and Kossowski, 2013). Failing to account for the dimensions of space and time risks reinforcing the state of stasis in EHB research (Lewis, 1999), a pattern consistent with Kuhn's (1970) observation that paradigms persist despite mounting anomalies.

The relevance of spatial effects extends well beyond geography, however, and is evident in many of the social sciences. The seminal work of Cliff and Ord (1973, 1981) on spatial autocorrelation established the statistical basis for detecting clustering and dependence across space. The field was subsequently systematised under the label of spatial econometrics by Paelinck and Klaassen (1979), framing it as a subfield of statistics concerned with spatial dependence between observations collected from points or regions in space (LeSage, 2008). These methods were rapidly taken up in epidemiology, where spatial clustering techniques were applied to detect patterns of disease incidence and transmission (Pfeiffer, Robinson, Stevenson, Stevens, Rogers, and Clements, 2008). More recently, the COVID-19 pandemic has reinforced the importance of such approaches, with studies employing global and local clustering (Butt, Nazia, Bedard, Tang, Sehar, and Law, 2022; Pranzo, Dai Prà, and Besana, 2023; Yin, Aiken, Harris, and Bamber, 2023; Zhang, Jia, Li, Chen, and Li, 2024). Spatio-temporal effects are commonly understood to include both spatial heterogeneity and spatial dependence (Florax and Nijkamp, 2003). In applied work, however, these two dimensions can be difficult to disentangle, as clustering may arise either from structural differences across regions or from genuine interdependence between them (Florax and Nijkamp, 2003). Recent reviews emphasise that failing to account for both risks model misspecification and biased inference (Anselin, 2010; Elhorst, 2014).

Tobler's (1970) first law of geography is captured in the concept of spatial autocorrelation. Spatial autocorrelation occurs when an observation exhibits spatial memory, making it partly predictable from neighbouring observations (Cliff and Ord, 1973; Griffith, 1992; Getis, 2008). It asks whether a variable's value in one region makes similar values in neighbours more or less likely (Thomas and Huggett, 1980). A series of spatially dependent observations contains less independent information (Cliff and Ord, 1981; Anselin, 1988; Cressie, 1993; Griffith, 2005). This parallels time-series econometrics, where forecasts of the future can be partly inferred from past outcomes (Engle and Granger, 1987; Johansen, 1991; Hamilton, 1994; Stock and Watson, 2002). However, the existence of spatial autocorrelation ensures that the spatial case is more complex (Cliff and Ord, 1973; Anselin, 1995; Florax and Nijkamp, 2003; Griffith, 2005). Measures of spatial autocorrelation may be global or local (Carracedo, Debón, Iftimi, and Montes, 2018). Global measures summarise spatial autocorrelation for the entire study area using a single value (Nelson and Boots, 2008). Common examples include Global Moran's Index (Moran, 1950) and the Getis-Ord statistic (Getis and Ord, 1992). Since Moran's (1950) seminal paper, the theoretical underpinnings and applications of spatial autocorrelation coefficients have been widely examined (Cliff and Ord, 1973; Goodchild, 1986; Griffith, 1992; Odland, 1988; Carracedo, Debón, Iftimi, and Montes, 2018; Carracedo and Debón, 2021; Zhang, Xu, and Zhuang, 2011). In financial geography, these tools have also been applied to examine clustering in asset markets and investor behaviour (Rey, Mack, and Koschinsky, 2012; Baltzer, Stolper, and Walter, 2013).

Identification of local clusters is carried out using the LISA methodology developed by Anselin (1995). Neighbours are defined through a spatial weight matrix, which specifies the nature of interactions for each country (Anselin, 1995; Ingram and Harbers, 2020). Two main types of spatial weights are commonly used: distance-based weights (Cliff and Ord, 1981; Darmofal, 2015; Abdallah, Dabbou, Gallali, and Hathroubi, 2025) and boundary-based weights such as contiguity (Abate, 2016; Carracedo, Debón, Iftimi, and Montes, 2018). Under the distance-based approach, connectivity is measured within a given radius (for example, less than 3,000 km). Under the boundary-based approach, neighbours are units that share a border or vertex. Applications of LISA to finance confirm its potential to identify localised dynamics in market integration and EHB (Rey, Mack, and Koschinsky, 2012).

Understanding spatio-temporal effects through the combined lenses of spatial dependence, spatial heterogeneity, joint space-time interaction, and dynamic spatial heterogeneity is central to advancing EHB research. These dimensions matter not only for identifying patterns in EHB estimates but also for informing real-world investment decisions. By extending beyond aspatial or static approaches, this study contributes to a growing body of research that positions geography (space) and temporality (time) as integral to financial analysis, culminating in the most recent attempt to map these interconnections in an atlas of finance (Wójcik, Iliopoulos, Ioannou, Keenan, Migozzi, Monteath, Pažitka, Torrance, and Urban, 2024).

4.3 Data

This section presents the data used in this study. The analysis employs the model-based form of EHB introduced in Chapter 3, which is calculated across 43 countries from 2001 through 2020 as listed in the MSCI ACWI benchmark. Recall the model-based EHB measure introduced in Chapter 3 Eq. [1].[63]

$$EHB_{i,t} = 1 - \frac{w_{i,t}^{A}}{w_{i,t}^{o}} \qquad [1]$$

where $EHB_{i,t}$ is the EHB of country i in time t. $w_{i,t}^{A}$ is the actual weight or holdings of country i in time t, (Eq. [2]) , and $w_{i,t}^{o}$ is the optimal weight of country i in time t, (Eq. [3]).

$$w_{i,t}^{A} = \frac{FEA_{i,t}}{FEA_{i,t} + mc_{i,t} - FEL_{i,t}} \qquad [2]$$

$$\omega_{i,t}^{o} = 1 - \frac{mc_{i,t}}{wmc_{t}} \qquad [3]$$

where $mc_{i,t}$ is the market capitalisation of country i in time t and wmc_t is the world market capitalisation in time t.

[63] Refer to Chapter 3 for more details.

To define the spatial weight matrix, two guiding questions are posed: who is your neighbour? and, how much does your neighbour matter? As an exploratory exercise, neighbourhood structures are constructed in two complementary ways. The first is a distance-based approach, which measures the proximity between the financial centres of the 43 countries in the sample (Z/Yen Group and Long Finance, 2025). Financial centres are selected because they are the primary nodes of equity market activity, the very infrastructure through which the production of returns is generated (Gehrig, 2000; Haberly and Wójcik, 2022; Wójcik, 2020; Wójcik, Keenan, Pažitka, Urban, and Wu, 2022). Geographic coordinates are obtained from the GeoNames database (GeoNames, 2025), and countries are identified using ISO3 standard codes (International Organization for Standardization, 2020). Spherical distances are then calculated using the World Geodetic System (WGS84) (Macomber, 1984), implemented via the geosphere package in R (Hijmans, 2025). Based on these distances, the k-nearest neighbours ($k = 2$ to 5) are selected without imposing a distance threshold. Neighbours are subsequently weighted using both equal weights ($1/n$) and inverse-distance weights ($1/d$).

4.4 Methodology

A formal framework for testing spatio-temporal effects (Figure 4.1) in EHB is conceptualised and implemented across both Chapters 4 and 5. The analysis undertaken in Chapter 4 is designed to address two central lines of inquiry within the spatio-temporal inference system: testing for *spatial dependence*; and, subsequently, *spatial heterogeneity*.[64]

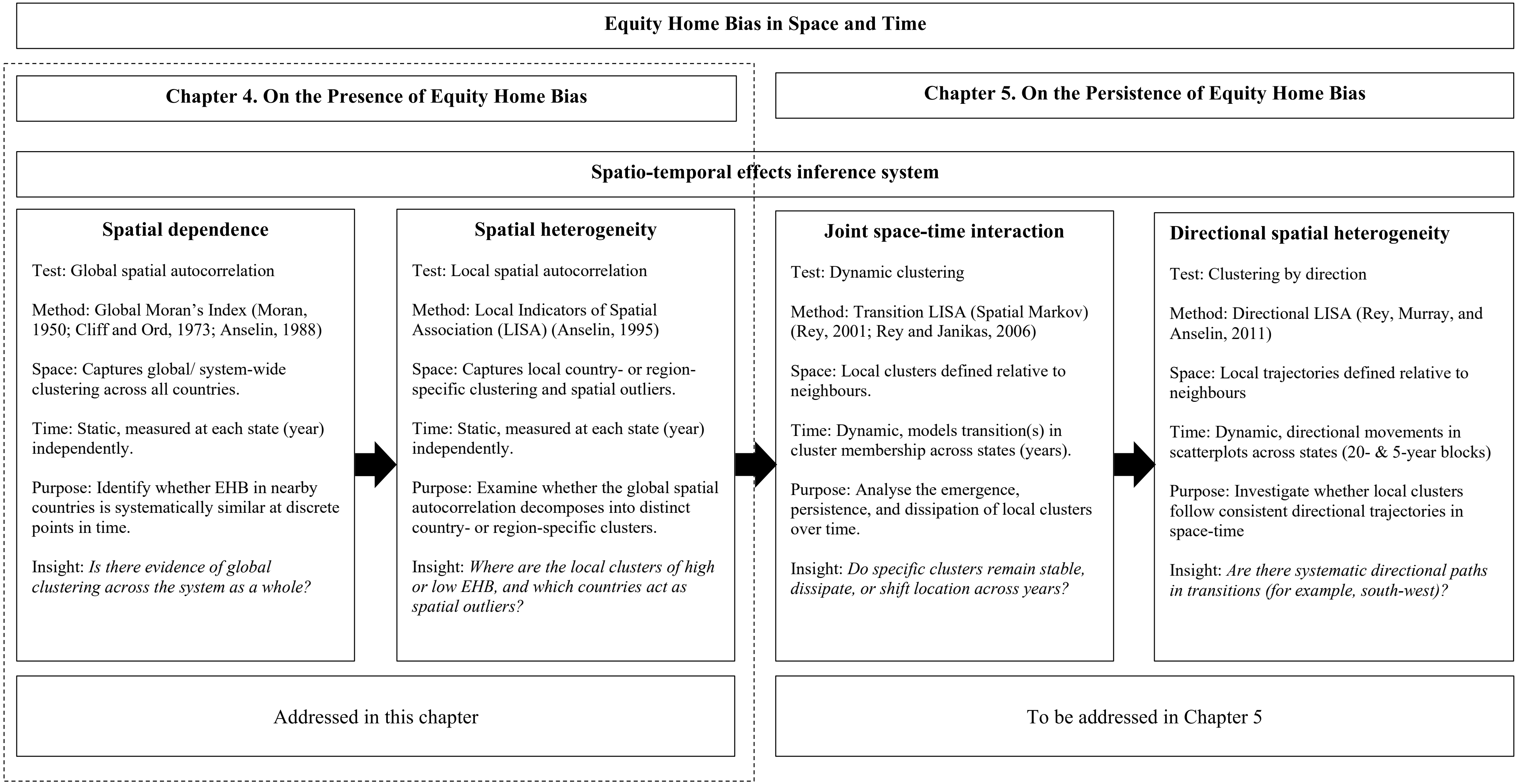
Spatial dependence refers to the extent to which EHB levels in one country are systematically related to those of its neighbours, reflecting the degree of global spatial autocorrelation (Moran, 1950; Cliff and Ord, 1973; Anselin, 1988) at a given state. Identifying such dependence is crucial for understanding how shocks, risks, or opportunities propagate across markets and regions worldwide (Rey and Anselin, 2010; Elhorst, 2014). In this study, spatial dependence is formally tested using Global Moran's Index, which provides a summary measure of the overall degree of autocorrelation across the *global system* (Moran, 1950; Cliff and Ord, 1981; Anselin, 1988).

[64] The spatial dimension is operationalised via a spatial weights matrix, which defines neighbourhood structures based on each country and its neighbours. The temporal dimension is introduced through annual data spanning 2001 through 2020, treated as independent states.

Spatial heterogeneity, by contrast, refers to structural differences in the relationships across space at a given time. In this study, heterogeneity captures the uneven geography of EHB, where some markets exhibit persistently high or low levels of EHB regardless of their neighbours (Florax and Nijkamp, 2003; Anselin, 2010; Elhorst, 2014). Recognising heterogeneity is important because it reflects institutional, cultural, and structural asymmetries that shape investor behaviour (Clark, Feldman, Gertler, and Wójcik, 2018; Wójcik, 2020). Spatial heterogeneity is tested using the Local Indicators of Spatial Association (LISA) methodology, which decomposes the global measure into local components, identifies specific countries where clusters emerge, and reveals which locations contribute most to high or low levels of EHB (Anselin, 1995).

Global Moran's Index and LISA provide complementary perspectives. Global Moran's Index identifies overall spatial autocorrelation at the system (or global) level, while LISA detects local spatial clustering and outliers. This combination captures both global association and local heterogeneity within the spatio-temporal framework outlined in Figure 4.1 (Florax and Nijkamp, 2003; Bivand, Hauke, and Kossowski, 2013).

Figure 4.1 Framework for testing spatio-temporal effects



4.4.1 Spatial dependence

From the foundational work of Cliff and Ord (1973, 1981) to more recent applications (Ghosh and Cartone, 2020; Siljander, Uusitalo, Pellikka, Isosomppi, and Vapalahti, 2022), there has been extensive focus on the statistical properties of spatial data, particularly in the study of spatial dependence. This body of research has laid the groundwork for understanding how spatio-temporal effects influence patterns across international finance. Testing for spatial autocorrelation in EHB involves analysing whether countries with geographically close or institutionally proximate neighbours tend to exhibit similar levels of EHB in their equity portfolios. Spatial autocorrelation analysis helps determine whether these observed patterns are the product of random variation or whether they reflect a spatial structure in the production of returns (Clark and Monk, 2017).[65]

Given the exploratory nature of this study, the choice of distance and proximity measures is deliberately staged, beginning with *topographical* notions of space, in which proximity is operationalised through physical distance between countries. This approach is consistent with standard practice in spatial analysis and provides a transparent and tractable basis for identifying spatial dependence and clustering across the global financial system (Cliff and Ord, 1981). Topographical distance offers a parsimonious representation of spatial structure that is comparable across countries and stable over time, which is particularly important for analysing long-run spatio-temporal patterns in EHB.

At the same time, it is recognised that proximity in international finance need not be defined solely in physical terms. Accordingly, the analysis subsequently extends to *topological* conceptions of space, which define proximity in terms of shared positions within institutional and market structures in addition to physical separation (Morse and Shive, 2011; Coe, Lai, and Wójcik, 2014; Clark and Monk, 2017). In this study, such topological relationships are operationalised through benchmark-defined neighbourhood structures, which reflect shared inclusion in global equity benchmarks (MSCI ACWI) and hence common institutional, informational, and investment linkages. These measures attempt to

[65] For independent events, the probability of a sequence of events occurring is calculated multiplicatively, based on the individual probabilities of each event (Feller, 1968; Casella and Berger, 2024). However, in the case of statistical dependence, this assumption breaks down, as the likelihood of one event occurring is conditional on the occurrence of another (Greene, 2018). That is, the probability of the second event depends on the outcome of the first, reflecting an interdependent structure rather than random independence. In the context of this study, the notion of spatial dependence is conceptually similar to general statistical dependence but is more specific, as the relationships among events are mediated through space, typically by distance or adjacency, at a given state (Cliff and Ord, 1981; Anselin, 1988; Florax and Nijkamp, 2003).

capture dimensions of financial connectedness that are not reducible to geographic distance alone and allow spatial dependence to be examined within the architecture of the global production of returns (Clark and Monk, 2017). The progression from distance-based to benchmark-based neighbourhood structures therefore reflects a shift from physical to relational space, enabling the analysis to assess whether observed patterns of EHB clustering are robust to alternative conceptions of proximity and more closely aligned with the institutional organisation of international finance.

4.4.1.1 Global Moran's Index

The most well-known statistic for testing spatial association in ordinal and interval data is the Global Moran's Index (Moran, 1950). It provides a summary measure of the strength and direction of spatial autocorrelation among geographic units, indicating whether similar values cluster together across the entire system at a given state in time:

$$\text{Global Moran's Index } (GM_t) = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(EHB_{it}-\overline{EHB}_t)(EHB_{jt}-\overline{EHB}_t)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}(EHB_{it}-\overline{EHB}_t)^2} \qquad [4]$$

Specifically, Global Moran's Index is calculated as a ratio of the spatial covariance between attribute values of adjacent geographic units (neighbours) and the overall variance of those attribute values across the entire study area (Lee and Li, 2017). In this formula (Eq. [4]), n is the number of countries (that is, 43 countries); EHB_{it} and EHB_{jt} are the EHB in countries i and j at time t; $\overline{EHB}_t$ is the average EHB value in the entire study sample at time t; and w_{ij} is the spatial weight between countries i and j. The spatial weight matrix $W = w_{ij}$ is a critical component of the Global Moran's Index statistic, as it defines the neighbourhood structure of the data by specifying the degree of spatial interaction or influence between each pair of countries based on their inverse spherical distance. The values of w_{ij} capture whether, and to what extent, country i and country j (Home and Neighbour, respectively) are considered as neighbours. This matrix operationalises the concept of a neighbourhood structure to test for spatial effects and ensures that the geographic configuration of the countries is incorporated directly into the analysis. Without this weighting scheme, the spatial aspect of the data would be ignored, reducing the Global Moran's Index to a non-spatial measure of association (Cliff and Ord, 1981; Anselin, 1988; LeSage and Pace, 2009).[66] Cliff and Ord (1973) derived the distribution of Eq. [4] to test the null hypothesis of no global spatial autocorrelation:

H_0: *There is no global spatial autocorrelation in the sample*
H_1: *There is global spatial autocorrelation in the sample*

Although Global Moran's Index has long been used by researchers, Wilcox (1995) argued that the approach is sensitive to outliers, which could change the slope of the regression line. To assess the robustness of the estimated Global Moran's Index, the Monte-Carlo test is performed by constructing random permutations of EHB for a given matrix of spatial weights (Moran, 1950; Wilcox, 1995; Florax and Nijkamp, 2003).[67] This method overcomes the disadvantage of the problem of asymptotic normality of the EHB distribution (Moran, 1950). Statistical inference can be based on the standardised or Z-value of Global Moran's Index (Z_{GM}), as follows:

$$Z_{GM} = [\mathrm{GM_t} - \mathrm{E(GM_t)}]/\mathrm{SD(GM_t)} \qquad [5]$$

where $\mathrm{E(GM_t)}$ is the expected $\mathrm{GM_t}$ and $\mathrm{SD(GM_t)}$ is the standard deviation of $\mathrm{GM_t}$. The moments of $\mathrm{GM_t}$ can be derived analytically, assuming that it follows a normal distribution, or as explained above can be approximated in a non-parametric framework using a randomisation approach (Moran, 1950; Florax and Nijkamp, 2003). The significance of Global Moran's Index Z statistic is assessed by the following confidence band at 5% level of significance. The decision rule:

$$5\%\ level\ of\ confidence\ band\ for\ the\ GM\ index:\ (Z_{GM} \geq 1.96\ or\ Z_{GM} \leq -1.96) \qquad [6]$$

[66] Global Moran's Index as a correlation coefficient, although its value is, strictly speaking, not restricted to the $[-1,1]$ interval. High positive values signal the occurrence of similar attribute values over space (either high or low values), and hence spatial clustering. Negative values indicate the joint occurrence of high and low attribute values in nearby locations. A value close to the expected value of Global Moran's Index in the absence of spatial correlation (which equals $-1/(n-1)$ and therefore approaches zero with increasing sample size) can be taken as evidence of a random allocation of attribute values over space (Florax and Nijkamp, 2003).
[67] The Monte-Carlo test uses random permutations of the EHB for the given matrix of spatial weights, to establish the rank of the observed statistic in relation to the 999 simulated values to overcome the problem of asymptotic normality (Hope, 1968; Cliff and Ord, 1973; Anselin, 1995).

It can be seen that GM_t in Eq. [4] is conceptually the equivalent of the slope of the least squares regression line that best fits the points between the EHB and its neighbours' weighted average. More specifically, the slope in a spatial lag regression, where the dependent variable is the EHB of a home country, and the independent variable is the average EHB of its neighbours (the spatial lag). Negative values of this index indicate that there is negative spatial autocorrelation, that is, the EHB of countries and their neighbours varies in a different direction (Florax and Nijkamp, 2003; Burt, Barber, and Rigby, 2009). Likewise, positive values indicate that there is positive spatial autocorrelation, which suggests that the EHB of countries and their neighbours go in the same direction (that is, both home and neighbours increase together, and vice-versa). Values of this index near zero indicate the absence of a spatial autocorrelation between the 43 countries.

4.4.1.2 Spatial weight matrix

Before calculating the spatial autocorrelation shown in Eq. [4], the first step is to establish how neighbourhood structures are defined and how observations are connected. This definition specifies the set of other observations with which each unit is expected to interact. The strength of these interactions is incorporated through the spatial weight or connectivity matrix (W). The spatial weight matrix is typically exogenously specified and plays a pivotal role in capturing the spatial structure of association or interdependence between neighbouring units. As Tobler's (1970) first law of geography reminds us, *"near things are more related than distant things (p. 236)."* What constitutes near can be defined in many ways; commonly, it is operationalised with geographical units, such as countries or provinces (Cliff and Ord, 1981; Anselin, 1988; Darmofal, 2015; Abdallah, Dabbou, Gallali, and Hathroubi, 2025). Common configurations of neighbourhood structures are reported in Table 4.1. The table summarises the alternative distance and proximity specifications used to construct the spatial weights matrices. The purpose of presenting multiple specifications is not to privilege a single notion of proximity, but to demonstrate that the presence of spatial clustering in equity home bias is robust to reasonable variation in how neighbourhood relationships are defined.

Table 4.1 Spatial weight matrix (generic)

	Type	Who is your neighbour?	How much does your neighbour matter?	Key literature
Distance-based	Proximity-limited neighbours	Units are neighbours if they fall within a fixed distance threshold. Threshold can combine with border length, population size, or economic similarity Examples: Countries within 3,000 km	▪ Equally weighted - binary (0/1 within threshold)[68] ▪ Distance-based weights[69] - row standardised[70]	Cliff and Ord (1981)
Distance-based	k-nearest neighbours	Each unit has exactly k-nearest neighbours. Distance can be Euclidean (planar) or geodesic/ spherical (Haversine, Vincenty) Examples: $k \in (2,3,4,5)$	▪ Equally weighted ▪ Distance-based weights - row standardised	Cressie (1993) Getis and Aldstadt (2004)
Boundary-based	Contiguity-based neighbours	Neighbours share a boundary or vertex. Can be restricted by region (within-region contiguity) or weighted by border length Examples: Rook (shared edge) or Queen (shared edge or vertex)[71]	▪ Equally weighted - binary (0/1 within contiguity) ▪ Distance-based weights - row standardised	Cliff and Ord (1981) Anselin (1988) Carracedo, Debón, Iftimi, and Montes (2018)
Boundary-based	Within-region/ localised neighbours	Neighbourhoods restricted to the same region, trade block, or benchmark group Examples: ASEAN, EU, G10, NAFTA; can combine distance and structural/economic. Similarly, neighbourhoods defined by a benchmark (such as MSCI ACWI)	▪ Equally weighted - binary (0/1 within boundary) ▪ Distance-based weights - row standardised	LeSage and Pace (2009) Fotheringham, Brunsdon, and Charlton (2002)

[68] Binary (0/1): Assign 1 if two units are neighbours, 0 otherwise; simplest and widely used in contiguity matrices (Cliff and Ord, 1981).

[69] Distance-based weights can be treated as inverse distance (weight decreases proportionally to distance), inverse squared distance (faster decay with distance: $w_{ij} = \frac{1}{d_{ij}^2}$), exponential decay where smooth decay with distance, Gaussian/ Kernel where continuous decay based on distance (Getis and Aldstadt, 2004).

[70] Row-standardised: Each row of the weight matrix sums to 1; ensures comparability across units (Cliff and Ord, 1981).

[71] Rook adjacency refers to neighbours that share a line segment. Queen adjacency refers to neighbours that share a line segment (or border) or a point (or vertex) (Carracedo, Debón, Iftimi, and Montes, 2018; Carracedo and Debón, 2021).

4.4.1.3 Defining neighbourhood structures

Defining neighbourhood structures is central because they capture how countries are embedded in spatio-temporal systems where proximity (geographic, economic, and/ or institutional) conditions behaviour and outcomes (Cliff and Ord, 1981; Anselin, 1988; Florax and Nijkamp, 2003; LeSage and Pace, 2009). In the context of EHB, they are essential for tracing how shocks, information, and investment flows move across spatially variegated markets through time. As part of this process, distance measures are important in the construction of spatial weight matrices, since they define what constitutes *nearness* between units (Macomber, 1984). This study employs two common neighbourhood structures, introduced previously, in Table 4.2: distance-based and boundary-based.

Geographic distance is measured as spherical (great-circle/ Haversine) distance between each country's financial centre, with the Earth approximated by the WGS84 oblate spheroid (equatorial/semi-major radius = 6,378.137 km) (Macomber, 1984; Cressie, 1993; Hijmans, 2025).[72] The spatial weight matrix is configured so that no country is considered its own neighbour, and the weights ($w_{i,j}$) are row-standardised, ensuring that the values in each row sum to one (Cliff and Ord, 1981; Anselin, 1988). A practical example is provided for Australia, where Sydney is adopted as the financial centre (Figure 4.2). Table 4.3 reports the spherical distances from Sydney to other global financial centres, while Table 4.4 shows how these distances are incorporated into the ten neighbourhood structures. This illustrates how Australia's position within the global financial system is operationalised in the analysis.

Importantly, distance is not solely a matter of physical proximity but can also capture the relational structures of global finance. Proximity to global hubs, such as New York, London, Singapore, or Sydney, often reflects deeper economic, political, and infrastructural connections through which the production of returns is organised (Wójcik, Keenan, Pažitka, Urban, and Wu, 2022). In this study, distances are calculated using the World Geodetic System (WGS84) (Macomber, 1984) and implemented in R via the geosphere package (Hijmans, 2025). These measures provide the basis for constructing both *k*-nearest neighbour weights and inverse-distance weighting schemes, which underpin the spatio-temporal tests for spatial dependence and heterogeneity in subsequent sections.

[72] The shape of the Earth closely resembles a flattened sphere (a spheroid) with equatorial radius of 6378.137km (World Geodetic System, 1984, by Macomber (1984). Spherical distances are calculated using the World Geodetic System (WGS84), implemented through the geosphere package in R (Hijmans, 2025).

Table 4.2 Spatial weight matrix (specific)

	Type	Who is your neighbour?	How much does your neighbour matter?	Key literature	Model
Distance-based	k-nearest neighbours	Each unit has exactly k-nearest neighbours Distance is measured as spherical distance using Haversine formula	▪ Equally weighted ▪ Distance based weights - row standardised	Cressie (1993) Getis and Aldstadt (2004)	✓ $k \in (2,3,4,5)$ ✓ $k \in (2,3,4,5)$
Boundary-based	MSCI-ACWI index neighbours	Neighbourhoods classified by a financial benchmark MSCI ACWI index	▪ Equally weighted ▪ Distance based weights - row standardised	LeSage and Pace (2009) Fotheringham, Brunsdon, and Charlton (2002)	✓ ✓

Table 4.3 Distance calculation between financial centres for home country: Australia

Neighbourhood structure	Financial centre	Latitude; Longitude	Distance
Australia (H_{AUS})	Sydney	-33.870; 151.210	
New Zealand (N_{NZL})	Auckland	-36.850; 174.760	$d_{AUS \rightarrow NZL}$ =2155.51 km
Indonesia (N_{IDN})	Jakarta	-6.180; 106.830	$d_{AUS \rightarrow IDN}$ = 5499.69 km
Philippines (N_{PHL})	Manila	14.620; 120.970	$d_{AUS \rightarrow PHL}$ = 6271.14 km
Singapore (N_{SIN})	Singapore	1.300; 103.850	$d_{AUS \rightarrow SGP}$ = 6299.96 km
Malaysia (N_{MYS})	Kuala Lumpur	3.160 ;101.710	$d_{AUS \rightarrow MYS}$ = 6614.92 km
Hong Kong (N_{HKG})	Hong Kong	22.285; 114.158	$d_{AUS \rightarrow HKG}$ = 7373.10 km
Japan (N_{JPN})	Tokyo	35.670; 139.770	$d_{AUS \rightarrow JPN}$ = 7823.38 km

Notes: Financial centres of the 43 countries in the sample (Z/Yen Group and Long Finance, 2025). Haversine formula is used to calculate the spherical-distance between two points on a sphere given their latitudes and longitudes ($d = 2R arcsin \sqrt{sin^2\left(\frac{\Delta \emptyset}{2}\right) + \cos(\emptyset_1)\cos(\emptyset_2) sin^2\left(\frac{\Delta\lambda}{2}\right)}$, where $\Delta\emptyset$ is the difference between latitudes (radians), $\Delta\lambda$ is the difference in longitudes (radians), R is the Earth's radius (approximately 6,378.137km at equator, d is the spherical distance along Earth's surface).

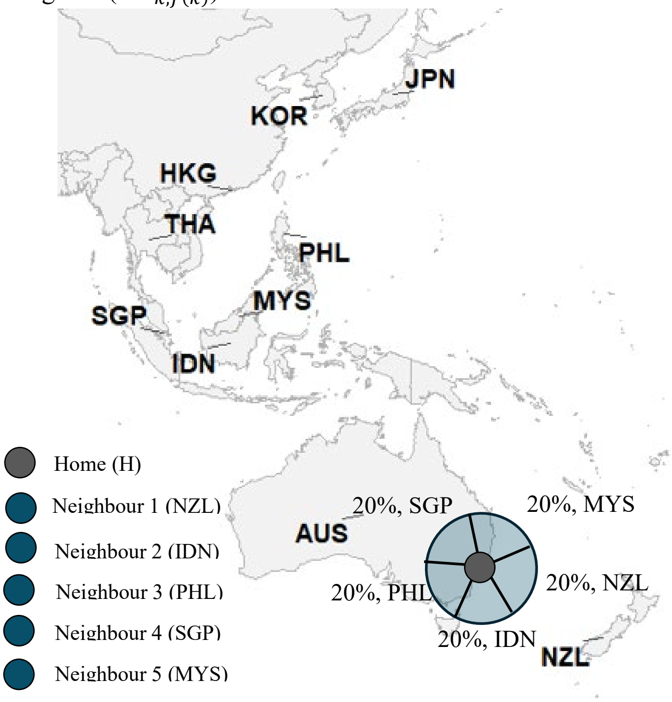
Table 4.4 Spatial weight matrix - worked examples for home country, Australia

	Type	Who is your neighbour?	How much does your neighbour matter?	Key literature	Model
Distance-based	k-nearest neighbours	k = 2: New Zealand; Indonesia	Equally weighted: 50%, 50%	Anselin (1988); Cliff and Ord (1981)	$HN_{k,f(k)}$
		k = 3: New Zealand; Indonesia; Philippines	Equally weighted: 33%, 33%, 33%	Anselin (1995); Tiefelsdorf and Boots (1995)	$HN_{k,f(k)}$
		k = 4: New Zealand; Indonesia; Philippines; Singapore	Equally weighted: 25%, 25%, 25%, 25%	Getis and Aldstadt (2004)	$HN_{k,f(k)}$
		k = 5: New Zealand; Indonesia; Philippines; Singapore, Malaysia	Equally weighted: 20%, 20%, 20%, 20%, 20%	Anselin, Syabri, and Kho (2006)	$HN_{k,f(k)}$
		k = 2: New Zealand; Indonesia	Distance weighted: 72%, 28%	Cliff and Ord (1973); Griffith (1996)	$HN_{k,df(k)}$
		k = 3: New Zealand; Indonesia; Philippines	Distance weighted: 57%, 23%, 20%	LeSage and Pace (2009)	$HN_{k,df(k)}$
		k = 4: New Zealand; Indonesia; Philippines; Singapore	Distance weighted: 48%, 19%, 17%, 16%	Kelejian and Prucha (2010)	$HN_{k,df(k)}$
		k = 5: New Zealand; Indonesia; Philippines; Singapore, Malaysia	Distance weighted: 42%, 16%, 14%, 14%, 14%	Elhorst (2014)	$HN_{k,df(k)}$
Boundary-based	MSCI-ACWI index neighbours	B = *Pacific*: New Zealand; Singapore; Hong Kong; Japan	Equally weighted: 25%, 25%, 25%, 25%	Bekaert and Harvey (1995)	$HN_{B,f(C_B)}$
		B = *Pacific*: New Zealand; Singapore; Hong Kong; Japan	Distance weighted: 53%, 18%, 15%, 14%	Bekaert, Hodrick and Zhang (2009); De Jong and De Roon (2005)	$HN_{B,df(C_B)}$

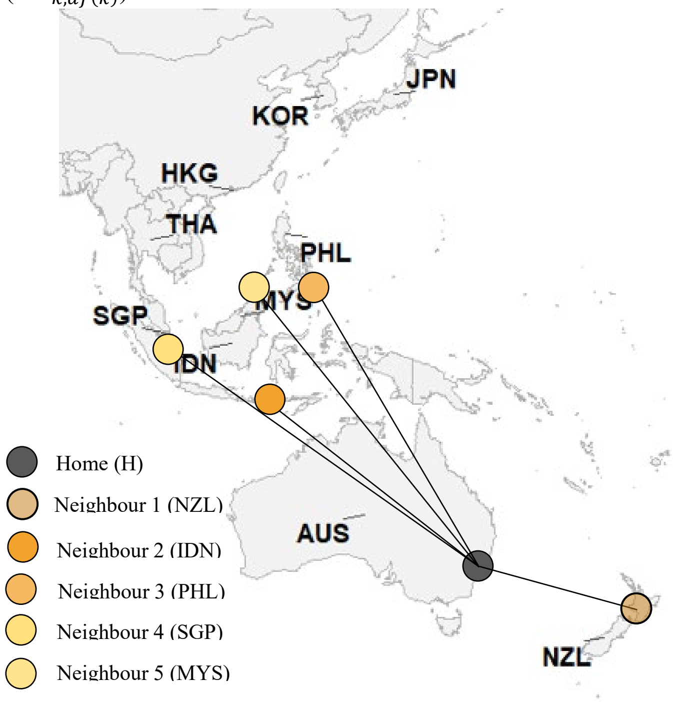
Notes: Here $k \in \{2, 3, 4, 5\}$ and
$B\ \{Americas\ (DM), Europe\ \&\ Middle\ East\ (DM), Pacific\ (DM), Americas\ (EM), Europe\ \&\ Middle\ East\ \&\ Africa\ (EM), Asia\ (EM)\}$.
$HN_{k,f(k)}$ defines neighbours based on k, where each neighbour is assigned an equal weight *f(k)*.
$N_{k,df(k)}$ also defines neighbours as k, but their influence is determined by *d(f(k)),* that is, distance-weighted weights.
$HN_{B,f(C_B)}$ defines neighbours by boundary B, where countries (C) within that boundary (C_B) are equally weighted, represented by $f(C_B)$.
$HN_{B,df(C_B)}$ defines neighbours by boundary B, where countries (C) within that boundary (C_B) are distance-weighted, represented by $d(f(C_B))$.

Figure 4.2 Neighbourhood structure example for home country, Australia

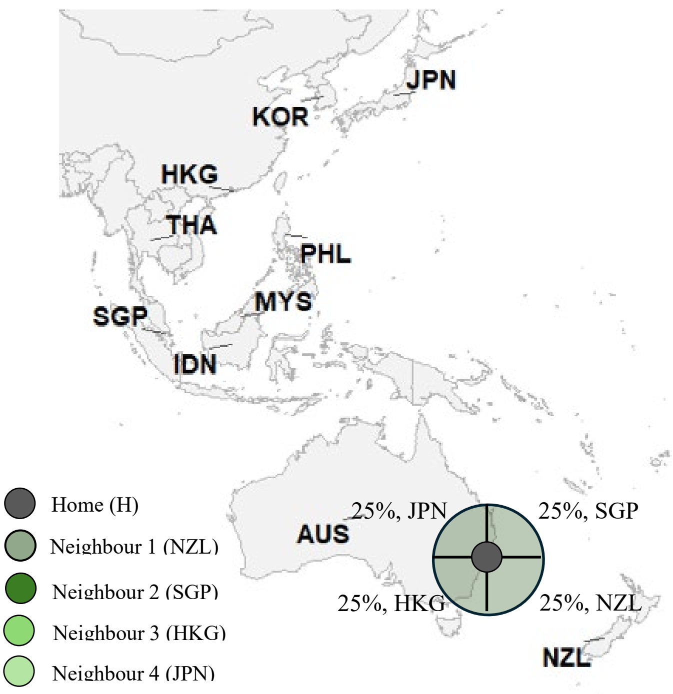
a) Distance-based: k-nearest neighbours (k = 5), equally weighted ($HN_{k,f(k)}$)



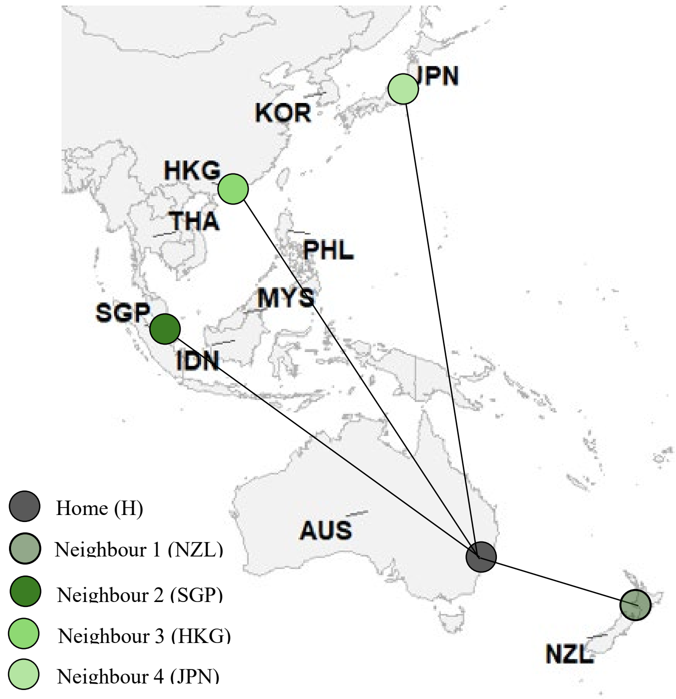
b) Distance-based: k-nearest neighbours, distance weighted ($HN_{k,df(k)}$)



c) Boundary-based: MSCI ACWI index neighbours (B = Pacific), equally weighted ($HN_{B,f(C_B)}$)



d) Boundary-based: MSCI ACWI index neighbours (B = Pacific), distance weighted ($HN_{B,d\ f(C_B)}$)



Notes: In the equally weighted approaches, identical weights are assigned for the selected neighbours using $k = 5$ and for the MSCI ACWI boundary case, where B = *Pacific,* countries in the Pacific region. In the distance-weighted approaches, the fading brown shading illustrates the distance decay between the home country (Australia) and its neighbours under the distance-based method, while the fading green shading reflects distance decay among boundary-based neighbours. ISO3 codes, financial centres of each country, and groupings are listed in Appendix 7.

A visual representation of the neighbourhood structures for Australia is provided in Figure 4.2, which shows the respective neighbour countries for the two types: distance-based and boundary-based. Table 4.4 and Figure 4.2 illustrate how Australia's neighbouring countries are classified under different spatial weight schemes, highlighting the impact of classification methods on the representation of regional relationships. Figure 4.2(a) illustrates the distance-based: *k*-nearest neighbours with an equally weighted approach, where in this scheme, Australia's five nearest neighbours; New Zealand, Indonesia, Philippines, Singapore, and Malaysia are identified based solely on geographical proximity. Each neighbour is then assigned an equal weight of 20% (1/5), reflecting an assumption that all neighbours have an identical influence on Australia's financial decisions leading to its EHB. While this approach simplifies the complexity of regional interactions, it may overlook the varying degrees of influence among neighbours (Cliff and Ord, 1981; Anselin, 1988).

Figure 4.2(b) illustrates distance-based: *k*-nearest neighbours with distance weighted approach, where Australia's five nearest neighbours (as above) are weighted according to their spherical distance from Australia. The closest neighbour, New Zealand, is weighted more than its most distant neighbour, Malaysia. While this approach provides a more nuanced representation of neighbourhood relationships, it may still include countries like Indonesia, Philippines, and Malaysia as neighbours, potentially distorting the analysis if their actual influence differs (Tiefelsdorf and Boots, 1995; Getis and Aldstadt, 2004).

Figure 4.2(c) illustrates boundary-based neighbours with an equally-weighted approach, where the boundary is assigned as MSCI ACWI benchmark, which bounds Australia into Pacific (DM). This deliberate assignment of a boundary (that is, MSCI ACWI) further screens Australia's neighbours by excluding Indonesia, Philippines, and Malaysia (as these countries are not included in the MSCI ACWI Pacific (DM)) and adding two new neighbours (Hong Kong and Japan) from the MSCI ACWI benchmark Pacific (DM). As shown visually in Figure 4.2(c), under this scheme, it may exclude countries that are geographically close but not part of the same boundary. After screening countries based on the boundary, this approach assigns equal weights to all countries within the boundary (25%, 1/4) within Pacific (DM) (LeSage and Pace, 2009) and consistent with regional classifications used in finance, such as Bekaert and Harvey (1995).

Finally, Figure 4.2(d) illustrates boundary-based neighbours with distance-weighted approach, where the boundary is chosen as MSCI ACWI benchmark as above. This approach to neighbours may offer a more accurate reflection of a country's financial relationships. For example, as visualised using Australia, Hong Kong and Japan receive a lower weight compared to New Zealand, and Singapore. This approach may further mitigate potential distortions and, it is argued, better reflects Tobler's (1970) first law of geography. Each of the above neighbourhood structure classification schemes offers a different perspective on Australia's neighbourhood relationships, with varying implications for the analysis of EHB decisions (Bekaert, Hodrick, and Zhang, 2009; De Jong and De Roon, 2005).

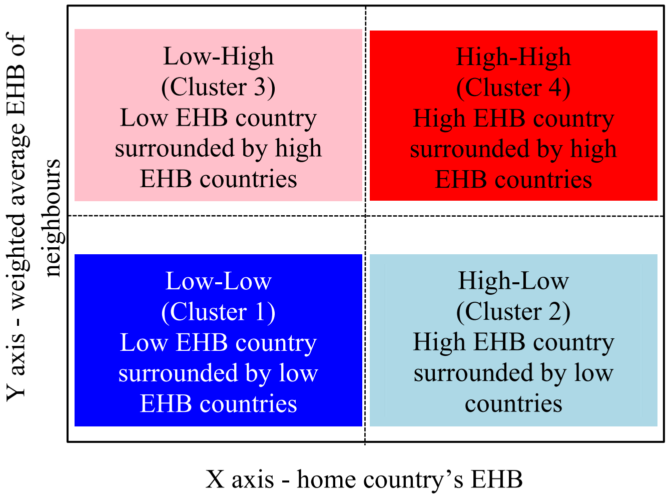
4.4.2 Spatial heterogeneity

During the 1990s, an important extension of the Global Moran's Index was developed to enhance exploratory spatial data analysis by moving beyond a single global measure. This extension, known as Local Indicators of Spatial Association (LISA), disaggregates the overall pattern of spatial dependence to detect and visualise local pockets of spatial clustering (Anselin, 1995; Florax and Nijkamp, 2003). Unlike the Global Moran's Index, which summarises spatial autocorrelation for the entire dataset (global), LISA identifies *where* local clusters occur and how they contribute to the global pattern, providing detailed insights into the spatial structure of the data. In fact, the sum of the local Moran statistics is proportional to the Global Moran's Index, ensuring theoretical consistency between the two approaches (Anselin, 1995).

4.4.2.1 Assigning LISA clusters

The first task in the analysis is to assign each neighbourhood structure to a local cluster. Following the commonly used notation for this task, the first letter, either 'Low' or 'High', indicates whether the home country's EHB (plotted on the x-axis of Figure 4.3) is below (Low) or above (High) the sample average for a given state (year). Similarly, the second letter refers to the weighted EHB of neighbour countries, denoting whether their weighted average value is below (Low) or above (High) the mean of all neighbour averages (see Figure 4.3). The vertical dotted line marks the sample average EHB for that year across all 43 countries (recall the Model-based estimates reported in Figure 3.2), while the horizontal dotted line indicates the mean of neighbours' average for the same year computed using the relevant spatial weight matrix (Ingram and Harbers, 2020). The four resulting quadrants are typically coloured using a standard scheme in this literature: blue for Low-Low, red for High-High, and pink and light blue for Low-High and High-Low, respectively (Anselin, 1995; Anselin, Syabri, and Kho, 2006).

Figure 4.3 LISA clusters



LISA Cluster	Home EHB value	Weighted average EHB of neighbours
Cluster 1	Below average	Below average
Cluster 2	Above average	Below average
Cluster 3	Below average	Above average
Cluster 4	Above average	Above average

Notes: The LISA cluster labels/ colour coding introduced here are applied consistently throughout the analysis. In the empirical analysis that follows (Section 4.5), these quadrant classifications: Low-Low, High-Low, Low-High, and, High-High are used to map and interpret the spatial structure of EHB across countries and through time.

4.4.2.2 Significance of LISA clusters

To assess the statistical significance of LISA clusters, the LISA index values alone are insufficient to establish the presence of significant spatial clustering or outliers. Statistical significance is typically assessed through *p-values* obtained via randomisation or permutation tests. Anselin (1995) introduced the concept of LISA (a local version of Global Moran's Index) for the identification of significant local spatial association through the following hypothesis.

$$H_0: There\ is\ no\ local\ spatial\ autocorrelation\ in\ the\ sample\ \left(LM_{i,t} = 0\right)$$

$$H_1: There\ is\ local\ spatial\ autocorrelation\ in\ the\ sample\ \left(LM_{i,t} \neq 0\right)$$

The null hypothesis tests whether the attribute values (EHB) are independently distributed across space for a given state, meaning the observed local cluster or outlier could just as well occur under spatial randomness (as opposed to the attribute values), which show local spatial dependence (for example, clustering of similar values or presence of spatial outliers):

$$LISA\ index\ value\ (LM_{i,t}) = \frac{(EHB_{i,t} - \overline{EHB}_t)}{S_t^2} \sum_j w_{ij} \, (EHB_{j,t} - \overline{EHB}_t) \qquad [7]$$

where $EHB_{i,t}$ is the EHB of country i at state t, $\overline{EHB}_t$ is the average EHB value in the entire study sample at time t; w_{ij} is the spatial weight between countries i and j; $S_t^2 = \frac{1}{n}\sum_{k=1}^{n}(EHB_{k,t} - \overline{EHB}_t)^2$ is the variance of EHB across all countries for each state t. Eq. [7] shows that the LISA index value is proportional to the Global Moran's Index up to a scaling constant (Anselin, 1995). Anselin (1995) and Tiefelsdorf and Boots (1995) discuss that the null distribution of the local statistic should not be approximated by the normal, but instead a randomisation approach should be used for statistical inference. LISA index value indicates two types of associations:

1. A positive $LM_{i,t}$ indicates two cluster types: A spatial cluster of countries with low values of EHB surrounded by neighbours also with low values of EHB denoted by Low-Low (Cluster 1); and, a spatial cluster of countries with high values of EHB surrounded by neighbours with high values of EHB, denoted by High-High (Cluster 4);
2. A negative $LM_{i,t}$ indicates two cluster types: A spatial cluster with countries with high values of EHB surrounded by neighbours with low values of EHB, denoted by High-Low (Cluster 2); and, a spatial cluster with countries with low values of EHB surrounded by neighbours with high values of EHB, denoted by Low-High (Cluster 3).

The statistical significance of the LISA index value for each country is tested through a permutation approach. The null hypothesis assumes spatial randomness, that is, the observed EHB of home country is independent of EHB values and its neighbour countries. To test this, the observed variable (EHB) is repeatedly permuted across spatial units (commonly 999 or more permutations (Anselin, 1995; Anselin, Syabri, and Kho, 2006), and the LISA index value is recalculated each time to generate a reference distribution. The computed LISA index value is then compared against this empirical distribution to determine its pseudo-*p* value. Low *p-values* ($p < 0.05$ or a user-defined threshold) suggest that the observed spatial association is unlikely to have arisen by chance, indicating significant clustering or spatial outliers. Since LISA index values produce a *p-value* for each country, multiple testing adjustments (for example, false discovery rate) are often recommended to avoid overstating significance.[73] Locations with significant *p-values* indicate areas where the observed clustering (High-High, Low-Low) or spatial outlier (High-Low, Low-High) patterns are unlikely to occur by chance. This hypothesis testing framework (see Eq. [7]) ensures that assigned LISA clusters are statistically robust and not artefacts of random spatial variation.

4.5 Analysis

Acknowledging the anecdotal nature of the results presented in Chapter 3, this study emphasises that ignoring potential spatio-temporal effects may lead to misleading inferences regarding the EHB puzzle (Florax and Nijkamp, 2003; LeSage and Pace, 2009). Although EHB appears largely homogeneous in form (see Chapter 2), country-level estimates seem to exhibit notable heterogeneity across both space and time (Chapter 3). Many questions emerge from the descriptive findings presented in Chapter 3. Why do investors in some countries remain chronically EHB through time (for example, India), while others do not (Mishra, 2015)? Why is it that some countries seemingly hold little EHB at all (say, Norway) (Baele, Pungulescu, and Ter Horst, 2007)? And, why have some countries recorded an increase in EHB estimates over the observation period (for instance, Ireland) (Ahearne, Griever, and Warnock, 2004)? The analysis section of Chapter 4 has two major lines of inquiry consistent with the empirical framework presented in Figure 4.3: first, spatial dependence (testing for global spatial autocorrelation using Global Moran's Index at a given

[73] To obtain the *p-values* of the LISA based on the number of neighbours in each home, the false discovery rate (FDR) adjustment was used (Benjamini and Hochberg, 1995). If the adjusted *p-value* is less than 0.05, the LISA value is classified as a significant association at 5% level of significance (Anselin, 1995).

state); and, second, spatial heterogeneity (testing for local spatial association in the form of clusters using LISA framework at a given state).

4.5.1 Testing for spatial dependence

The Global Moran's Index results indicate whether countries with similar levels of EHB tend to be geographically clustered across the system as a whole. Positive and statistically significant values of Global Moran's Index imply that countries are not distributed randomly, but instead exhibit spatial dependence, with high (low) equity home bias values tending to occur near other high (low) values. These results provide system-wide evidence of spatial clustering, demonstrating that the observed patterns are consistent and structured rather than the result of random variation or noise. This evidence of global spatial dependence justifies and motivates the subsequent local analysis, which explores spatial heterogeneity and identifies specific local clusters of interest within the global system.

As such, the Global Moran's Index is a summary measure of the intensity of the global spatial autocorrelation between geographical units. Spatial autocorrelation coefficients have received much attention for being able to provide quantitative assessments of spatial dependence in the data that describe certain aspects of geographic objects or events (Griffith, 2005; LeSage and Pace, 2009; Rey and Anselin, 2010; Carracedo, Debón, Iftimi, and Montes, 2018). The null hypothesis is that there is no spatial autocorrelation, with *p-values* obtained either from the asymptotic distribution or from Monte Carlo permutation tests (Bivand, Hauke, and Kossowski, 2013; Anselin, 1995). The result of the Global Moran's Index and associated statistics, such as standard errors and *p-values,* are shown in Tables 4.5 to 4.8, which include years from 2001 through 2020 for the distance-based (for $k = 5$ example), and the two boundary-based approaches discussed above (see Table 4.1). The *p-values* obtained for all states are significant at 5% level of significance (that is, all *p-values* < 0.05 for all years), indicating that there is a significant global spatial autocorrelation in EHB.

Table 4.5 Global Moran's Index values for distance-based, equally weighted neighbours ($HN_{k=5,f(k=5)}$)

	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
GM_t	**0.368**	0.391	0.394	0.446	**0.472**	0.479	0.467	0.409	0.443	**0.411**	0.311	0.385	0.393	0.362	**0.371**	0.390	0.386	0.386	0.373	**0.370**
Standard Error	**0.010**	0.010	0.010	0.010	**0.010**	0.010	0.010	0.010	0.010	**0.010**	0.010	0.010	0.010	0.010	**0.010**	0.010	0.010	0.010	0.010	**0.010**
p-value	**0.000**	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**

Note: Statistical significance is assessed using the associated *p-value*; a small *p-value* (p *value* < 0.05) suggests global spatial dependence.

Table 4.6 Global Moran's Index values for distance-based, distance weighted neighbours ($HN_{k=5,df(k=5)}$)

	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
GM_t	**0.387**	0.401	0.409	0.462	**0.487**	0.492	0.472	0.422	0.446	**0.415**	0.336	0.370	0.364	0.338	**0.360**	0.380	0.369	0.372	0.354	**0.343**
Standard Error	**0.006**	0.007	0.007	0.007	**0.007**	0.007	0.007	0.007	0.007	**0.007**	0.007	0.007	0.007	0.007	**0.007**	0.007	0.007	0.007	0.007	**0.007**
p-value	**0.000**	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**

Note: Statistical significance is assessed using the associated *p-value*; a small *p-value* (p *value* < 0.05) suggests global spatial dependence.

Table 4.7 Global Moran's Index values for boundary-based, equally weighted neighbours ($HN_{B=MSCI\ ACWI,f(C_{B=MSCI\ ACWI})}$)

	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
GM_t	**0.555**	0.585	0.615	0.657	**0.692**	0.689	0.668	0.639	0.644	**0.635**	0.605	0.622	0.604	0.576	**0.587**	0.619	0.642	0.655	0.626	**0.589**
Standard Error	**0.007**	0.008	0.007	0.007	**0.008**	0.008	0.008	0.008	0.008	**0.008**	0.007	0.008	0.008	0.008	**0.008**	0.008	0.008	0.008	0.008	**0.008**
p-value	**0.000**	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**

Note: Statistical significance is assessed using the associated *p-value*; a small *p-value* (p *value* < 0.05) suggests global spatial dependence.

Table 4.8 Global Moran's Index values for boundary-based, distance weighted neighbours ($HN_{B=MSCI\ ACWI,d(f(C_{B=MSCI\ ACWI}))}$)

	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
GM_t	**0.601**	0.638	0.681	0.717	**0.741**	0.729	0.707	0.646	0.674	**0.643**	0.580	0.664	0.648	0.603	**0.604**	0.636	0.663	0.673	0.646	**0.611**
Standard Error	**0.009**	0.010	0.009	0.009	**0.010**	0.010	0.010	0.010	0.010	**0.010**	0.009	0.010	0.010	0.010	**0.010**	0.010	0.010	0.010	0.010	**0.010**
p-value	**0.000**	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**	0.000	0.000	0.000	0.000	**0.000**

Note: Statistical significance is assessed using the associated *p-value*; a small *p-value* (p *value* < 0.05) suggests global spatial dependence.

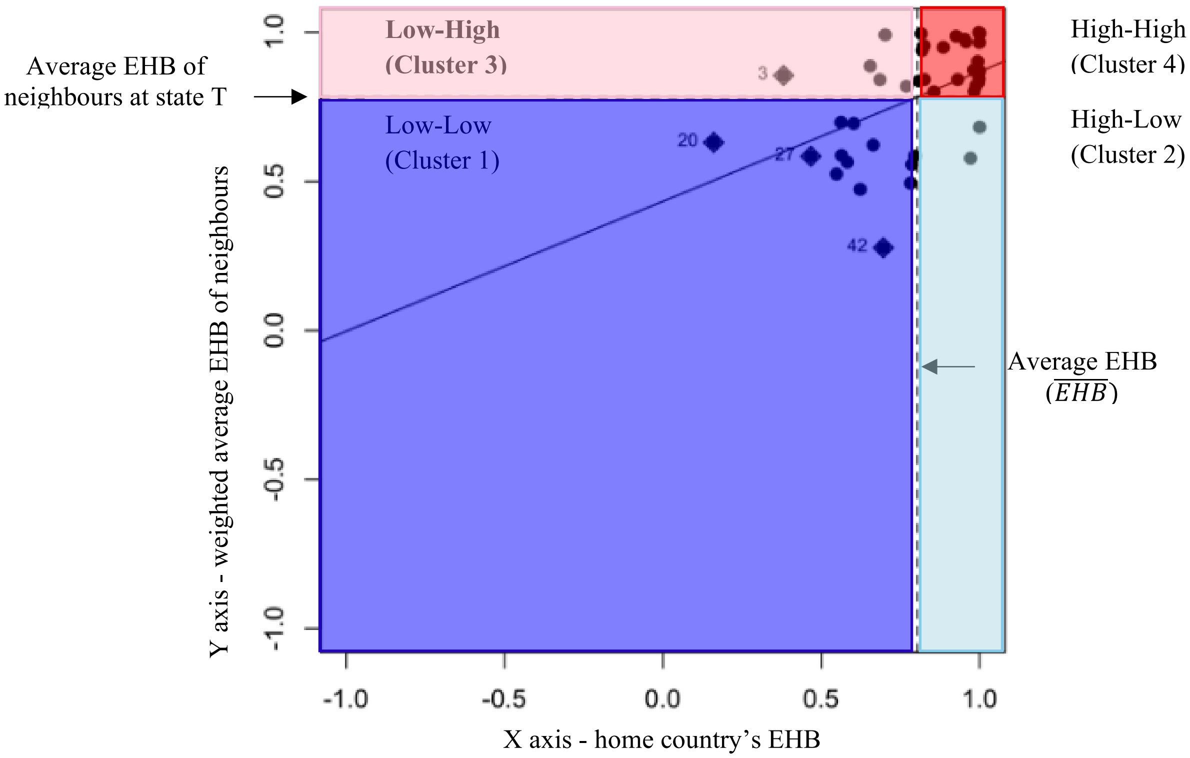
4.5.2 Testing for spatial heterogeneity

While the Global Moran's Index provides an overall measure of spatial autocorrelation across all countries in a given year, it does not reveal where these spatial patterns occur or how they vary locally. To address this, a LISA analysis is applied as a complementary tool (Anselin, 1995). The LISA statistic identifies local clusters by pinpointing areas where similar or dissimilar values are grouped together, thereby decomposing the global statistic into location-specific contributions (Anselin, 1995; Florax and Nijkamp, 2003; Anselin, Syabri, and Kho, 2006).

4.5.2.1 LISA cluster assignment

The LISA clusters are formed compared to the home country's overall EHB average and weighted average of the neighbours. The standard notation of LISA indicates four types of associations: Low-Low (Cluster 1); High-Low (Cluster 2); Low-High (Cluster 3); and High-High (Cluster 4) (Anselin, 1995; Anselin, Syabri, and Kho, 2006). Figure 4.4 presents the positioning of these clusters within a Global Moran's scatter plot, illustrating how countries relate to both their own EHB levels and those of their neighbours. For instance, Figure 4.4 highlights country IDs #3, #20, #27, and #42 showing their placement within the selected neighbourhood structure and demonstrating the application of the LISA classification.

Figure 4.4 Placing LISA clusters in a Global Moran's scatterplot at a given state (illustrative)



Figures 4.5 through 4.8 illustrate the LISA cluster assignments for the distance-based (k = 5) and the two boundary-based approaches discussed above. These figures provide a detailed view of spatial clustering by highlighting local pockets of similarity (or dissimilarity) in EHB across countries. Figures 4.5 and 4.6 focus on the distance-based approach with k = 5, where each country is assigned its five closest geographical neighbours, with their influence weighted either equally or by distance (distance-based). Figures 4.7 and 4.8 use the MSCI ACWI boundary specification, and with neighbours again weighted either equally (1/n) or by distance (1/d) (boundary-based).[74]

[74] The LISA cluster maps decompose the global measure of spatial association into local patterns, identifying where statistically significant clusters of high-high and low-low equity home bias occur. These maps show that spatial dependence is not uniformly distributed across countries, but is concentrated in specific regions. The persistence of similar cluster types across years supports the interpretation that spatial structure in equity home bias is systematic rather than episodic.

Figure 4.5 LISA cluster classification for distance-based, equally weighted neighbours ($HN_{k=5,f(k=5)}$)

ISO3	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ARG	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH
AUS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	HH	HH	LH	LH	LH	HH
AUT	LH	LH	LH	LH	LH	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
BEL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
BRA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
CAN	LL	LL	LL	LL	LL	LL	LL	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
CHL	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
COL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
CZE	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL
DNK	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EGY	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HL	HH	HH	HL	HL	HL	HH	HH	HH	HH
FIN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LH
FRA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
DEU	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
GRC	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	LH	HH	HH	HH	HH	HH
HKG	HH	HH	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
HUN	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
IND	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
IDN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
IRL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL
ISR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	HH	HH	HH	LH	LH	LH
ITA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
JPN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
KOR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
MYS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
MEX	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HL	HL
NLD	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
NZL	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
NOR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
PAK	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
PHL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
POL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PRT	HL	LL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
RUS	HH	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
SGP	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
ZAF	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
ESP	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL
SWE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
CHE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
THA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
TUR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HL	HH	HH	HL	HL	HH	HH	HH	HH	HH
GBR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
USA	LL	LL	LL	LL	LL	LL	LL	LL	LH	LH	LL	LH	LH	LH	LH	LH	LH	LH	LH	LH
Low-Low	15	16	14	15	15	16	16	16	15	15	16	14	15	15	16	16	16	16	16	15
High-Low	4	4	6	5	5	5	5	4	4	4	6	5	4	6	5	4	3	3	4	4
Low-High	3	4	3	4	3	2	3	3	4	4	4	5	7	7	6	5	6	7	8	8
High-High	21	19	20	19	20	20	19	20	20	20	17	19	17	15	16	18	18	17	15	16

Notes: LISA cluster classification using a distance-based, equally weighted neighbourhood structure for five nearest neighbours.

Figure 4.6 LISA cluster classification for distance-based, distance weighted neighbours ($HN_{k=5,d\,f(k=5)}$)

ISO3	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ARG	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH
AUS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	HH	HH	LH	LH	LH	HH
AUT	LH	LH	LH	LH	LH	LH	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
BEL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
BRA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
CAN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LH	LH	LH	LL	LH	LH	LH
CHL	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
COL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
CZE	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL
DNK	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EGY	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
FIN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
FRA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
DEU	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
GRC	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	LH	HH	HH	HH	HH	HH
HKG	HH	HH	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
HUN	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
IND	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
IDN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
IRL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL
ISR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	HH	HH	HH	LH	LH	LH
ITA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
JPN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
KOR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
MYS	HH	HL	HL	HL	HL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
MEX	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
NLD	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
NZL	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
NOR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
PAK	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
PHL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
POL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PRT	HL	LL	HL	LL	LL	LL	LL	LL	LL	LL	LH	LH	LH	LH	LL	LL	LL	LL	LL	LL
RUS	HH	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
SGP	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
ZAF	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
ESP	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL
SWE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
CHE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
THA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
TUR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HL	HH	HH	HH	HH	HH	HH	HH	HH	HH
GBR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
USA	LL	LH	LL	LL	LL	LL	LL	LL	LH	LH	LH	LH	LH	LH	LL	LH	LL	LL	LL	LL
Low-Low	15	15	14	15	15	15	16	17	16	16	15	14	15	14	17	16	18	17	17	17
High-Low	4	5	7	6	6	5	5	4	4	4	5	5	4	4	3	3	3	3	3	3
Low-High	3	5	3	4	3	3	3	2	3	3	5	5	7	8	5	5	4	6	7	6
High-High	21	18	19	18	19	20	19	20	20	20	18	19	17	17	18	19	18	17	16	17

Notes: LISA cluster classification using a distance-based, distance weighted neighbourhood structure for five nearest neighbours.

Figure 4.7 LISA cluster classification for boundary-based, equally weighted neighbours ($HN_{B=MSCI\ ACWI, f(C_{B=MSCI\ ACWI})}$)

Continent	ISO3	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
AM_DM	CAN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
AM_DM	USA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	AUT	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	BEL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	DNK	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	FIN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	FRA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	DEU	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	IRL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL
EME_DM	ISR	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	HL	HL	HL	LL	LL	LL
EME_DM	ITA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	NLD	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	NOR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	PRT	HL	LL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	ESP	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL
EME_DM	SWE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	CHE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	GBR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
PAC_DM	AUS	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	HL	HL	LL	LL	LL	HL
PAC_DM	HKG	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PAC_DM	JPN	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PAC_DM	NZL	LH	LL	LL	LL	LL	LH	LL	LH	LH	LH	LH	LH	LL	LL	LL	LL	LL	LL	LL	LL
PAC_DM	SGP	LL	LL	LL	LL	LL	LL	LL	LH	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LH	LH
AM_EM	ARG	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH
AM_EM	BRA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AM_EM	CHL	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
AM_EM	COL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AM_EM	MEX	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	CZE	LH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
EMEA_EM	EGY	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	GRC	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	LH	HH	HH	HH	HH	HH
EMEA_EM	HUN	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
EMEA_EM	POL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	RUS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	ZAF	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	TUR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	IND	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	IDN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	KOR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	MYS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	PAK	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	PHL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	THA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
	Low-Low	16	18	17	17	18	17	18	16	17	17	17	17	19	19	18	18	19	20	19	18
	High-Low	6	5	6	6	5	5	5	5	5	5	5	5	4	4	5	5	4	3	3	4
	Low-High	2	2	0	0	0	1	1	3	2	2	3	2	3	3	4	3	3	3	5	5
	High-High	19	18	20	20	20	20	19	19	19	19	18	19	17	17	16	17	17	17	16	16

Notes: LISA cluster classification using a boundary-based, equally weighted neighbourhood structure for MSCI ACWI benchmark as the boundary.

Figure 4.8 LISA cluster classification for boundary-based, distance weighted neighbours $((HN_{B=MSCI\ ACWI,d(f(C_{B=MSCI\ ACWI}))})$

Continent	ISO3	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
AM_DM	CAN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
AM_DM	USA	LL	LH	LL	LL	LL	LL	LL	LL	LL	LH	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	AUT	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	BEL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	DNK	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	FIN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	FRA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	DEU	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	IRL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL
EME_DM	ISR	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	HL	HL	HL	LL	LL	LL
EME_DM	ITA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	NLD	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	NOR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	PRT	HL	LL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	ESP	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL
EME_DM	SWE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	CHE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	GBR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
PAC_DM	AUS	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	HL	HL	LL	LL	LL	HL
PAC_DM	HKG	HL	HL	HL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PAC_DM	JPN	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HH
PAC_DM	NZL	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LL	LL	LL	LL	LH
PAC_DM	SGP	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
AM_EM	ARG	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH
AM_EM	BRA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AM_EM	CHL	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
AM_EM	COL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AM_EM	MEX	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	CZE	LH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
EMEA_EM	EGY	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	GRC	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	LH	HH	HH	HH	HH	HH
EMEA_EM	HUN	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
EMEA_EM	POL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	RUS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	ZAF	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	TUR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	IND	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	IDN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	KOR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	MYS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	PAK	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	PHL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	THA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
	Low-Low	15	15	15	17	16	16	16	16	16	15	16	16	17	17	16	17	18	19	19	17
	High-Low	6	5	6	4	5	5	5	5	5	5	5	5	4	4	5	5	4	3	3	3
	Low-High	3	5	2	2	2	2	3	3	3	4	4	3	5	5	6	4	4	4	5	6
	High-High	19	18	20	20	20	20	19	19	19	19	18	19	17	17	16	17	17	17	16	17

Notes: LISA cluster classification using a boundary-based, distance weighted neighbourhood structure for MSCI ACWI benchmark as the boundary.

Moving from a distance-based specification to a boundary-based specification represents a radical shift in the definition of neighbourhoods. Distance-based approaches capture physical proximity by treating countries as neighbours if they are geographically close, thereby emphasising spatial dependence in the sense of Tobler's law (Tobler, 1970; Cliff and Ord, 1981). In contrast, boundary-based approaches (such as MSCI ACWI) reflect institutional classifications, which may group together countries that are geographically distant but integrated through global financial centres (and developed and emerging market designations). This shift has direct implications for local association: countries can change cluster assignment not because of a change in their own EHB values, but because the set of neighbours against which they are compared is entirely redefined (Anselin, 1995; Florax and Nijkamp, 2003; Anselin, Syabri, and Kho, 2006). In practice, distance-based neighbourhoods emphasise geographic contiguity (Figures 4.5 and 4.6), while boundary-based neighbourhoods highlight an investment benchmark classification-driven form of clustering (Figures 4.7 and 4.8), two very conceptually distinct logics of spatial association.

For instance, in the Americas (DM), the United States and Canada remain in the Low-Low cluster throughout most years (Figures 4.7 and 4.8). However, under the distance-based specification, their cluster assignment shifts to Low-High, largely due to the exclusion of Mexico as a direct neighbour (Figure 4.5 and 4.6). In contrast, the emerging markets of the Americas (Argentina, Brazil, Chile, Colombia, and Mexico) are predominantly classified as High-High over time, reflecting strong regional clustering. Nonetheless, occasional deviations are observed, for example, Argentina in 2002 and Chile in 2009 fall into the Low-High category, though the overall pattern remains one of persistent high clustering.

Another noteworthy case is Australia. Under the distance-based approach, Australia is frequently classified as High-High, reflecting the influence of nearby high-EHB neighbours such as Indonesia, the Philippines, and Thailand. In the boundary-based approach, however, Australia more often falls into the High-Low category, with intermittent shifts to Low-Low across certain years. This divergence highlights how the choice of neighbourhood structure can meaningfully alter detected spatial dependence patterns (Tiefelsdorf and Boots, 1995; LeSage and Pace, 2009).

In this study, the MSCI ACWI index serves as the boundary-based definition of neighbourhoods because it mirrors the practical benchmark logic investors apply globally. The MSCI ACWI captures approximately 85% of the global investable equity universe (spanning both emerging and developed markets), making it the primary global benchmark for portfolio construction and performance evaluation (Scott, Balsamo, McShane, and

Tasopoulus, 2017). Its widespread use among investors, who rely on it both as an investment policy guide and a passive investment return/ risk target, highlights how benchmarks embed benchmark logic into the production of returns (Goldman Sachs Asset Management, 2021).

Taken together, the results show that the presence and persistence of local EHB clusters are not artefacts of measurement but reflect spatio-temporal effects. This directly addresses the core research question by demonstrating that the geography of EHB is shaped both by distance and by institutional boundaries, reinforcing the need for spatio-temporal approaches to understand investor behaviour (Clark and Wójcik, 2007; Coe, Lai, and Wójcik, 2014).

4.5.2.2 Testing significance of LISA clusters

The use of LISA classifications requires testing for statistical significance, since raw cluster assignments may reflect random spatial variation rather than meaningful local association. Permutation tests ensure that the observed clusters represent genuine patterns of spatial dependence (Anselin, 1995; Tiefelsdorf and Boots, 1995; Anselin, Syabri, and Kho, 2006). The null hypothesis assumes spatial randomness, that is, the observed value at a given country is independent of values at its neighbours. In addition to the introduced colours (Low-Low in blue, High-Low in light-blue, Low-High in pink, High-High in red), clusters with non-significant *p-values* are shown in white. Each Local Moran's statistic is compared against a reference distribution generated through repeated random permutations (Anselin, 1995; Benjamini and Hochberg, 1995). If the pseudo *p-value* is less than 0.05, the null is rejected, indicating the observed clustering pattern is unlikely to have occurred by chance.

Since multiple countries are tested simultaneously, the issue of multiple comparisons arises (Benjamini and Hochberg, 1995). To control the rate of false positives, the false discovery rate (FDR) adjustment is applied. This ensures that highlighted clusters reflect statistically robust spatial dependence rather than artefacts of multiple hypothesis testing. Figures 4.9 to 4.12 depict the LISA clusters, shading only significant clusters in their assigned colour and leaving non-significant ones white (though still classified). They also compare the proportion of significant clusters across alternative neighbourhood structures.

Figure 4.9 Statistical significance of LISA clusters for distance-based, equally weighted neighbours ($HN_{k=5,f(k=5)}$)

ISO3	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ARG	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH
AUS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	HH	HH	LH	LH	LH	HH
AUT	LH	LH	LH	LH	LH	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
BEL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
BRA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
CAN	LL	LL	LL	LL	LL	LL	LL	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
CHL	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
COL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
CZE	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL
DNK	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EGY	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HL	HH	HH	HL	HL	HL	HH	HH	HH	HH
FIN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LH
FRA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
DEU	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
GRC	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	LH	HH	HH	HH	HH	HH
HKG	HH	HH	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
HUN	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
IND	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
IDN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
IRL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL
ISR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	HH	HH	HH	LH	LH	LH
ITA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
JPN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
KOR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
MYS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
MEX	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HL	HL
NLD	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
NZL	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
NOR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
PAK	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
PHL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
POL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PRT	HL	LL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
RUS	HH	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
SGP	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
ZAF	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
ESP	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL
SWE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
CHE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
THA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
TUR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HL	HH	HH	HL	HL	HH	HH	HH	HH	HH
GBR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
USA	LL	LL	LL	LL	LL	LL	LL	LL	LH	LH	LL	LH	LH	LH	LH	LH	LH	LH	LH	LH
Low-Low	15	16	14	15	15	16	16	16	15	15	16	14	15	15	16	16	16	16	16	15
High-Low	4	4	6	5	5	5	5	4	4	4	6	5	4	6	5	4	3	3	4	4
Low-High	3	4	3	4	3	2	3	3	4	4	4	5	7	7	6	5	6	7	8	8
High-High	21	19	20	19	20	20	19	20	20	20	17	19	17	15	16	18	18	17	15	16
% Significance	40%	33%	23%	35%	42%	47%	40%	42%	63%	58%	58%	44%	40%	51%	40%	42%	42%	49%	44%	33%

Notes: LISA state classification using a distance-based, equally weighted neighbourhood structure for five nearest neighbours.

Figure 4.10 Statistical significance of LISA clusters for distance-based, distance weighted neighbours ($HN_{k=5,d(f(k=5))}$)

ISO3	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
ARG	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH
AUS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	HH	HH	LH	LH	LH	HH
AUT	LH	LH	LH	LH	LH	LH	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
BEL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
BRA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
CAN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LH	LH	LH	LL	LH	LH	LH
CHL	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
COL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
CZE	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL
DNK	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EGY	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
FIN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
FRA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
DEU	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
GRC	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	LH	HH	HH	HH	HH	HH
HKG	HH	HH	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
HUN	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
IND	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
IDN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
IRL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL
ISR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	HH	HH	HH	LH	LH	LH
ITA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
JPN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
KOR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
MYS	HH	HL	HL	HL	HL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
MEX	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
NLD	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
NZL	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
NOR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
PAK	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
PHL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
POL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PRT	HL	LL	HL	LL	LL	LL	LL	LL	LL	LL	LH	LH	LH	LH	LL	LL	LL	LL	LL	LL
RUS	HH	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
SGP	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
ZAF	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
ESP	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL
SWE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
CHE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
THA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
TUR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HL	HH	HH	HH	HH	HH	HH	HH	HH	HH
GBR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
USA	LL	LH	LL	LL	LL	LL	LL	LL	LH	LH	LH	LH	LH	LH	LL	LH	LL	LL	LL	LL
Low-Low	15	15	14	15	15	15	16	17	16	16	15	14	15	14	17	16	18	17	17	17
High-Low	4	5	7	6	6	5	5	4	4	4	5	5	4	4	3	3	3	3	3	3
Low-High	3	5	3	4	3	3	3	2	3	3	5	5	7	8	5	5	4	6	7	6
High-High	21	18	19	18	19	20	19	20	20	20	18	19	17	17	18	19	18	17	16	17
% Significance	40%	28%	30%	30%	37%	37%	35%	37%	40%	40%	37%	56%	44%	44%	47%	40%	47%	44%	47%	37%

Notes: LISA state classification using a distance-based, distance weighted neighbourhood structure for five nearest neighbours.

Figure 4.11 Statistical significance of LISA clusters for boundary-based, equally weighted neighbours ($HN_{B=MSCI\ ACWI, f(C_{B=MSCI\ ACWI})}$)

Continent	ISO3	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
AM_DM	CAN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
AM_DM	USA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	AUT	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	BEL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	DNK	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	FIN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	FRA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	DEU	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	IRL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL
EME_DM	ISR	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	HL	HL	HL	LL	LL	LL
EME_DM	ITA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	NLD	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	NOR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	PRT	HL	LL	HL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	ESP	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL
EME_DM	SWE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	CHE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	GBR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
PAC_DM	AUS	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	HL	HL	LL	LL	LL	HL
PAC_DM	HKG	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PAC_DM	JPN	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PAC_DM	NZL	LH	LL	LL	LL	LL	LH	LL	LH	LH	LH	LH	LH	LL	LL	LL	LL	LL	LL	LL	LL
PAC_DM	SGP	LL	LL	LL	LL	LL	LL	LL	LH	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LH	LH
AM_EM	ARG	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH
AM_EM	BRA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AM_EM	CHL	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
AM_EM	COL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AM_EM	MEX	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	CZE	LH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
EMEA_EM	EGY	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	GRC	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	LH	HH	HH	HH	HH	HH
EMEA_EM	HUN	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
EMEA_EM	POL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	RUS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	ZAF	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	TUR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	IND	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	IDN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	KOR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	MYS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	PAK	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	PHL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	THA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
	Low-Low	16	18	17	17	18	17	18	16	17	17	17	17	19	19	18	18	19	20	19	18
	High-Low	6	5	6	6	5	5	5	5	5	5	5	5	4	4	5	5	4	3	3	4
	Low-High	2	2	0	0	0	1	1	3	2	2	3	2	3	3	4	3	3	3	5	5
	High-High	19	18	20	20	20	20	19	19	19	19	18	19	17	17	16	17	17	17	16	16
	Significance	71%	73%	71%	73%	71%	71%	71%	63%	69%	58%	58%	60%	60%	56%	53%	58%	63%	63%	67%	63%

Notes: LISA cluster classification using a boundary-based, equally weighted neighbourhood structure for MSCI ACWI benchmark as the boundary.

Figure 4.12 Statistical significance of LISA clusters for boundary-based, distance weighted neighbours ($HN_{B=MSCI\ ACWI,d(f(C_{B=MSCI\ ACWI}))}$)

Continent	ISO3	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
AM_DM	CAN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
AM_DM	USA	LL	LH	LL	LL	LL	LL	LL	LL	LL	LH	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	AUT	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	BEL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	DNK	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	FIN	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	FRA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	DEU	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	IRL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL
EME_DM	ISR	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	HL	HL	HL	LL	LL	LL
EME_DM	ITA	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	NLD	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	NOR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	PRT	HL	LL	HL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	ESP	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	LL	LL	LL	LL
EME_DM	SWE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	CHE	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
EME_DM	GBR	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL	LL
PAC_DM	AUS	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	HL	HL	LL	LL	LL	HL
PAC_DM	HKG	HL	HL	HL	LL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL
PAC_DM	JPN	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HH
PAC_DM	NZL	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LL	LL	LL	LL	LH
PAC_DM	SGP	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
AM_EM	ARG	HH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH
AM_EM	BRA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AM_EM	CHL	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
AM_EM	COL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AM_EM	MEX	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	CZE	LH	LH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH
EMEA_EM	EGY	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	GRC	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	LH	HH	HH	HH	LH	HH	HH	HH	HH	HH
EMEA_EM	HUN	HH	HH	HH	HH	HH	HH	HH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH	LH
EMEA_EM	POL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	RUS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	ZAF	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
EMEA_EM	TUR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	IND	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	IDN	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	KOR	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	MYS	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	PAK	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	PHL	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
AS_EM	THA	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH	HH
	Low-Low	15	15	15	17	16	16	16	16	16	15	16	16	17	17	16	17	18	19	19	17
	High-Low	6	5	6	4	5	5	5	5	5	5	5	5	4	4	5	5	4	3	3	3
	Low-High	3	5	2	2	2	2	3	3	3	4	4	3	5	5	6	4	4	4	5	6
	High-High	19	18	20	20	20	20	19	19	19	19	18	19	17	17	16	17	17	17	16	17
	Significance	67%	67%	70%	70%	67%	60%	60%	53%	58%	53%	56%	53%	58%	53%	53%	53%	56%	58%	58%	53%

Notes: LISA cluster classification using a boundary-based, distance weighted neighbourhood structure for MSCI ACWI benchmark as the boundary.

Table 4.9 Spatial weight matrix (proportion of significance)

	Type	Who is your neighbour?	How much does your neighbour matter?	Key literature	Model	Proportion of significance
Distance-based	*k*-nearest neighbours	k =2	Equally weighted	Anselin (1988); Cliff and Ord (1981)	$HN_{k,f(k)}$	40%
		k =3	Equally weighted	Anselin (1995); Tiefelsdorf and Boots (1995)	$HN_{k,f(k)}$	39%
		k =4	Equally weighted	Getis and Aldstadt (2004)	$HN_{k,f(k)}$	41%
		k =5	Equally weighted	Anselin, Syabri and Kho (2006)	$HN_{k,f(k)}$	43%
		k =2	Distance weighted	Cliff and Ord (1973); Griffith (1992, 1996)	$HN_{k,df(k)}$	40%
		k =3	Distance weighted	LeSage and Pace (2009)	$HN_{k,df(k)}$	39%
		k =4	Distance weighted	Kelejian and Prucha (2010)	$HN_{k,df(k)}$	40%
		k =5	Distance weighted	Elhorst (2014)	$HN_{k,df(k)}$	40%
Boundary-based	MSCI ACWI index neighbours	B = *MSCI ACWI*	Equally weighted	Bekaert and Harvey (1995)	$HN_{B,f(c_B)}$	62%
		B = *MSCI ACWI*	Distance weighted	Bekaert, Hodrick and Zhang (2009); De Jong and De Roon (2005)	$HN_{B,d(f(c_B))}$	60%

Unlike the Global Moran's Index results in the previous section, which establish that EHB is globally spatially autocorrelated, statistically significant LISA clusters identify where in the system these patterns are concentrated, revealing local geographies of EHB that drive the overall global association (Anselin, 1995; Rey and Anselin, 2010). Figures 4.9 to 4.12 (and Table 4.9) report the significant LISA clusters across both distance-based and boundary-based neighbourhoods. The results strongly reinforce the 'two-regime' structure introduced earlier in this chapter. Developed markets in Europe and the Middle East are consistently classified as Low-Low clusters, reflecting relatively integrated markets with low and spatially correlated levels of EHB. In contrast, emerging markets in Asia are predominantly classified as High-High clusters, highlighting persistent regional clustering of elevated EHB. These patterns are consistent with earlier findings that institutional integration in developed markets reduces EHB, while capital controls and informational frictions in emerging markets sustain high levels (Ahearne, Griever, and Warnock, 2004; Mishra, 2015). The significant LISA results also provide confirmation of the two-regime structure in the geography of EHB.

The comparison of Figures 4.9 to 4.12 shows clear differences in detection rates between distance- and boundary-based specifications. Under distance-based k = 5 approaches (Figures 4.9 and 4.10), significant clustering is present but accounts for a relatively modest share (approximately 40% of observations), as also reported in Table 4.9. By contrast, boundary-based specifications using MSCI ACWI (Figures 4.11 and 4.12) consistently yield higher proportions of significant clusters (60% and more in Table 4.9). This demonstrates that benchmark-based definitions seem more effective in capturing interdependence across markets than purely geographic measures. Again, the results corroborate the role of MSCI ACWI as a bellwether index for investors, suggesting that benchmark classifications are not neutral: they shape the production of returns and condition observed patterns of investor behaviour (Florax and Nijkamp, 2003; Clark and Wójcik, 2007; Haberly and Wójcik, 2022; Wójcik, Keenan, Pažitka, Urban, and Wu, 2022). The next section turns to a detailed Australian case study to illustrate how these dynamics operate in practice. This is followed by a more detailed analysis of the results of the boundary-based, distance-weighted ($HN_{B,d(f(C_B))}$) approach to the spatial weight matrix.

4.5.3 LISA example (Australia)

The case of Australia provides an instructive example of how LISA values vary under alternative neighbourhood definitions. Building on Figure 4.2, *Neighbourhood structure example for home country, Australia*, which outlined Australia's position within both distance-based and boundary-based structures, Tables 4.10 through 4.13 report the associated LISA statistics. These results demonstrate how the classification of local clusters is contingent on the specification of neighbour relations, and hence how methodological choices condition the interpretation of spatial dependence (Anselin, 1995; Florax and Nijkamp, 2003).[75]

Under the distance-based approach for $k=5$ equally weighted neighbours (Table 4.10), where Australia is linked to New Zealand, Indonesia, the Philippines, Singapore, and Malaysia, the country is consistently classified as High-High from 2001 to 2012. In subsequent years, cluster membership becomes less stable, with Australia frequently shifting into Low-High (2013, 2014, 2017, 2018, 2019) before returning to High-High in 2020. This trajectory is consistent with the oscillations shown in the Sankey diagram in Chapter 3 (Figure 3.5), where Australia moves above and below the global mean line across time. While Table 4.11 shows the sensitivity of local classification to distance decay, the results are consistent.

The boundary-based specification using the MSCI ACWI Pacific (DM) classification (Tables 4.12 and 4.13) repositions Australia within an institutional rather than geographic frame, aligning it with New Zealand, Singapore, Hong Kong, and Japan. In Table 4.12, Australia is predominantly classified as High-Low between 2001 and 2012, reflecting persistently higher levels of EHB relative to the benchmark group average. In later years (2013-2019), Australia occasionally shifts into Low-Low clusters, before returning to High-Low in 2020. Table 4.13, which applies distance-weighted weights within the MSCI ACWI Pacific (DM) boundary, reinforces this pattern. The institutional framing of the MSCI ACWI boundary therefore positions Australia differently from its geographic neighbours: rather than clustering with nearby Asian markets in High-High regimes, Australia appears as a relatively high-EHB outlier (until more recent times) within its developed Pacific benchmark grouping.

[75] For the remaining 42 countries, results across all 10 neighbourhood structures, namely distance-based (equally weighted), distance-based (distance-weighted) for $k = 2, 3, 4$, and 5, as well as boundary-based (equally weighted and distance-weighted) over the 20-year period, LISA values are available upon request (43 countries × 10 approaches × 20 years).

Table 4.10 LISA Index values example for home country, Australia for distance-based, equally weighted neighbours ($HN_{k=5,f(k=5)}$)

	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
LISA cluster	**HH**	HH	HH	HH	**HH**	HH	HH	HH	HH	**HH**	HH	HH	LH	LH	**HH**	HH	LH	LH	LH	**HH**
$LM_{i,t}$	**0.030**	0.022	0.042	0.079	**0.054**	0.080	0.039	0.049	0.086	**0.081**	0.057	0.029	-0.004	-0.008	**0.009**	0.004	-0.011	-0.029	-0.028	**0.030**
Standard Error	**0.001**	0.001	0.008	0.016	**0.009**	0.012	0.003	0.006	0.013	**0.012**	0.004	0.001	0.000	0.000	**0.000**	0.000	0.000	0.001	0.001	**0.001**
p-value	**0.286**	0.323	0.376	0.304	**0.331**	0.272	0.285	0.310	0.280	**0.285**	0.254	0.271	0.285	0.251	**0.248**	0.266	0.249	0.270	0.269	**0.286**

Note: LISA cluster colours indicate High-High (red), Low-Low (blue), and spatial outliers High-Low (light blue) and Low-High (pink).

Table 4.11 LISA Index values example for home country, Australia for distance-based, distance weighted neighbours ($HN_{k=5,df(k=5)}$)

	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
LISA cluster	**HH**	HH	HH	HH	**HH**	HH	HH	HH	HH	**HH**	HH	HH	LH	LH	**HH**	HH	LH	LH	LH	**HH**
$LM_{i,t}$	**0.005**	0.001	0.008	0.005	**0.017**	0.003	0.004	0.010	0.012	**0.016**	0.010	0.001	0.000	-0.002	**0.003**	0.001	-0.004	-0.009	-0.009	**0.019**
Standard Error	**0.004**	0.002	0.011	0.021	**0.011**	0.015	0.004	0.008	0.017	**0.016**	0.006	0.002	0.000	0.000	**0.000**	0.000	0.000	0.001	0.001	**0.001**
p-value	**0.498**	0.470	0.457	0.483	**0.425**	0.491	0.477	0.463	0.472	**0.448**	0.499	0.495	0.496	0.477	**0.459**	0.481	0.445	0.455	0.445	**0.445**

Note: LISA cluster colours indicate High-High (red), Low-Low (blue), and spatial outliers High-Low (light blue) and Low-High (pink).

Table 4.12 LISA Index values example for home country, Australia for boundary-based, equally weighted neighbours ($HN_{B=Pacific,f(C_{B=Pacific})}$)

	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
LISA cluster	**HL**	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	HL	HL	LL	LL	LL	HL
$LM_{i,t}$	**-0.023**	-0.024	-0.074	-0.086	**-0.069**	-0.068	-0.035	-0.042	-0.066	**-0.066**	-0.024	-0.021	0.003	0.005	**-0.005**	-0.003	0.007	0.016	0.015	**-0.012**
Standard Error	**0.003**	0.002	0.010	0.020	**0.011**	0.015	0.003	0.007	0.017	**0.015**	0.006	0.002	0.000	0.000	**0.000**	0.000	0.000	0.001	0.001	**0.001**
p-value	**0.363**	0.316	0.281	0.301	**0.281**	0.321	0.295	0.368	0.351	**0.340**	0.390	0.344	0.364	0.355	**0.378**	0.320	0.313	0.362	0.379	**0.373**

Note: LISA cluster colours indicate High-High (red), Low-Low (blue), and spatial outliers High-Low (light blue) and Low-High (pink).

Table 4.13 LISA Index values example for home country, Australia for boundary-based, distance weighted neighbours ($HN_{B=Pacific,d(f(C_{B=Pacific}))}$)

	2001	2002	2003	2004	**2005**	2006	2007	2008	2009	**2010**	2011	2012	2013	2014	**2015**	2016	2017	2018	2019	**2020**
LISA cluster	**HL**	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	HL	LL	LL	HL	HL	LL	LL	LL	**HL**
$LM_{i,t}$	**-0.048**	-0.039	-0.108	-0.135	**-0.127**	-0.134	-0.069	-0.094	-0.150	**-0.149**	-0.062	-0.043	0.006	0.008	**-0.009**	-0.005	0.011	0.028	0.028	**-0.023**
Standard Error	**0.005**	0.002	0.015	0.029	**0.016**	0.022	0.005	0.011	0.023	**0.021**	0.007	0.002	0.000	0.000	**0.000**	0.000	0.000	0.002	0.002	**0.002**
p-value	**0.280**	0.279	0.278	0.284	**0.232**	0.270	0.258	0.248	0.238	**0.225**	0.279	0.267	0.282	0.352	**0.318**	0.321	0.310	0.295	0.320	**0.376**

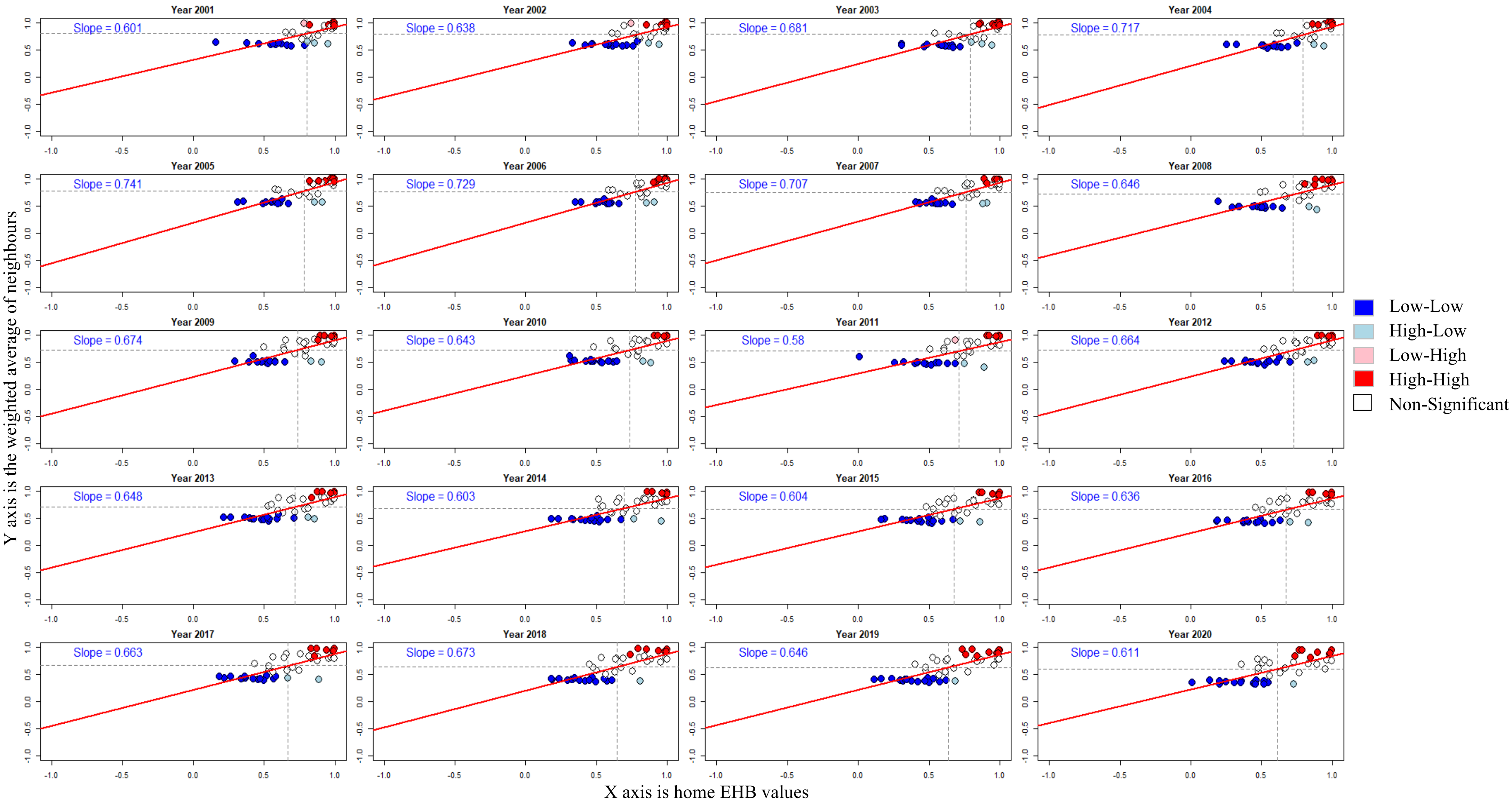
Note: LISA cluster colours indicate High-High (red), Low-Low (blue), and spatial outliers High-Low (light blue) and Low-High (pink).

4.5.4 Boundary-based, distance-weighted neighbours

The results in Figure 4.13 highlight how the specification of the neighbourhood structure materially influences the detection of spatial dependence. When equal neighbour weights are applied, all neighbouring units are treated uniformly, irrespective of their actual geographic distance. This uniformity dilutes the role of proximity, thereby attenuating the spatial signal and leading to comparatively higher *p-values* (Cliff and Ord, 1981; Griffith, 2005). In contrast, distance-weighted neighbours emphasise closer locations, consistent with Tobler (1970). By embedding this spatial gradient into the weight matrix, distance-based structures sharpen the detection of clustering, resulting in stronger and more statistically significant evidence of local spatial dependence (Anselin, 1995; Rey and Anselin, 2010). To ensure that the weight matrix reflects meaningful spatial interactions, this study adopts boundary-based, distance-weighted neighbours for the subsequent analysis.

Turning to the global evidence, Figure 4.13 complements Table 4.8 by plotting Global Moran's Index values for all four neighbourhood structures over the 2001-2020 period. The slope coefficients of the Global Moran's Index trends confirm that global spatial dependence remained relatively stable across the sample window, regardless of neighbourhood definition (Anselin, 1995; Moran, 1950). However, the scatter plots in Figure 4.13 (constructed for the boundary-based, distance-weighted structure) reinforce that significant and persistent global autocorrelation is present across states. The plots adopt the conventional LISA colour scheme, with significant clusters (5% level) highlighted and non-significant associations shaded in white. This visualisation strengthens the conclusion that spatial dependence is not an artefact of a single weighting rule, but a systematic feature of the data (Rey, 2004; Anselin, Syabri, and Kho, 2006).

Figure 4.13 Global Moran's Index representation with LISA cluster significance for all states 2001 through 2020



Building on this global evidence, the LISA cluster analysis provides a more granular view of localised spatial dependence. The LISA maps reveal enduring High-High clusters (red) in countries such as India, Brazil, Colombia, Egypt, Indonesia, Korea, Malaysia, Mexico, South Africa, Thailand, and Turkey, all of which persist in this state for the full 20-year period. In contrast, a set of Low-Low clusters (blue) is observed in Netherlands, Belgium, Denmark, Finland, France, Germany, Italy, Norway, Switzerland, and Sweden, also stable across the sample horizon. At the margins, transitions occur: for example, Australia shifts intermittently from a High-Low (light blue) outlier to a Low-Low (blue) during 2013-2014 and 2017-2019, before returning to High-Low in 2020. These shifts underscore the heterogeneity of spatial dependence, highlighting not only where clustering is most entrenched but also where exceptions and reclassifications emerge (Rey, 2001; Anselin, 1995).

The joint evidence from Global Moran's Index and LISA clusters offers a complementary and internally consistent picture. The relatively stable global index values support the reliability of the local clusters, while the LISA maps identify the precise locations where clustering, persistence, and spatial outliers arise. Importantly, this combination confirms that spatial dependence in EHB is both statistically significant and geographically uneven. The identification of persistent High-High and Low-Low regimes, alongside occasional transitions, provides the empirical foundation for the deeper investigation of clustering and path dependency in Chapter 5, where temporal dynamics (for example, year-to-year and 20- and 5-year block-to-block variation) are explicitly tested.

4.6 Conclusion

Chapter 4 employs a spatio-temporal analytical framework to deepen understanding of EHB across both spatial and temporal dimensions. This approach directly addresses gaps in the literature, which has tended to treat EHB as a static and aspatial phenomenon (French and Poterba, 1991; Lewis, 1999; Karolyi and Stulz, 2003), thereby overlooking the geographically embedded and dynamically evolving nature of global investment behaviour (Clark and Wójcik, 2018; Haberly and Wójcik, 2022).

The chapter first established the presence of spatial dependence in the EHB estimates across the 43 country sample using Global Moran's Index. The results decisively rejected the null hypothesis of spatial randomness for all states (years) under review, showing that EHB is systematically clustered rather than evenly dispersed (Moran, 1950; Cliff and Ord, 1973;

Anselin, 1995). It is important to emphasise, however, that Global Moran's Index is a static test, assessing spatial autocorrelation within each cross-sectional state (year), rather than tracing dynamics across time. This provided the foundation for a more granular investigation with the LISA framework, which revealed four distinct local spatial clusters (Low-Low, High-Low, Low-High, and High-High), demonstrating that a country's EHB levels are systematically related to those of its neighbours (Rey and Anselin, 2010; Anselin, Syabri, and Kho, 2006). As with Global Moran's Index, LISA is also a static diagnostic, capturing local clustering patterns at a given point in time rather than their evolution.

These findings suggest that EHB may not only be shaped by country-specific factors, such as: regulatory regimes (Porta, Lopez-de-Silanes, Shleifer, and Vishny, 1998); cultural preferences (Stulz and Williamson, 2003; Guiso, Sapienza, and Zingales, 2006; Chui, Titman, and Wei, 2010); and/ or differences in market microstructure arrangements (Glosten and Milgrom, 1985; Kyle, 1985; Pagano and Röell, 1996; O'Hara, 1995; Madhavan, 2000), but also by supra-national dynamics, that may include regional economic integration (Frankel and Rose, 1998; Baele, Bekaert, and Inghelbrecht, 2010); geopolitical shifts (Obstfeld and Rogoff, 2000; Hurrell, 2024); and/ or shared market sentiment among geographically proximate countries (Rouwenhorst, 1999; Kaminsky, Lyons, and Schmukler, 2004; Wójcik, 2020).

These results advance the argument that global investment decisions are embedded in a spatio-temporal context. This challenges the assumptions of the neoclassical finance tradition, which abstracts from space and time (Markowitz, 1952; Sharpe, 1964; Solnik, 1974; Ross, 1976; Fama, 1970). In contrast, the evidence presented in this study demonstrates that investment risk is both dynamic and spatially uneven, arising from an opportunity set shaped by temporal volatility and geographic interdependence (Clark and Monk, 2017). The asset class in focus, global equities, represents the single largest contributor to an institutional investor's risk budget (MSCI, 2020; Asimit, Chong, Tunaru, Zhou, 2025). In this sense, the production of returns is not an abstract financial exercise but a geographically embedded process shaped by institutions, financial centres, and governance arrangements (Clark, 2005; Clark and Wójcik, 2007; Wójcik, 2012; Ioannou, Wójcik, and Pažitka, 2021; Haberly and Wójcik, 2022). Recognising this embeddedness underscores the practical significance of EHB, linking localised investment behaviours to the global geographies of financial return generation.

From a scholarly perspective, this chapter contributes to a literature that has yet to fully explore the spatio-temporal dynamics of EHB. While spatial econometrics has for decades investigated spatial dependence and temporal dynamics (Cliff and Ord, 1973; Anselin, 1995; Anselin, 2010; Rey, 2001), its application to international investment remains limited and largely novel (Portes and Rey, 2005; Baele, Bekaert, and Inghelbrecht, 2007). By applying measures such as Global Moran's Index and LISA, this study provides evidence that EHB is jointly shaped by spatial context and temporal interdependencies, rather than solely by isolated, country-specific factors. This perspective enriches both financial geography and international finance by providing a more nuanced and geographically informed representation of EHB worldwide (Clark and Wójcik, 2018; Wójcik, Keenan, Pažitka, Urban, and Wu, 2022).

The chapter documents the emergence of a two-regime pattern for a given state: a Low-Low clustering regime centred on EMEA developed markets, and a High-High clustering regime in Asian emerging markets. These regimes seemingly persist across the 2001-2020 period and reinforce the claim that EHB is not an artefact of measurement but a structural, geographically embedded phenomenon. As Kuhn (1970) reminds us, paradigms persist despite anomalies, and the persistence of EHB in these two regimes underscores the limitations of neoclassical finance while validating insights from financial geography (Wójcik, 2018; Haberly and Wójcik, 2022).

Finally, this chapter sets the stage for the analysis in Chapter 5, which investigates the *dynamic* persistence and directional evolution of spatial clusters over time. In particular, techniques such as Directional LISA (Rey, 2001) enable the tracking of spatial trajectories within the Global Moran's Index scatterplot, shedding light on systematic trends of convergence, divergence, and persistence in global investment patterns (Rey and Anselin, 2010).

5. On the Persistence of Equity Home Bias

5.1 Introduction

Chapter 5 addresses the final research question posed in this study, specifically, does equity home bias (EHB) persist across space and through time? In doing so, the chapter shifts the analysis from the presence of spatio-temporal effects (Chapter 4) to their persistence. Drawing directly on the findings from Chapter 4, which revealed the presence of spatial dependence for given states at both global and local levels using Global Moran's Index (Moran, 1950; Cliff and Ord, 1973; Anselin, 1988) and Local Indicators of Spatial Association (LISA) (Anselin, 1995), the analysis in this chapter moves from the static to the dynamic.

While Global Moran's Index and Local Indicators of Spatial Association (LISA) capture static clustering for a given state, they do not reveal whether spatial relationships crank forward, enduring or evolving, through time. This gap is key to understanding the EHB puzzle. As discussed, the neoclassical finance tradition considers deviations from equilibrium as anomalies that arbitrage should eventually eliminate (Fama, 1970; Ross, 1976). In this tradition, there is an *a priori* expectation that both the presence and persistence of EHB will dissipate with deepening global financial integration, as returns and risk premia converge due to the reduction of capital controls and information asymmetries (Bekaert and Harvey, 1995; Lewis, 1999; Obstfeld and Rogoff, 2000; Karolyi and Stulz, 2002; Coeurdacier and Rey, 2013).[76] Yet, as reported in Chapter 2, voluminous studies have documented high and enduring levels of EHB across both countries and regions (French and Poterba, 1991; Tesar and Werner, 1995; Mishra, 2015).

To address this limitation, this study employs two complementary methods. First, the Transition LISA (Spatial Markov chain) framework is used to assess whether country-level transitions are conditioned by the states of neighbouring countries (Quah, 1993; Rey, 2001; Rey and Janikas, 2006; Rey, 2014).[77] Next, the Directional LISA methodology tests for the magnitude and orientation of directional co-movements within the Moran (1950) scatter plot

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[76] The future of global financial integration and lessons from the EHB puzzle are discussed in Chapter 6.

[77] Consistent with the field, the Transition LISA framework is also referred to as a Spatial Markov chain as it extends the classic Markov chain approach, developed to model stochastic transitions between states (Markov, 1906; Grimmett and Stirzaker, 2020), by conditioning transition probabilities on the spatial state of neighbouring units (however defined). Specifically, for this study, it captures how persistence (or mobility) in a given country's EHB depends not only on its own past state, but also on the contemporaneous clustering of its neighbours (Quah, 1993; Rey, 2001, 2014; Rey and Janikas, 2006).

across states, specifically, 20-year and five-year blocks (Rey, Murray, and Anselin, 2011; Rey, 2014; Rey and Sastré Gutiérrez, 2010; Murray, Grubesic, Wei, and Mack, 2011).

The chapter begins with an examination of whether there is an interaction between space and time, that is, a *joint space-time interaction* in the distribution of EHB, using the Transition LISA (Spatial Markov chain) framework (Rey, 2001, 2014) and the Directional LISA methodology. While Global Moran's Index and LISA are effective for detecting static spatial clustering (Chapter 4), they do not capture how local spatial relationships persist or shift through time, since classifications are defined relative to the distribution of EHB within each state (Moran, 1950; Anselin, 1995). The Transition LISA extends this by explicitly modelling the temporal mobility of LISA clusters in a spatial context, offering a richer understanding of the joint spatio-temporal interactions (Quah, 1993; Rey, 2001; Rey and Janikas, 2006; Rey, 2014). The framework is applied to the LISA clusters identified in Chapter 4 across the observation period (2001 through 2020), to provide systematic evidence on the persistence and dynamics of home countries' EHB conditioned on the states of neighbourhood structures. This responds to long-standing calls in the field of geography to consider persistence and path dependence (Arthur, 1989; North, 1990; Clark and Wójcik, 2007; Haberly and Wójcik, 2022).

Next, to investigate the direction and magnitude of co-movements in EHB between a home country and its neighbours, Chapter 5 adopts the Directional LISA methodology developed by Rey, Murray, and Anselin (2011) and further elaborated by Rey (2014), which tracks spatial trajectories within the Moran (1950) scatterplot over time. As discussed, Directional LISA incorporates a directional dimension that enables analysis of the orientation *and* persistence of spatial trajectories through a given state (Rey and Le Gallo, 2009; Murray, Grubesic, Wei, and Mack, 2011; Sastré Gutiérrez and Rey, 2013). This approach provides new insights into the role of spatio-temporal effects in EHB dynamics by identifying whether countries and their neighbours move in parallel trajectories (convergence), diverge in opposite directions (divergence), or reinforce existing regimes. For instance, the Directional LISA provides a dynamic visualisation of whether neighbourhood structures consolidate around persistent Low-Low states in Europe or remain locked into High-High regimes in Asia over given blocks of time (Clark and Wójcik, 2007; Coe, Lai, and Wójcik, 2014; Haberly and Wójcik, 2022). The Directional LISA methodology evaluates spatial change over time by representing movements as vectors and combining map-based displays with statistics on standardised trajectories (Rey and Le Gallo, 2009; Rey and Sastré Gutiérrez, 2010; Sastré Gutiérrez and Rey, 2013). This approach captures systematic trends in EHB clusters across 20- and five-year blocks, shedding light on convergence and persistence.

The key finding from the Transition LISA (Spatial Markov chain) framework is that EHB clusters are highly persistent across the 2001 through 2020 period. Countries overwhelmingly remain in their initial cluster states, with very high probabilities of staying in Low-Low, High-Low, Low-High, or High-High regimes year after year (Quah, 1993; Rey, 2001, 2014; Rey and Janikas, 2006). The Low-Low clusters in Europe and the Middle East are consistently stable, reflecting integrated neighbourhood structures with low EHB, while the High-High clusters in emerging Asia also remain entrenched (Clark and Wójcik, 2007). The null hypothesis of independence between home and neighbour transitions is rejected, confirming that a country's EHB trajectory is jointly determined by the persistence of its neighbours and not independent of the surrounding spatial context (Rey, Mack, and Koschinsky, 2012). Strikingly, transitions across regimes are virtually absent, even during systemic shocks such as the GFC. The reported steady-state distributions confirm this persistence over the 20-year observation period, underscoring structural 'lock-in' and the path dependence of EHB (Arthur, 1989; North, 1990; Rey, 2014). The Transition LISA findings show that EHB is not a temporary anomaly awaiting arbitrage, but a deeply embedded, persistent feature of the global financial system.

The results from the Directional LISA provide complementary insights by capturing the direction and orientation of trajectories of the neighbourhood structures.[78] Over the full 20-year block, the reported rose diagram (polar histogram) shows 40 of 43 neighbourhood structures exhibit a SW orientation in the Moran (1950) scatterplot, signalling *joint downward convergence* where both home countries and their neighbours reduce EHB together.[79] Only three cases (Egypt, Ireland, and South Africa) move to the SE quadrant, reflecting *home-led divergence* in which domestic bias increased while regional neighbours moved toward capital market openness (Rey, Murray, and Anselin, 2011; Sastré Gutiérrez

[78] As is reported, the Directional LISA illustrates how a country (home) *and* its neighbours (that is, the neighbourhood structure) moves relative to their EHB positions over time Rey (2014). The quadrants in the Moran (1950) scatterplot have the following meaning: Quadrant 1 (North-East, NE) means *joint upward convergence*, both the home country and its neighbours increase EHB; Quadrant 2 (North-West, NW) means *neighbour-led divergence*, the home country reduces EHB while its neighbours increase theirs; Quadrant 3 (South-West, SW) means *joint downward convergence*, both the home country and its neighbours reduce EHB; and, finally, Quadrant 4 (South-East, SE) means home-led divergence, the home country increases EHB while its neighbours reduce theirs.

[79] The reported rose diagrams (polar histograms) provide a graphical summary of directional movement vectors, showing the frequency of trajectories by quadrant (Murray, Grubesic, Wei, and Mack, 2011; Sastré Gutiérrez and Rey, 2013).

and Rey, 2013). The five-year block analysis provides deeper insights. The respective rose diagrams show how these orientations map onto distinct historical contexts. From 2001 through 2005, most neighbourhood structures shifted SW (*joint downward convergence*), though divergence was evident: Chile, Hungary, Mexico, and the United States moved NW (*neighbour-led divergence*), while Egypt, Ireland, and South Africa shifted SE (*home-led divergence*), indicating uneven adjustment in the wake of the dot.com bubble and post-9/11 uncertainty (Clark and Wójcik, 2007; Akata, 2024). For the 2005 through 2010 block, the impacts of the GFC saw a decisive SW shift (*joint downward convergence*), with no countries sustaining NE (*joint upward convergence*) positions and many accelerating reductions in EHB (Mishra, 2015). For 2010 through 2015, SW (*joint downward convergence*) consolidation continued, but Eurozone sovereign debt pressures produced heterogeneity, with some peripheral states adjusting more slowly. Finally, during 2015 through 2020, SW remained dominant, yet SE (*home-led divergence*) persisted in cases such as Ireland and South Africa, suggesting that while most neighbourhoods moved toward lower EHB, some countries moved against the prevailing trend as well as the onset of COVID-19 at the end of this block (Goldstein, Koijen, and Mueller, 2021; Haberly and Wójcik, 2022; Rajput, 2022). In summary, these findings show that while EHB regimes are persistent, the directions of movement vary across blocks, with episodes of convergence (joint upward and joint downward) and divergence (*home-led* and *neighbour-led*) shaping uneven trajectories of EHB across space and time.

The remainder of this study is organised as follows. Section 5.2 reviews the relevant literature in the field. Section 5.3 provides an overview of the data and variables used in both methodologies. Section 5.4 sets out the methodological framework, formalising the Transition LISA framework and Directional LISA. Section 5.5 reports the empirical results, and Section 5.6 concludes.

5.2 Literature review

Despite growing recognition that context matters (Clark, 1998; Clark, 2005), most empirical EHB research remains tied to aspatial, equilibrium-based frameworks and time-series econometrics (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015). Such approaches treat countries as independent observations, with little consideration of spatial dependence. Neglecting spatio-temporal effects risks biased or inefficient estimates (Anselin, 1995; Rey and Le Gallo, 2009). Critically, formal consideration of possible transition dynamics is absent from the EHB literature. This omission is potentially significant, as the persistence of anomalies (such as EHB) challenges the predictions of the neoclassical finance tradition that arbitrage should eliminate them over time (Fama, 1970; Ross, 1976; Lewis, 1999).

Consistent with the methodological approach in Chapter 4, the ongoing difficulties in reconciling theoretical predictions with empirical evidence have led researchers to adopt exploratory tests for spatio-temporal effects (Rey and Le Gallo, 2009).[80] These approaches have been widely applied across fields, including: spatial pattern recognition in crime data (Messner, Anselin, Baller, Hawkins, Deane, and Tolnay, 1999); to the analysis of regional income distributions and convergence (Rey and Montouri, 1999; Dall'Erba, 2005; Le Gallo and Ertur, 2003); the identification of broader spatio-temporal structures in shopping centre data (Yu, Zhang, Wang, Wang, and Lu, 2025); and to the study of urban development using directional LISA methods (Sastré Gutiérrez and Rey, 2013; Vallone and Chasco, 2020). These types of methodological approaches draw on quantitative geography and directional statistics, employing methods such as rose diagrams to map the orientation of movement within distributions (Murray, Grubesic, Wei, and Mack, 2011; Sastré Gutiérrez and Rey, 2013). They capture whether countries with similar levels of home bias cluster together in space in non-random ways (Anselin, 1995; Rey and Le Gallo, 2009) and whether those clusters persist, diverge, or converge over time through transition and directional dynamics (Rey, Murray, and Anselin, 2011; Rey, 2014). In doing so, they move the analysis of EHB beyond static averages to account for joint space-time interactions, directional trajectories, and regional clustering effects (Clark and Wójcik, 2007; Haberly and Wójcik, 2022). At the time of writing, this is the first attempt to adopt such methods to investigate the EHB puzzle.

5.3 Data

Chapter 5 uses the model-based EHB measure across 43 countries from 2001 through 2020 (Chapter 3), together with the boundary-based, distance-weighted neighbourhood structures (Chapter 4). As in Chapter 3, the model-based EHB measure is defined in Eq. [1].[81]

[80] By way of context, the analysis undertaken in Chapter 4 tested for static spatio-temporal effects for a given state (Anselin, 1995). Chapter 5 attempts to address this limitation by incorporating the temporal dimension through Transition and Directional LISA for 20-year and five-year blocks (Rey, Murray, and Anselin, 2011). The former has been denoted as Exploratory spatial data analysis (ESDA) and the latter Exploratory Space-Time Data Analysis (ESTDA) (Rey, Murray, and Anselin, 2011).

[81] Refer to Chapter 3 for more details.

$$EHB_{i,t} = 1 - \frac{w_{i,t}^{A}}{w_{i,t}^{o}} \quad [1]$$

where $EHB_{i,t}$ is the EHB of country i in time t, $w_{i,t}^{A}$ is the actual weight or holdings of country i in time t, (Eq. [2]) , and $w_{i,t}^{o}$ is the optimal weight of country i i time t, (Eq. [3]).

$$w_{i,t}^{A} = \frac{FEA_{i,t}}{FEA_{i,t} + mc_{i,t} - FEL_{i,t}} \quad [2]$$

$$\omega_{i,t}^{o} = 1 - \frac{mc_{i,t}}{wmc_{t}} \quad [3]$$

where $mc_{i,t}$ is the market capitalisation of country i in time t and wmc_{t} is the world market capitalisation in time t.

To define the neighbourhood structures, Chapter 5 uses the boundary-based, distance-weighted neighbourhoods ($HN_{B=MSCI\ ACWI, d(f(C_{B=MSCI\ ACWI}))}$). This is identical to the approach used in Chapter 4, where the boundary is set by the MSCI ACWI benchmark groups and the distance is measured as the spherical distance between financial centres of the 43 countries in the sample (Z/Yen Group and Long Finance, 2025).[82] This specification allows the analysis to compare institutional benchmark logics (captured by boundary-based neighbourhoods) with geographic proximity (captured by distance-weighted neighbourhoods), ensuring continuity with the methodological design in Chapter 4.

[82] Refer to Chapter 4 for more details.

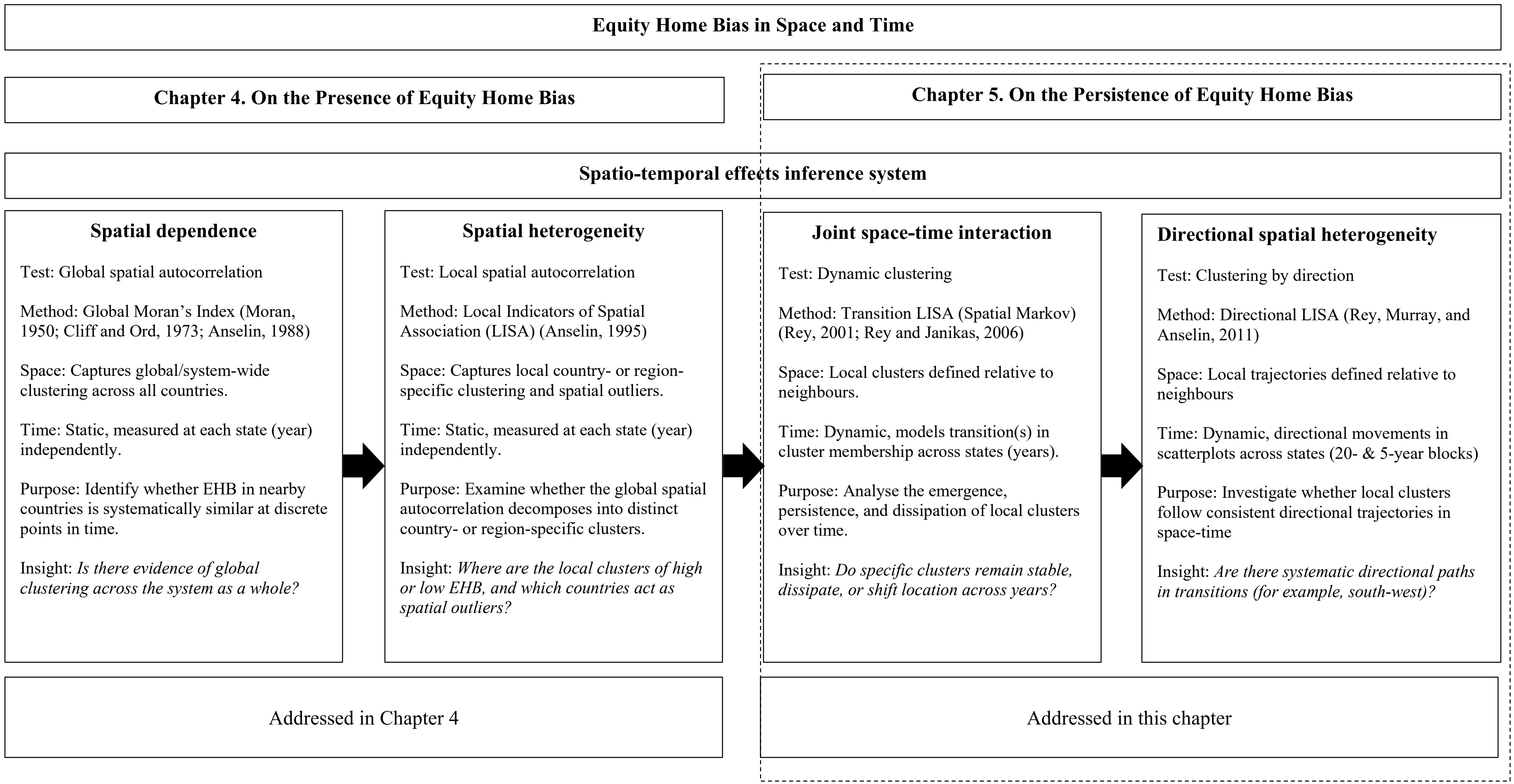
5.4 Methodology

Chapter 4 introduced the Framework for testing spatio-temporal effects (Figure 4.1) in EHB. Chapter 4 addressed two central lines of inquiry within the spatio-temporal inference system: the testing of spatial dependence and the testing of spatial heterogeneity. Upon confirming the *presence* of EHB, and its spatial dependence at both global and local levels, Chapter 5 builds upon that foundation to test for the *persistence* of EHB, specifically: *joint space-time interaction*; and, *directional spatial heterogeneity* (Figure 5.1).

Joint space-time interaction refers to the extent to which EHB trajectories across countries are jointly determined by persistence in their own bias (home) and spillover effects from neighbouring countries' bias, producing coordinated patterns rather than independent dynamics (Rey, Murray, and Anselin, 2011, Rey, 2014). Identifying such joint space-time interaction is crucial for understanding spatial path dependencies (Rey, 2001). In this study, joint space-time interaction is formally tested using Transition LISA (Spatial Markov), which examines whether the *persistence* of EHB in a country depends on the EHB levels of its neighbouring countries, capturing joint space-time dependence.

In contrast, directional spatial heterogeneity focuses on testing whether the spatial relationship of EHB evolves over time at the level of individual countries, and is examined using Directional LISA (Rey, Murray, and Anselin, 2011; Rey, 2014). Each arrow in the Moran (1950) scatterplot represents the movement of a country in LISA space, illustrating shifts from an initial state to a later state for both the home country and its spatial neighbours, while rose diagrams summarise the frequency and orientation of these arrows across all observations (Murray, Grubesic, Wei, and Mack, 2011; Rey and Sastré Gutiérrez, 2010; Sastré Gutiérrez and Rey, 2013). Identifying such directional dynamics is important because it reveals whether changes in EHB are reinforcing existing spatial clusters, breaking away from them, or moving toward new configurations. This provides insights into the *persistence* or reconfiguration of spatial dependence over time and highlights which countries act as sources of convergence or divergence in global EHB patterns (Rey, 2001, 2014).

Figure 5.1 Framework for testing spatio-temporal effects



5.4.1 Joint space-time interaction

As discussed, the Global Moran's Index (global spatial dependence) and LISA analysis (local spatial heterogeneity) are cross-sectional tools for a given state (Moran, 1950; Cliff and Ord, 1981; Anselin, 1988). The analysis conducted in Chapter 5 begins its examination of the joint interaction between space and time by examining the year-to-year changes of the LISA clusters (transitions) of each neighbourhood structure (Rey, Murray, and Anselin, 2011; Rey, 2014). To do this, the study adopts the Transition LISA (spatial Markov) framework originally developed by Quah (1993) to analyse the dynamics of regional income distributions and then further extended by Rey (2014) to account explicitly for spatial context. This method allows for an investigation of how local spatial clusters evolve over time, providing a richer understanding of spatio-temporal effects on the EHB puzzle.

5.4.1.1 Transition LISA

The Transition LISA (Spatial Markov chain) framework extends the conventional Markov chain analysis by explicitly incorporating the role of spatial dependence in state transitions by using the LISA clusters computed in Chapter 4. While a standard Markov chain examines the probability that a country's EHB persists in, or moves between, different states over time (Markov, 1906; Grimmett and Stirzaker, 2020), the Transition LISA framework conditions these transition probabilities on the states of neighbouring countries, embedding spatial context into the temporal dynamics (Quah, 1993; Rey, 2001; Rey and Janikas, 2006; Rey, 2014).

In this framework, the transition probability matrix captures the likelihood that a given country's LISA cluster status will change from one cluster to another over time. By analysing these probabilities, it is possible to assess the stability or mobility of local spatial clusters, and to determine whether high- or low-EHB regimes persist, dissipate, or shift over time (Rey, 2001; Rey and Janikas, 2006). The stationary distribution (Markov chain) derived from this matrix indicates the long-run equilibrium distribution of LISA clusters if the same transition dynamics continue indefinitely. Together, the transition probabilities and stationary distribution offer valuable insights into the persistence, convergence, or divergence of spatio-temporal effects and reveal whether clustering in EHB is temporary or long lasting (Rey, Murray, and Anselin, 2011; Rey, 2014).

A stationary distribution of a Markov chain is a probability distribution that remains constant as time progresses (Grimmett, and Stirzaker, 2020). Once the Markov chain reaches its stationary distribution, the probabilities of a country belonging to each spatial cluster remain constant with further transitions. Stationary distributions are fundamental for understanding the long-term behaviour of Markov processes and are often used to characterise steady-state conditions in various applications, including spatio-temporal models such as transition LISA.

The following hypothesis is set up regarding the joint space-time interaction in the movement of a neighbourhood structure:

H_0: *There is no joint space-time interaction in the movement between a home country and its neighbour countries.*
H_1: *There is a joint space-time interaction in the movement between a home country and its neighbour countries.*

The above hypothesis is tested using the following steps.

Step 1: The transition LISA matrix (observed counts matrix) - The EHB of each country (home, H) and the weighted average EHB of its neighbour countries (neighbours) are classified into four states (using the LISA clusters introduced in Chapter 4) across two periods, as detailed in the matrix presented in Eq. [1] (Anselin, 1995; Rey and Janikas, 2006).

$$v(home\ EHB, neighbours\ EHB) = \begin{pmatrix} v_{11}\ v_{12}\ v_{13}\ v_{14} \\ v_{21}\ v_{22}\ v_{23}\ v_{24} \\ v_{31}\ v_{32}\ v_{33}\ v_{34} \\ v_{41}\ v_{42}\ v_{43}\ v_{44} \end{pmatrix} \qquad [1]$$

The observed joint transition counts in Eq. [1] is a 4×4 matrix representing the transition counts between the four states for the period 2001 to 2020. Here, v_{lm} denotes the counts of a home country and its neighbours transitioning from state l to state m over the period 2001 to 2020, where $l = \{1, 2, 3, 4\}$ and $m = \{1, 2, 3, 4\}$ are ordered as shown in Figure 4.3. For example, v_{12} is the joint count of a neighbourhood structure moving from LISA cluster 1 (which is the Low-Low cluster) to LISA cluster 2 (which is the High-Low cluster) from 2001 to 2020.

Step 2: The transition LISA matrix (observed probability matrix) - Using the count details in the matrix presented in Eq. [1], the observed joint transition probabilities are computed by dividing each cell count by the row sum as presented in Eq. [2] (Rey, 2001; Rey and Janikas, 2006).

$$p(home\ EHB, neighbours\ EHB) = \begin{pmatrix} p_{11}\ p_{12}\ p_{13}\ p_{14} \\ p_{21}\ p_{22}\ p_{23}\ p_{24} \\ p_{31}\ p_{32}\ p_{33}\ p_{34} \\ p_{41}\ p_{42}\ p_{43}\ p_{44} \end{pmatrix} \quad [2]$$

Step 3: Spatial Markov chain for steady-state - A stationary distribution of a Spatial Markov chain is a probability distribution that remains unchanged in the Spatial Markov chain as time progresses. To estimate p_{lm} for a stationary chain, it is necessary to obtain the observed number of transitions (counts) v_{lm} from l to m over the period 2001 to 2020 in a matrix of dimension 4×4. Typically, the stationary chain is represented as a row vector π whose entries are probabilities summing to 1, and given transition matrix P, it satisfies $\pi P = \pi$ (Grimmett and Stirzaker, 2020; Rey, 2014).

Step 4: Test for joint space-time interactions - From the EHB data observed from 2001 to 2020, the transition probability matrices for a home chain (p(*home EHB*)) and neighbour chain ($p(neighbours\ EHB)$) can be estimated separately, both with dimensions of 2×2 where each of these chains have two states High and Low as per the LISA framework. Under the null hypothesis of independence or lack of spatial dynamics:[83]

$$p(\widehat{country\ EHB, neighbours}\ EHB) = p(\widehat{country\ E}HB) \otimes p(\widehat{neighbours}\ EHB)$$

The estimated joint transition probability matrix with dimensions of 4×4 is:

$$p(country\ \widehat{EHB, neighbours}\ EHB) = \widehat{p_{lm}}.$$

[83] Where $\otimes$ represents the Kronecker product and under null hypothesis, it tests whether the joint transition process can be factored into separate marginal processes (home and neighbour EHB evolving independently).

Estimates of the corresponding observed (p_{lm}) and estimated ($\widehat{p_{lm}}$) joint transition probability matrices are compared, and a formal test χ^2 permits testing of the equality of both matrices. Under the null hypothesis $p_{lm} = \widehat{p_{lm}}$.

$$\sum_{m=1}^{4} v_l^* \frac{(p_{lm} - \widehat{p_{lm}})^2}{\widehat{p_{lm}}} \qquad [3]$$

has an asymptotic χ^2 distribution with 9 ($(4-1) \times (4-1)$) degrees of freedom where $v_l^* = \sum_{m=1}^{4} v_{lm}$. Rejection of the null hypothesis means that the Spatial Markov chain associated with a given neighbourhood structure joint space-time interaction is not separable (that is, the evolution of a home country's EHB is not independent of its neighbours' EHB evolution) indicating that a joint spatio-temporal interaction exists (Rey, Mack, and Koschinsky, 2012; Carracedo, Debón, Iftimi, and, Montes, 2018).

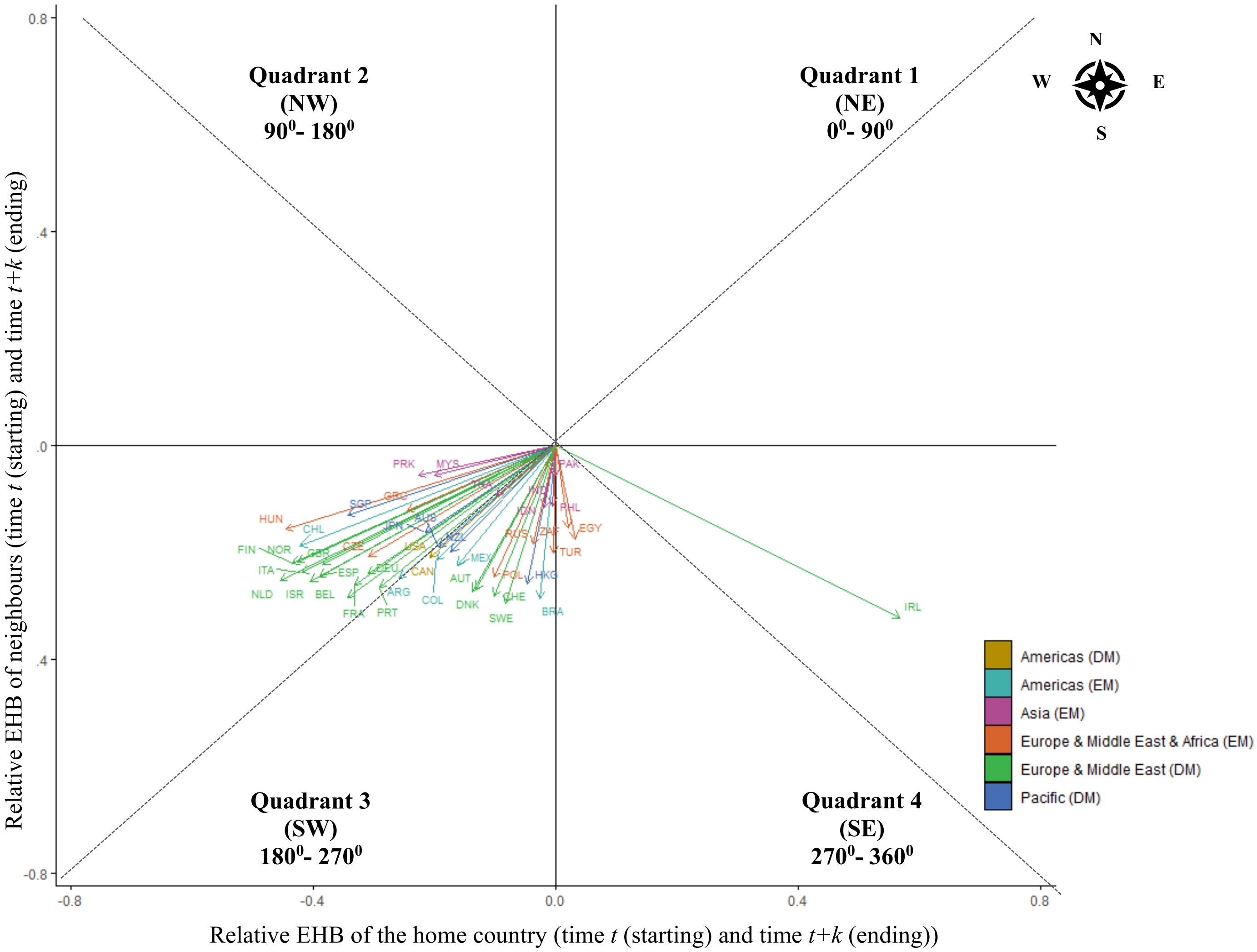
5.4.2 Directional spatial heterogeneity

The test of joint space-time interaction using the Transition LISA matrix estimates the probability that a neighbourhood structure will move between LISA states over time. While this approach provides valuable information on persistence and change, it does not allow the evolution of these movements to be visualised. To capture this dynamic graphically, the Directional LISA methodology represents movements as arrows in the Moran (1950) scatterplot and summarises their orientation and frequency through rose diagrams (Rey, Murray, and Anselin, 2011; Carracedo, Debón, Iftimi, and, Montes, 2018).

5.4.2.1 Directional LISA

Directional LISA is designed to visualise how EHB moves over time within neighbourhood structures. It does this by creating origin-standardised movement vectors, that is, arrows that show how a country and its neighbours shift between two points in time (for instance, comparing Global Moran scatterplots for 2001 and 2020) (Rey and Sastré Gutiérrez, 2010; Sastré Gutiérrez and Rey, 2013). The novelty of this approach is that it combines cluster identification with directional information, allowing researchers to see not just where clusters exist, but also how they move. In this way, Directional LISA provides insights into both the direction and the magnitude of changes in EHB over time.

Figure 5.2 Directional LISA plot 2001-2020 example - Standardised to the origin (2001)



In the Directional LISA example (Figure 5.2), the four quadrants capture distinct spatial and directional dynamics of EHB movements:

- Quadrant 1 (North-East, NE): *Joint upward convergence*, both the home country and its neighbours increase EHB;
- Quadrant 2 (North-West, NW): *Neighbour-led divergence*, the home country reduces EHB while its neighbours increase theirs;
- Quadrant 3 (South-West, SW): *Joint downward convergence*, both the home country and its neighbours reduce EHB; and
- Quadrant 4 (South-East, SE): *Home-led divergence*, the home country increases EHB while its neighbours reduce theirs.

This quadrant framework allows for a clear interpretation of directional dynamics, showing whether changes in EHB represent convergence (joint upward or joint downward) or divergence (home-led or neighbour-led). In a Directional LISA analysis, the goal is to examine how the spatial relationship of EHB evolves over time for each observation. Each arrow in the plot represents the movement of a unit in space, showing changes from an initial state to a final state both for the home country and its spatial neighbours. Figure 5.2 illustrates how the distribution and orientation of these arrows are summarised using a rose diagram, which provides a concise way of visualising the overall directional patterns across all neighbourhood structures and periods (Murray, Grubesic, Wei, and Mack, 2011; Rey and Sastré Gutiérrez, 2010; Sastré Gutiérrez and Rey, 2013). To determine whether these directional changes are statistically meaningful, the following hypothesis test is applied:

H_0: *Observed directional changes are random with respect to spatial structure*
H_1: *Observed directional changes are not random*

The null hypothesis establishes that directional movements of an observation and its neighbours are independent, meaning that any pattern of clustering or movement could occur by chance (no spatial association). The test involves repeatedly randomizing the values of neighbours according to the spatial weights matrix, recalculating the directional vectors, and comparing the resulting distribution of angles or magnitudes to the observed data by permuting the neighbours 999 times. From this, *p-values* are derived for each directional bin or observation, indicating the probability that the observed change could occur under the null hypothesis. Significant movements (that is, $p\ value \leq 0.05$) suggest that the directional change is unlikely to be due to random chance, highlighting meaningful shifts in the spatial pattern. These significance results can be visualised either as shading or transparency on the arrows themselves, or in an accompanying rose plot, providing a clear visual summary of both the direction and reliability of spatial changes.

In this analysis, the above hypothesis is first tested for a 20-year block (the full sample period, 2001 through 2020). Then, four, five-year blocks (2001 to 2005; 2005 to 2010; 2010 to 2015; 2015 to 2020) are considered to understand the directional changes of EHB across each five-year block. It is important to acknowledge that this analysis employs *overlapping* five-year blocks to trace directional changes in EHB. Specifically, each block begins at the final year of the previous block to preserve continuity (specifically: 2001-2005; 2005-2010; 2010-2015; and, 2015-2020). This overlapping design is used to capture medium-term dynamics and the impact of systemic shocks (such as the GFC), while ensuring that transitions at the boundaries of periods are not missed (Rey and Montouri, 1999; Fratzscher, 2009; Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2012). For completeness, a country-level case study for Australia is reported to provide a home-country perspective to the analysis.

To visualise the Directional LISA movement patterns, rose diagrams are employed to summarise the orientation and frequency of movement vectors across all observations (Sastré Gutiérrez and Rey, 2013; Vallone and Chasco, 2020). As discussed, rose diagrams provide a graphical representation of the Directional LISA inference results, illustrating how often countries and their neighbours move in each direction (NE, NW, SW, SE). The null hypothesis assumes that the distribution of vectors across the circular segments reflects independence in the movements of the home country and its spatial lag (neighbours). Statistical inference is conducted using random spatial permutations under this null hypothesis, allowing for the identification of statistically significant arrows in the Directional LISA plot and corresponding sectors in the rose diagram (Rey, Murray, and Anselin, 2011).

Operationally, the estimation follows the approach of Murray, Grubesic, Wei, and Mack (2011), who use circular histograms to analyse angular motion. A circular partition scheme is applied, where each directional vector is assigned to one of four partitions (P = 4 circular segments), corresponding to the quadrants of directional movement: Quadrant 1 (NE); Quadrant 2 (NW); Quadrant 3 (SW); Quadrant 4 (SE). This framework facilitates interpretation of both the magnitude (length of arrows) *and* the orientation (direction of arrows) of spatial changes in EHB over defined blocks (Rey and Sastré Gutiérrez, 2010).

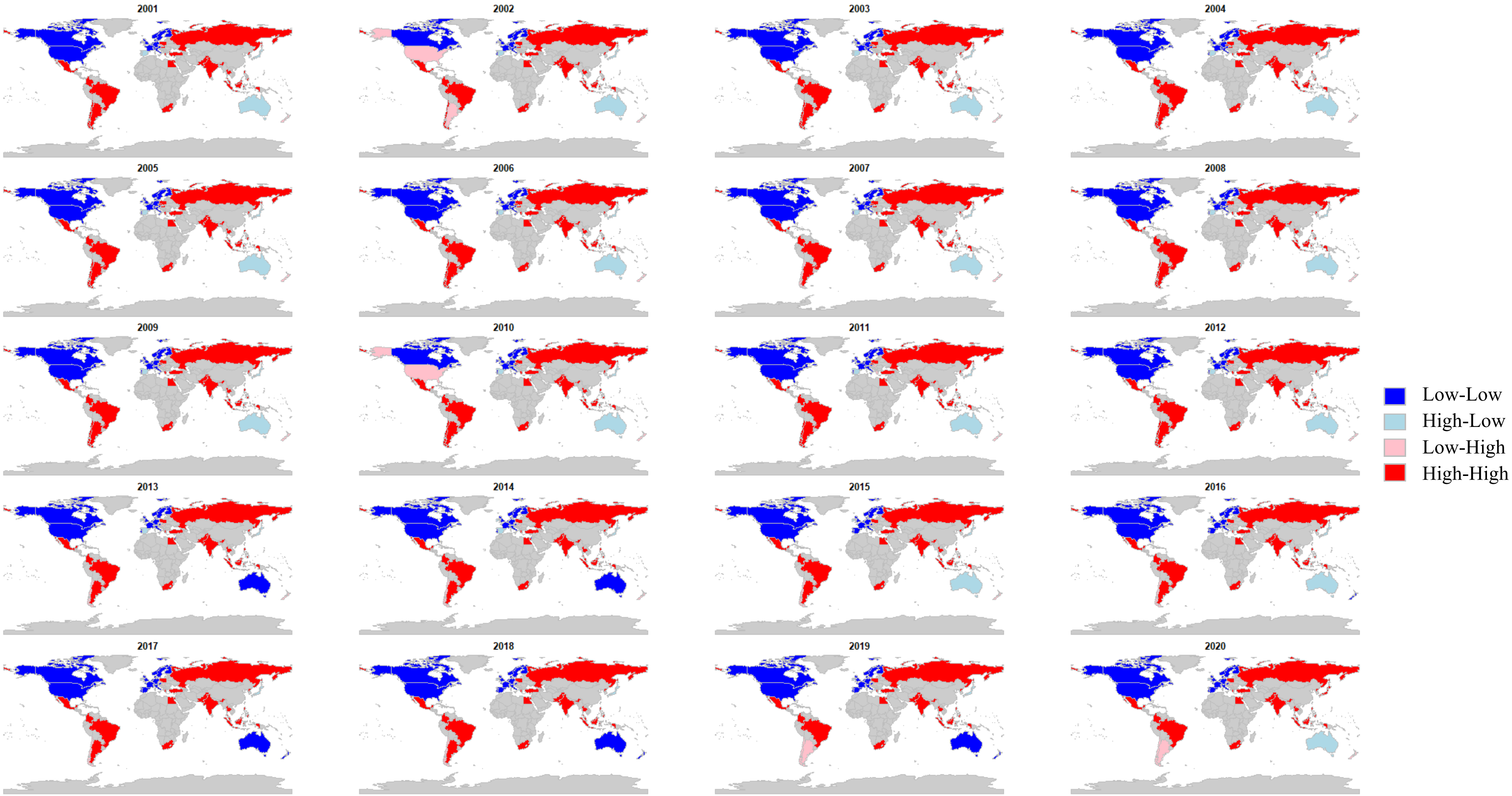
5.5 Analysis

The study now turns to specific questions related to the *persistence* of EHB. Three related questions are posed: Do EHB patterns exhibit joint space-time movements? Do specific clusters remain stable, dissipate, or shift location across years? And, are there systematic directional paths in these transitions (for example, SW movements)? The analysis presented in Chapter 5 follows two main lines of inquiry, consistent with the empirical framework in Figure 5.1: first, joint space-time interaction, tested using Transition LISA; and, second, directional spatial heterogeneity, examined using Directional LISA to assess the directional movements of neighbourhood structures.

5.5.1 Testing for joint space-time interaction

Chapter 5 begins by summarising the LISA classifications from Chapter 4. Figure 5.3 presents, for each state (year) from 2001 to 2020, whether each neighbourhood structure belongs to a Low-Low, High-Low, Low-High, or High-High cluster, using the boundary-based MSCI ACWI index as the benchmark and applying distance-weighted neighbourhoods, neighbourhoods ($HN_{B=MSCI\ ACWI,d(f(C_{B=MSCI\ ACWI}))}$). However, as noted previously, these annual maps only highlight local patterns at a given state and do not capture their temporal evolution. To track these changes explicitly, the observed transitions between LISA states are reported. Table 5.1 lists, for each neighbourhood structure and year, the transition from its LISA state in year t to its LISA state in year t+1 (this reflects the Transition LISA framework of Rey and Janikas (2006), based on Anselin's 1995 LISA classification). Finally, Table 5.2 provides a summary of the observed transition counts across the sample, aggregating the year-to-year moves to show which transitions are frequent (for instance, staying in the same state) and which are rarely observed. Having established the observed transitions, Transition LISA framework converts these counts into transition probabilities to estimate the implied steady-state distribution, thereby assessing the persistence of EHB regimes over the full sample period.

Figure 5.3 LISA cluster classification for boundary-based, distance weighted neighbours ($HN_{B=MSCI\ ACWI,d(f(c_{B=MSCI\ ACWI}))}$)



Notes: LISA state classification using a boundary-based, distance-weighted neighbourhood structure. The map highlights spatial clusters of Low-Low (blue), High-Low (light blue), Low-High (pink), and High-High (red) for each state.

Table 5.1 Observed number of transitions from state for a country and its neighbourhood to the next period

	Group	ISO3	2001 2002	2002 2003	2003 2004	2004 2005	2005 2006	2006 2007	2007 2008	2008 2009	2009 2010	2010 2011	2011 2012	2012 2013	2013 2014	2014 2015	2015 2016	2016 2017	2017 2018	2018 2019	2019 2020
	AM_DM	CAN	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	AM_DM	USA	1,3	3,1	1,1	1,1	1,1	1,1	1,1	1,1	1,3	3,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	AUT	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	BEL	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	DNK	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	FIN	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	FRA	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	DEU	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	IRL	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2
	EME_DM	ISR	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,1	1,1	1,1	1,2	2,2	2,2	2,1	1,1	1,1
	EME_DM	ITA	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	NLD	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	NOR	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	PRT	2,1	1,2	2,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	ESP	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	SWE	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	CHE	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	EME_DM	GBR	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1	1,1
	PAC_DM	AUS	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,1	1,1	1,2	2,2	2,1	1,1	1,1	1,2
	PAC_DM	HKG	2,2	2,2	2,1	1,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2
	PAC_DM	JPN	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,2	2,4
	PAC_DM	NZL	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,1	1,1	1,1	1,1	1,3
	PAC_DM	SGP	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3
	AM_EM	ARG	4,3	3,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,3	3,3
	AM_EM	BRA	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AM_EM	CHL	4,4	4,4	4,4	4,4	4,4	4,3	3,4	4,4	4,4	4,4	4,4	4,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3
	AM_EM	COL	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AM_EM	MEX	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4

	EMEA_EM	CZE	3,3	3,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3
	EMEA_EM	EGY	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	EMEA_EM	GRC	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,3	3,4	4,4	4,4	4,3	3,4	4,4	4,4	4,4	4,4
	EMEA_EM	HUN	4,4	4,4	4,4	4,4	4,4	4,4	4,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3	3,3
	EMEA_EM	POL	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	EMEA_EM	RUS	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	EMEA_EM	ZAF	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	EMEA_EM	TUR	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AS_EM	IND	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AS_EM	IDN	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AS_EM	KOR	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AS_EM	MYS	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AS_EM	PAK	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AS_EM	PHL	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4
	AS_EM	THA	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4	4,4

Note: 1 stands for Low-Low, 2 stands for High-Low, 3 stands for Low-High, and, 4 stands for High-High. Transitions from LISA cluster 1 in the previous year to LISA cluster 1 in the next year is (1,1). Transitions from LISA cluster 1 in the previous year to LISA cluster 2 in the next year is (1,2) etc.

Table 5.2 Summary of observed counts of transitions by columns in Table 5.1

LISA id in time T to T+1	LISA state in time T to T+1	2001 2002	2002 2003	2003 2004	2004 2005	2005 2006	2006 2007	2007 2008	2008 2009	2009 2010	2010 2011	2011 2012	2012 2013	2013 2014	2014 2015	2015 2016	2016 2017	2017 2018	2018 2019	2019 2020	Row sum
1,1	Low- Low to Low-Low	14	14	15	16	16	16	16	16	15	15	15	16	17	15	16	17	18	19	17	**303**
1,2	Low- Low to High-Low	0	1	0	1	0	0	0	0	0	0	1	0	0	2	0	0	0	0	1	**6**
1,3	Low- Low to Low-High	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	**3**
1,4	Low- Low to High-High	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
2,1	High-Low to Low- Low	1	0	2	0	0	0	0	0	0	0	1	1	0	1	0	1	1	0	0	**8**
2,2	High-Low to High-Low	5	5	4	4	5	5	5	5	5	5	4	4	4	3	5	4	3	3	2	**80**
2,3	High-Low to Low-High	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
2,4	High-Low to High-High	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	**1**
3,1	Low-High to Low- Low	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	**3**
3,2	Low-High to High-Low	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
3,3	Low-High to Low-High	3	2	2	2	2	2	2	3	3	3	3	3	5	5	4	4	4	4	5	**61**
3,4	Low-High to High-High	0	2	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	**5**
4,1	High-High to Low- Low	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
4,2	High-High to High-Low	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
4,3	High-High to Low-High	1	0	0	0	0	1	1	0	0	1	0	2	0	1	0	0	0	1	0	**8**
4,4	High-High to High-High	18	18	20	20	20	19	18	19	19	18	18	17	17	16	16	17	17	16	16	**339**
Column sum		43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	43	**817**

5.5.1.1 Results of Transition LISA (Spatial Markov)

The Transition LISA results summarise how countries move between local spatial regimes through time. Persistence is indicated when countries remain in the same cluster type across periods, while mobility is reflected in transitions between regimes. High probabilities along the main diagonal therefore signal temporal stability in local spatial relationships, whereas off-diagonal elements capture changes in neighbourhood structure. Tables 5.1 and 5.2, Table 5.3 reports the observed LISA transition counts for all neighbourhood structures over the full period (2001 through 2020). In each period, a home country and its weighted neighbours can be classified into four mutually exclusive categories: Low-Low (1); High-Low (2); Low-High (3); and, High-High (4). As there are four possible starting quadrants and four possible destination quadrants for the next period, each neighbourhood structure has 4 × 4 = 16 potential transitions from one period to the next. The colour coding scheme of Table 5.2 is retained in Table 5.3 to assist the traceability.

Table 5.3 The transition LISA matrix (counts) for the period 2001-2020 (observed counts matrix)

		LISA state in time = T +1				
		Low-Low = 1	High-Low = 2	Low-High = 3	High-High = 4	Row sum
LISA state in time = T	Low-Low = 1	**303**	6	3	0	**312**
	High-Low = 2	8	**80**	0	1	**89**
	Low-High = 3	3	0	**61**	5	**69**
	High-High = 4	0	0	8	**339**	**347**
	Column sum	314	86	72	345	**817**

Note: Number of transitions from Cluster 1 (Low-Low) in year T to Cluster 1 (Low-Low) in T+1 is 303. Number of transitions from Cluster 1 (Low-Low) in year T to Cluster 2 (High-Low) in T+1 is 6, etc.

Next, Table 5.3 (observed counts) is converted into a transition probability matrix (Table 5.4) by dividing each cell count by the corresponding row sum. These probabilities are estimated under the assumption of temporal homogeneity across the sample (Rey and Ye, 2010; Rey, 2001; Rey and Janikas, 2006). The resulting probability matrix provides the basis for estimating the Spatial Markov chain. Before turning to the steady-state distribution, however, it is useful to examine the observed transition probabilities themselves, since they reveal how frequently countries remain within, or move between, LISA clusters from one year to the next.

Table 5.4 The transition LISA matrix (probabilities) for the period 2001-2020 (observed probability matrix)

		LISA state in time = T +1				
		Low-Low = 1	High-Low = 2	Low-High = 3	High-High = 4	Row sum
LISA state in time = T	Low-Low = 1	**0.9712**	0.0192	0.0096	0.0000	**1**
	High-Low = 2	0.0899	**0.8989**	0.0000	0.0112	**1**
	Low-High = 3	0.0435	0.0000	**0.8841**	0.0725	**1**
	High-High = 4	0.0000	0.0000	0.0231	**0.9769**	**1**

Note: Probability of transitions from Cluster 1 (Low-Low) in year T to Cluster 1 (Low-Low) in T+1 is 0.9712. Probability of transitions from Cluster 1 (Low-Low) in year T to Cluster 2 (High-Low) in T+1 is 0.0192, etc. The rows add to 1.

Having examined the transition counts in Table 5.3, the next step is to convert these into transition probabilities in order to standardise the results and make comparisons across states more meaningful. Table 5.4 reports the transition LISA matrix (probabilities) for the period 2001 through 2020 (observed probability matrix) and the extent to which *persistence* (clearly) dominates over mobility in the EHB distribution across space and through time.

First, movements are more frequent within quadrants (diagonals with high counts) than between them, confirming the anecdotal evidence found in Chapter 3; most countries tend to stay in the same spatial cluster (that is, High-High remains in High-High; Low-Low remains in Low-Low). For example, the 0.9712 value corresponding to the transition LL to LL (first cell) means that the probability that a low EHB country with low neighbours will remain in this same state for the next period is 97.12%. These within-state transitions (diagonal in Table 5.3) are more common than shifts to a different spatial type. This shows strong persistence over time in both the level and spatial structure of EHB. Examples of some neighbourhood structures in Low-Low state during the whole period from 2001 through to 2020 include Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Sweden, Switzerland, and, United Kingdom in the Europe & Middle East (DM) group, and, Canada in the Americas (DM) group.

The results in Tables 5.3 and 5.4 also show that it is virtually impossible for a neighbourhood structure to move directly between opposite states (that is, from High-High to Low-Low; from Low-Low to High-High; from Low-High to High-Low; or, from High-Low to Low-High). These off-diagonal transitions (see Tables 5.3 and 5.4) have counts and probabilities of zero. In other words, a simultaneous change in both the 'home' and 'neighbour' LISA clusters does not occur. In short, across the entire observation period, such transitions were not realised. These results (again) highlight why it is potentially misleading to treat the LISA classification as a static identifier (Anselin, 1995; Rey, 2001, 2014; Grimmett and Stirzaker, 2020; Rey and Janikas, 2006).

5.5.1.2 Spatial Markov chain for steady-state

Building on the insights from the observed transition matrices, we now turn to the estimation of the steady-state distribution implied by the Spatial Markov chain. The implied steady-state distribution of the Spatial Markov chain is estimated using the transition probabilities reported in Table 5.4. A stationary distribution of a Spatial Markov chain is a probability distribution that remains unchanged in the Spatial Markov chain as time progresses. Typically, it is represented as a row vector π whose entries are probabilities summing to 1, and for a given transition matrix P, it satisfies $\pi P = \pi$. The corresponding equations to calculate the spatial Markov chain are visualised in Table 5.5.

Table 5.5 Spatial Markov chain calculation

P =

		LISA state in time = T +1				Row sum
		Low - Low = 1	High - Low = 2	Low - High = 3	High - High = 4	
LISA state in time = T	Low - Low = 1	$P_{1,1}$	$P_{1,2}$	$P_{1,3}$	$P_{1,4}$	**1**
	High - Low = 2	$P_{2,1}$	$P_{2,2}$	$P_{2,3}$	$P_{2,4}$	**1**
	Low - High = 3	$P_{3,1}$	$P_{3,2}$	$P_{3,3}$	$P_{3,4}$	**1**
	High - High = 4	$P_{4,1}$	$P_{4,2}$	$P_{4,3}$	$P_{4,4}$	**1**

		LISA state in time = T +1				Row sum
		Low - Low = 1	High - Low = 2	Low - High = 3	High - High = 4	
LISA state in time = T	Low - Low = 1	**0.9712**	0.0192	0.0096	0.0000	**1**
	High - Low = 2	0.0899	**0.8989**	0.0000	0.0112	**1**
	Low - High = 3	0.0435	0.0000	**0.8841**	0.0725	**1**
	High - High = 4	0.0000	0.0000	0.0231	**0.9769**	**1**

π = $[\pi_1 \ \ \pi_2 \ \ \pi_3 \ \ \pi_4]$

$$\pi P = \left[\sum_{i=1}^{4} \pi_i P_{i,1} \quad \sum_{i=1}^{4} \pi_i P_{i,2} \quad \sum_{i=1}^{4} \pi_i P_{i,3} \quad \sum_{i=1}^{4} \pi_i P_{i,4}\right]$$

$$0.9712 * \pi_1 + 0.0899 * \pi_2 + 0.0435 * \pi_3 + 0.0000 * \pi_4 = \pi_1$$

$$0.0192 * \pi_1 + 0.8989 * \pi_2 + 0.0000 * \pi_3 + 0.0000 * \pi_4 = \pi_2$$

$$0.0096 * \pi_1 + 0.0000 * \pi_2 + 0.8841 * \pi_3 + 0.0231 * \pi_4 = \pi_3$$

$$0.0000 * \pi_1 + 0.0112 * \pi_2 + 0.0725 * \pi_3 + 0.9769 * \pi_4 = \pi_4$$

$$\pi_1 + \pi_2 + \pi_3 + \pi_4 = 1$$

Solving these equations, the Spatial Markov chain for steady-state is obtained as presented in Table 5.6:

Table 5.6 The Spatial Markov chain

Low - Low = 1	High - Low = 2	Low - High = 3	High - High = 4
π_1	π_2	π_3	π_4
0.4470	0.0850	0.1030	0.3660

The steady-state distribution in Table 5.6 shows that the Low-Low cluster has the highest long-run probability (44.70%), suggesting that neighbourhood structures exhibit a persistent tendency toward lowering their EHB positions over time. The second-highest steady-state probability is for the High-High cluster (36.60%), indicating that once neighbourhood structures are in high-EHB positions, they are likely to remain there, implying difficulty in reducing EHB. This highlights the long-run stability and spatial persistence of EHB, reinforcing the presence of spatial heterogeneity (Rey, 2001; Rey and Janikas, 2006; Rey, 2014).

5.5.1.3 Hypothesis testing for joint space-time interaction

Using the derived Spatial Markov chain, the final step is to formally test for joint space-time interaction, that is, the Transition LISA (Rey, Mack, and Koschinsky, 2012). This can be performed by decomposing the Spatial Markov chain into a pair of chains: one for the country of interest (home) and the other for its neighbours. Each chain has two states: High; and, Low:

- Home chain: the Markov chain describes how a country's own LISA cluster evolves over time (that is, whether its EHB moves from Low to High); and
- Neighbour chain: the Markov chain describes how the weighted average of neighbours evolves over time.

Separately, these are each 2×2 chains. Together, they define a joint process (the Spatial Markov chain). Summarising LISA transition counts for the period 2001 through 2020, the home chain (Tables 5.7 and 5.8) and neighbour chain (Tables 5.9 and 5.10) can be calculated as follows:

Table 5.7 Home chain (counts)

	Low	High	Row sum
Low	370	11	381
High	16	420	436

Table 5.8 Home chain (probabilities)

	Low	High	Row sum
Low	0.9711	0.0289	1
High	0.0367	0.9633	1

Table 5.9 Neighbour chain (counts)

	Low	High	Row sum
Low	397	4	401
High	3	413	416

Table 5.10 Neighbour chain (probabilities)

	Low	High	Row sum
Low	0.9900	0.0099	1
High	0.0072	0.9928	1

Using these two chains for home and neighbours, the expected probability matrix is calculated under the null of independence. That is, if the home *and* neighbour transitions are independent, the joint transition matrix can be calculated by multiplying the above two chains using the Kronecker product (Table 5.11 provides illustration of calculating the expected probabilities).[84]

[84] In addition, a worked example illustrating how the transition probabilities for both the home chain and the neighbour chain are computed is provided in Appendix 8. This includes step-by-step calculations of observed transitions, relative frequencies, and the derivation of the transition matrices for the Spatial Markov analysis.

Table 5.11 Calculating the expected probabilities

Home chain (probabilities)		Neighbour chain (probabilities)		Joint chain using the Kronecker product
$\begin{bmatrix} 0.9711 & 0.0289 \\ 0.0367 & 0.9633 \end{bmatrix}$	$\otimes$	$\begin{bmatrix} 0.9900 & 0.0099 \\ 0.0072 & 0.9928 \end{bmatrix}$	=	$\begin{matrix} 0.9711 \begin{bmatrix} 0.9900 & 0.0099 \\ 0.0072 & 0.9928 \end{bmatrix} & 0.0289 \begin{bmatrix} 0.9900 & 0.0099 \\ 0.0072 & 0.9928 \end{bmatrix} \\ 0.0367 \begin{bmatrix} 0.9900 & 0.0099 \\ 0.0072 & 0.9928 \end{bmatrix} & 0.9633 \begin{bmatrix} 0.9900 & 0.0099 \\ 0.0072 & 0.9928 \end{bmatrix} \end{matrix}$

Table 5.12 The LISA transition matrix (probabilities) for the period 2001-2020 (expected probability matrix)

		LISA state in time = T +1				Row Sum
		1	2	3	4	
LISA state in time = T	1	0.9711×0.9900 = 0.9614	0.9711×0.0099 = 0.0096	0.0289×0.9900 = 0.0286	0.0289×0.0099 = 0.0003	1
	2	0.9711×0.0072 = 0.0069	0.9711×0.9928 = 0.9642	0.0289×0.0072 = 0.0002	0.0289×0.9928 = 0.0287	1
	3	0.0367×0.9900= 0.0363	0.0367×0.0099 = 0.0004	0.9633×0.9900 = 0.9537	0.9633×0.0099 = 0.0095	1
	4	0.0367×0.0072 = 0.0003	0.0367×0.9928 = 0.0364	0.9633×0.0072 = 0.0069	0.9633×0.9928 = 0.9564	1

Table 5.13 The LISA transition matrix (counts) for the period 2001-2020 (expected counts matrix)

		LISA state in time = T +1				Row Sum
		1	2	3	4	
LISA state in time = T	1	0.9614×312 = 299.95	0.0096×312 =3.00	0.0286×312 = 8.93	0.0003×312 = 0.09	312
	2	0.0069×89 =0.62	0.9642×89 = 85.81	0.0002×89 = 0.02	0.0287×89 = 2.55	89
	3	0.0363×69 = 2.50	0.0004×69 = 0.03	0.9537×69 = 65.80	0.0095×69 = 0.66	69
	4	0.0003×347 = 0.09	0.03364×347 = 12.64	0.0069×347 = 2.41	0.9564×347 = 331.86	347

The final step is to compare the expected counts in Table 5.13 (under the null of independence assumption) with the observed counts in Table 5.3. Test χ^2 test statistic under the null hypothesis of independence is given by:

$$\chi^2 = \sum_{m=1}^{4} v_l^* \frac{(p_{lm} - \widehat{p_{lm}})^2}{\widehat{p_{lm}}}$$

The statistic follows a χ^2 distribution, where the null hypothesis is the independence of the two chains (Carracedo, Debón, Iftimi, and Montes, 2018). In this case, the null and alternative hypotheses are:

H_0: *There is no joint space-time interaction of the movement of a home country and its neighbour countries;*

H_1: *There is a joint space-time interaction of the movement of a home country and its neighbour countries.*

Table 5.3 The LISA transition matrix (counts) for the period 2001-2020 (observed counts matrix)

		LISA state in time = T +1				Row sum
		LL = 1	HL = 2	LH = 3	HH = 4	
LISA state in time = T	LL = 1	**303**	6	3	0	**312**
	HL = 2	8	**80**	0	1	**89**
	LH = 3	3	0	**61**	5	**69**
	HH = 4	0	0	8	**339**	**347**
	Column sum	314	86	72	345	**817**

Table 5.13 The LISA transition matrix (counts) for the period 2001-2020 (expected counts matrix)

		LISA state in time = T +1				Row sum
		LL = 1	HL = 2	LH = 3	HH = 4	
LISA state in time = T	LL = 1	299.95	3.00	8.93	0.09	**312**
	HL = 2	0.62	85.81	0.02	2.55	**89**
	LH = 3	2.50	0.03	65.80	0.66	**69**
	HH = 4	0.09	12.64	2.41	331.86	**347**
	Column sum	**303**	**102**	**77**	**335**	**817**

The calculated test statistic under the null hypothesis of independence is:

$$\chi^2_{df=9} = \sum_{m=1}^{4} \nu_l^* \frac{(p_{lm} - \widehat{p_{lm}})^2}{\widehat{p_{lm}}}$$

$$= \frac{(303-299.95)^2}{299.95} + \frac{(6-3)^2}{3} + \frac{(3-8.93)^2}{8.93} + \frac{(0-0.09)^2}{0.09} + \frac{(8-0.62)^2}{0.62} + \frac{(80-85.81)^2}{85.81} + \frac{(0-0.02)^2}{0.02} +$$

$$\frac{(1-2.55)^2}{2.55} + \frac{(3-2.50)^2}{2.50} + \frac{(0-0.03)^2}{0.03} + \frac{(61-65.80)^2}{65.80} + \frac{(5-0.66)^2}{0.66} + \frac{(0-0.09)^2}{0.09} + \frac{(0-12.64)^2}{12.64} +$$

$$\frac{(8-2.41)^2}{2.41} + \frac{(339-331.86)^2}{331.86}$$

= 151.02

The statistic reports a value of $\chi^2_{df=9}$= 151.02 > critical value of 16.92 at 5% level of significance. Accordingly, the null is rejected, and it is concluded that the joint space-time interaction is significant. This provides evidence that *persistence* in EHB is not an isolated, country-specific phenomenon, but is jointly structured across space and time, meaning that how a country's EHB evolves depends partly on the trajectories of its neighbours.

5.5.2 Testing for directional spatial heterogeneity

This section applies the Directional LISA methodology developed by Rey, Murray, and Anselin (2011) to assess directional spatial heterogeneity in EHB. It complements visual inspection of the LISA clusters (Chapter 4) by providing a framework to test and quantify directional dependencies and systematic spatial patterns over time.

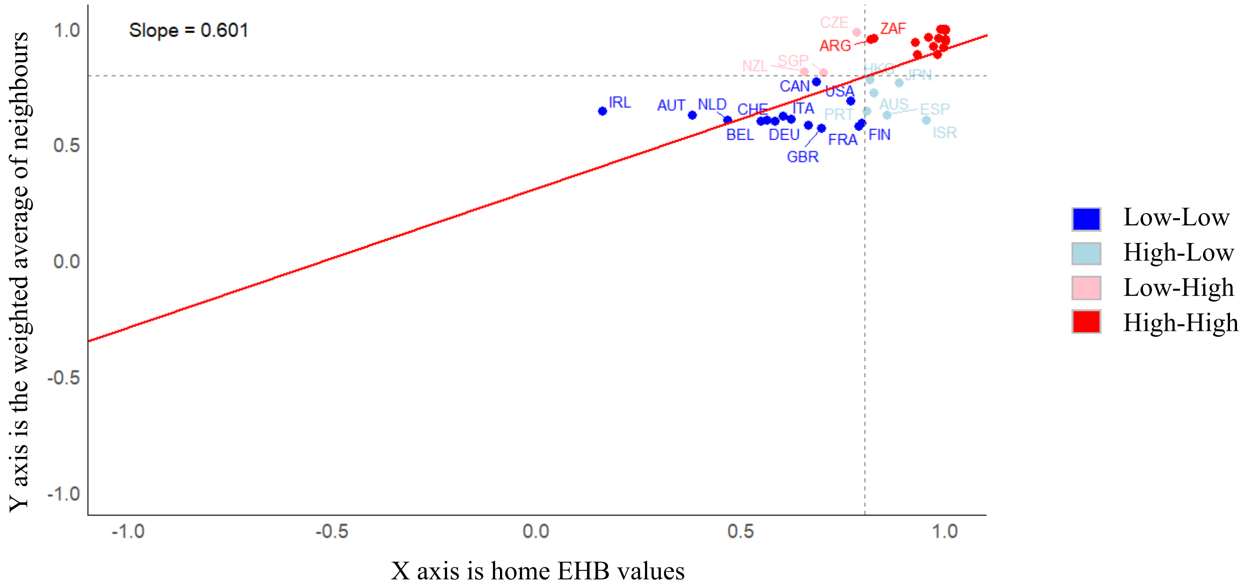
5.5.2.1 Directional LISA analysis

Directional LISA analysis provides additional insight into the nature of spatial dynamics by distinguishing between movements that reinforce existing clustering patterns and those that represent divergence from them. The predominance of reinforcing movements indicates that changes in EHB tend to occur in ways that preserve existing spatial configurations, supporting the conclusion that spatial dependence is path-dependent through time. This section presents a preliminary descriptive analysis of the spatial and temporal evolution of global EHB. Figures 5.4(a) and (b) display Moran (1950) scatterplots for 2001 and 2020, providing a single-state perspective at the starting and ending points of the sample (Moran, 1950; Anselin, 1995). To assess these plots comparatively, the analysis considers three aspects: (i) the number of neighbourhood structures (cardinality) in each quadrant; (ii) overall fit; and, (iii) quadrant heterogeneity (Sastré Gutiérrez and Rey, 2013).

Comparing the 2001 (Figure 5.4(a)) and 2020 (Figure 5.4(b)) scatterplots, it is clear that cluster cardinality and dispersion both change substantially over the two decades. Observations in all quadrants appear more dispersed in 2020, while the fit around the main diagonal is tighter in 2001. By visual inspection, heterogeneity within clusters also seems to increase over time. However, these static plots cannot reveal the intervening dynamics that occur between the two endpoints (Rey and Janikas, 2006; Rey, 2014). For instance, visual inspection of the final state smooths over intervening events (such as the GFC) making it impossible to distinguish whether increased dispersion within quadrants results from localised dynamics or from broader distributional shifts. Moreover, the Low-Low cluster shows both higher cardinality and greater dispersion between 2001 and 2020, but the underlying dynamics producing these changes remain unobserved. For illustration purposes, the dotted lines along the *x*-axis in Figures 5.4(a) and (b) represent the sample's average EHB in 2001 and 2020, which are 0.768 and 0.612, respectively. Since LISA clusters are defined relative to these averages and their neighbour equivalents (which also declined), neighbourhood structures face increasing difficulty in remaining in the Low-Low cluster over time (Rey and Le Gallo, 2009). Nonetheless, these graphics alone are insufficient to identify integrated spatial dynamics or underlying movement patterns.

Figure 5.4 Directional comparison across starting state (2001) and ending state (2020)

a) Global Moran's Index representation with LISA cluster significance for state 2001



b) Global Moran's Index representation with LISA cluster significance for state 2020

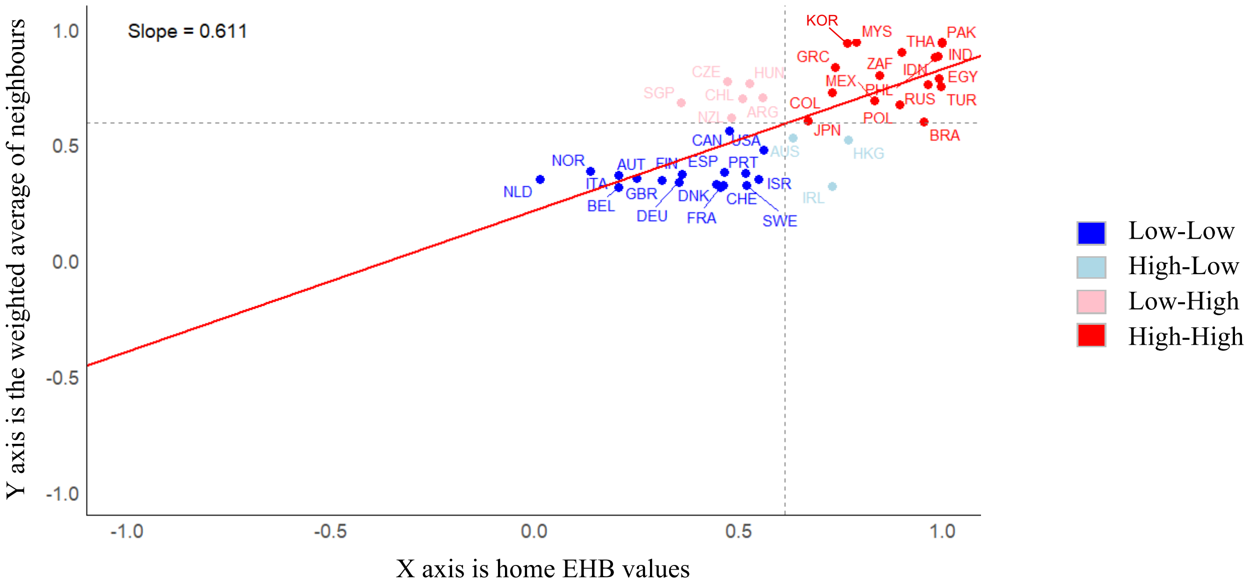
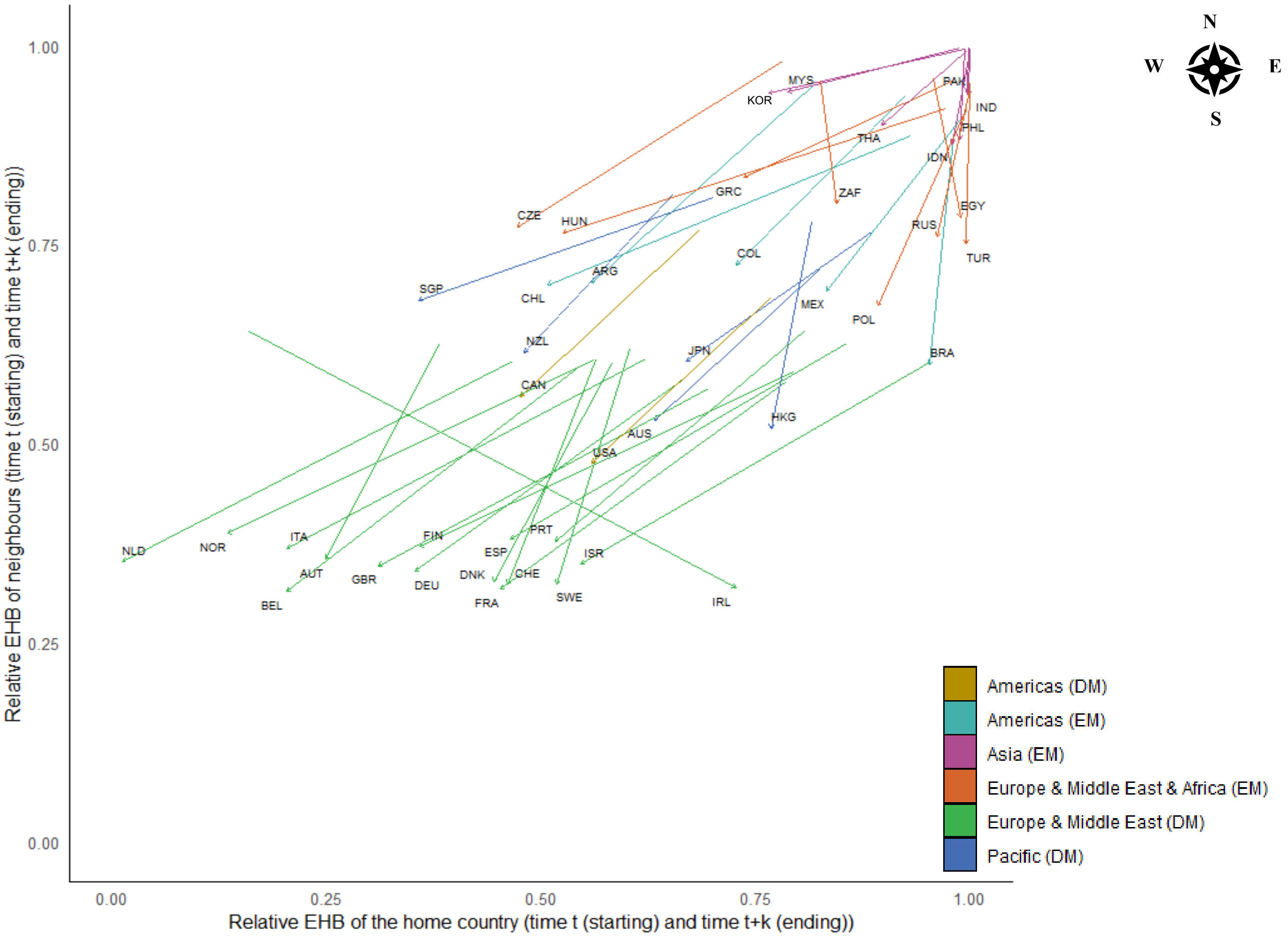


Figure 5.5 illustrates the movement within the Directional LISA plot, extending the information presented in the previous comparative statics (unstandardised Directional LISA plot). This visualisation highlights the types of movements that contribute to increased dispersion and downward shifts in the Low-Low cluster, as previously noted. However, even from a single-step perspective, it is difficult to isolate the impact of each individual movement on the overall distribution due to considerable heterogeneity (Rey and Sastré Gutiérrez, 2010; Sastré Gutiérrez and Rey, 2013).

Figure 5.5 Directional LISA plot 2001-2020 (unstandardised)



Note: The arrows are colour coded based on the MSCI ACWI country groups.

To facilitate interpretation, the next step is to standardise the movements to a common origin (the starting state in 2001, in the case of Figure 5.5), preserving only their *length* and *direction*. The standardised Directional LISA plot is shown in Figure 5.6. The standardisation has several advantages. By fixing all observations to the same origin while retaining vector length and direction, it allows consistent comparison across countries, regions, and block periods. Finally, the arrowheads in the reported rose diagrams indicate the destination quadrants of movements, and the approach makes the results more interpretable, comparable, and sensitive to meaningful spatial patterns over time (Murray, Grubesic, Wei, and Mack, 2011; Rey and Sastré Gutiérrez, 2010; Sastré Gutiérrez and Rey, 2013).

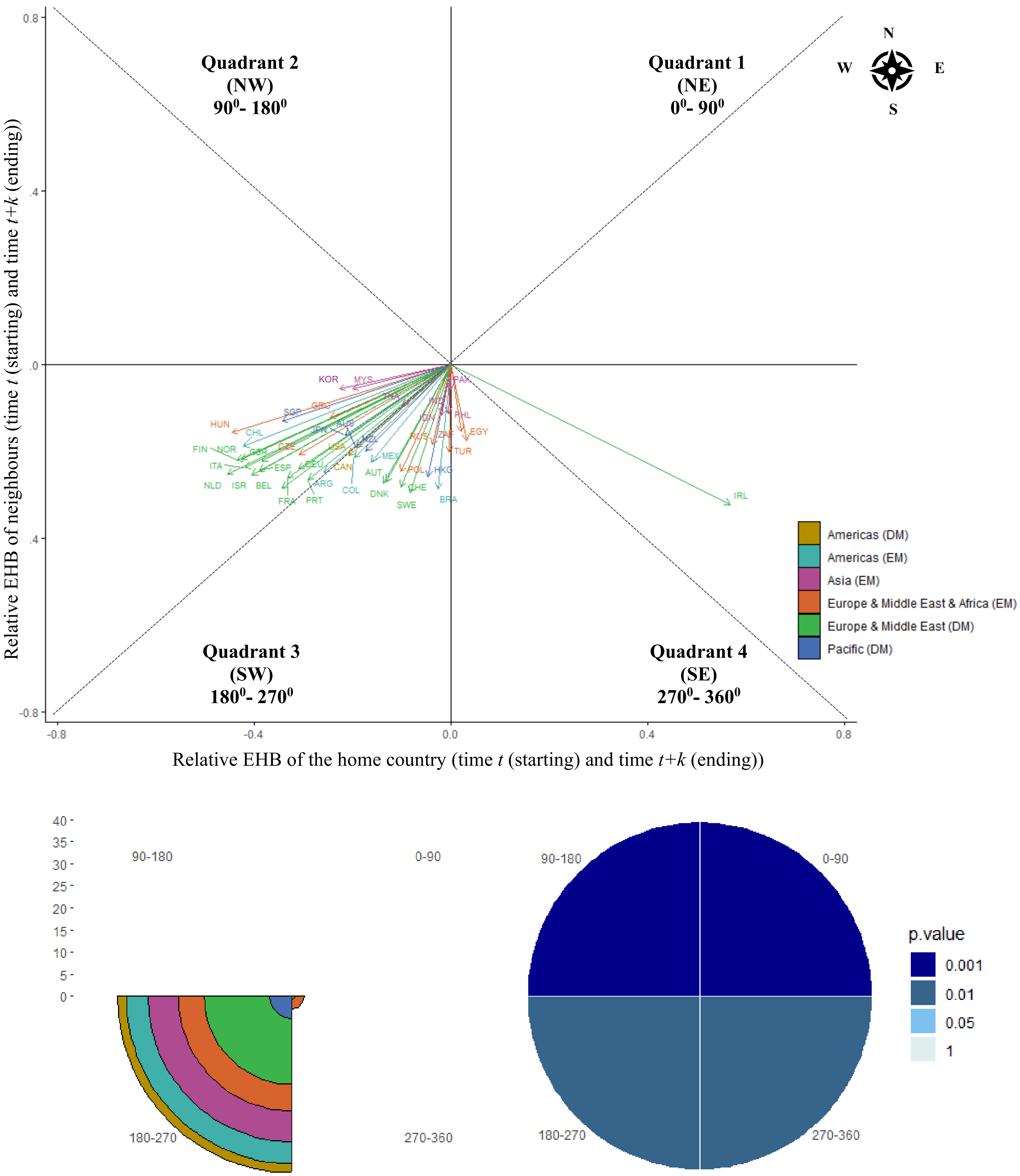
5.5.2.1.a Directional LISA analysis (20-year block)

Having established the descriptive patterns from the unstandardised plots (Figure 5.5), this section introduces the standardised Directional LISA analysis, which fixes all movements to a common origin (2001) in order to provide a clearer and more comparable view of the magnitude and direction of spatial dynamics over the full sample period. Figure 5.6 shows the standardised Directional LISA plot standardised to 2001 as the starting year, preserving the information of neighbourhood structures on *length* and *direction* (Rey and Sastré Gutiérrez, 2010; Sastré Gutiérrez and Rey, 2013).

The length (magnitude) of a given arrow in the Directional LISA plot reflects the strength of movement between two time points: a longer arrow indicates a larger change in the spatial relationship relative to the baseline year. The direction (angle) of an arrow indicates whether countries are moving toward or away from particular LISA clusters (say, shifting from High-High toward High-Low), thereby showing whether spatial association is strengthening, weakening, or changing sign over time (Rey, Murray, and Anselin, 2011). By standardising to 2001, all observations share a fixed reference point, which avoids distortions from scale differences and ensures that subsequent changes can be attributed to true spatial heterogeneity rather than shifts in global averages (Rey and Le Gallo, 2009).

The Directional LISA plot and the rose diagram (with accompanying *p-values*) in Figure 5.6, indicates that 40 of 43 neighbourhood structure movement vectors are directed towards the SW quadrant (joint downward convergence), indicating lowering of EHB for both the home country and its neighbours. Only 3 of 43 neighbourhood structures (Egypt, Ireland, and South Africa) are directed towards the SE quadrant (home-led divergence), reflecting increasing EHB in the home country but lowering EHB in their neighbours. The hypothesis is set up to test whether the observed distributional behaviour for each direction between year t (starting year, 2001) and $t+k$ (ending year, 2020) conforms to the hypothesised distributional condition under the null, namely, the independence of directional co-movement counts in space (Carracedo, Debón, Iftimi, Montes, 2018).

Figure 5.6 Directional LISA plot 2001-2020 (standardised to the origin, 2001)



Note: The arrows are colour coded based on the MSCI ACWI country groups.

In expectation, each of the four quadrants should contain the number of countries implied by the probability distribution of directional co-movements, which depends on the number of countries and the spatial weights matrix (neighbour relationships) under the null of spatial randomness. In practice, however, the observed counts in each quadrant often differ, with some quadrants over-represented and others under-represented. The Directional LISA test statistic compares the observed distribution of co-movements to an expected distribution generated under a permutation-based reference of spatial randomness in order to determine whether particular directional patterns are spatially clustered rather than random (Murray, Grubesic, Wei, Mack, 2011; Sastré Gutiérrez and Rey, 2013). Table 5.14 reports the results of this test. The null hypothesis of spatial randomness is rejected in all four quadrants, indicating that directional co-movements of EHB between neighbourhood structures are not random but systematically clustered.

Table 5.14 Directional LISA significance test 2001-2020

	NE 0^0- 90^0	NW 90^0- 180^0	SW 180^0- 270^0	SE 270^0- 360^0
Observed counts	0^{**}	0^{**}	40^{**}	3^{**}
Expected counts	0.120	0.418	34.864	7.595
p-values	0.001	0.001	0.010	0.010

Note: ** indicates significant at 5%; * indicates significant at 10%.

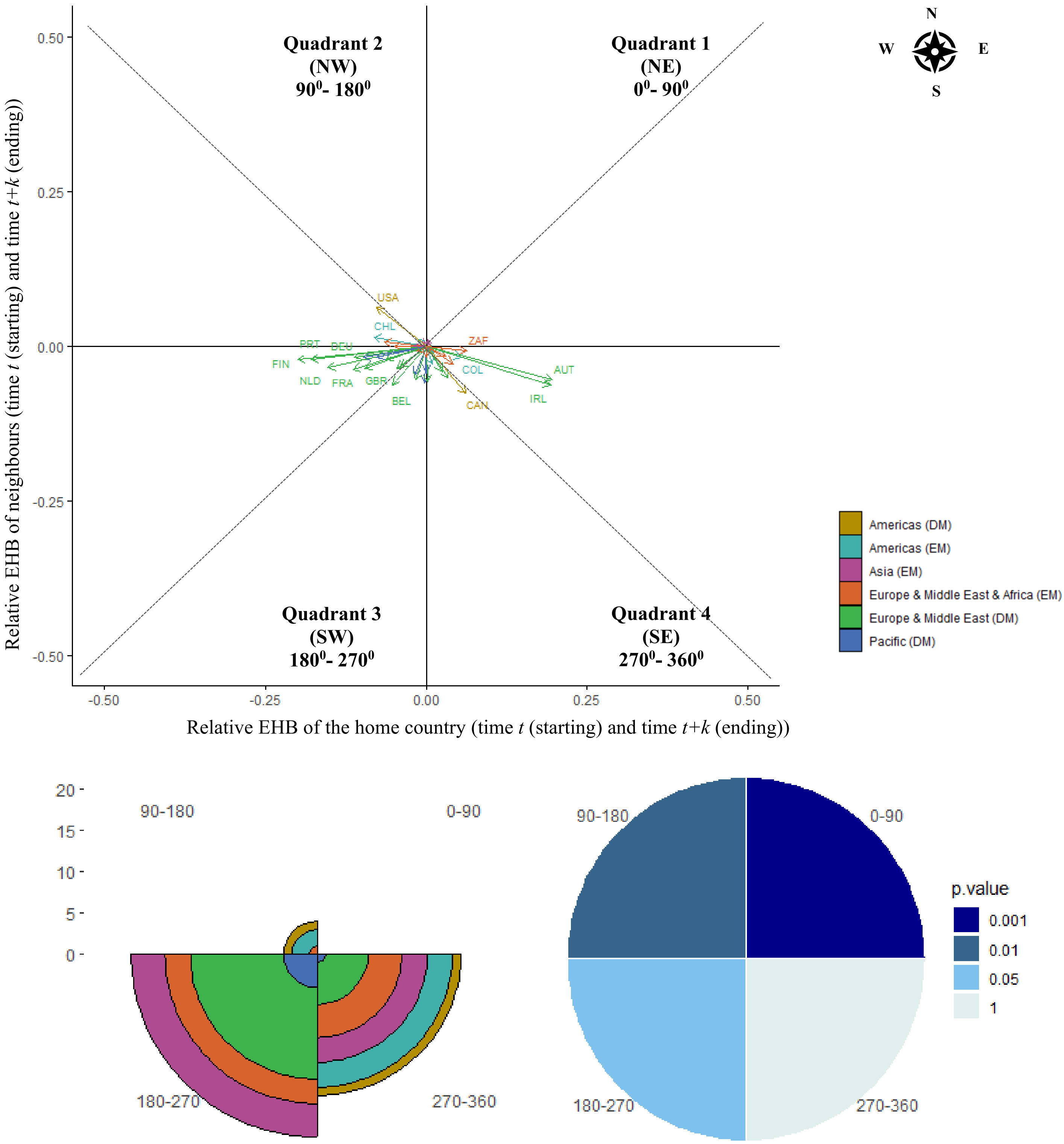
Table 5.14 reports that the null hypothesis of spatial randomness is rejected in directional co-movements between neighbourhood structures in all directions during 2001 to 2020. Several points are worth highlighting from this inferential perspective, particularly when contrasted with the insights drawn from the standardised Directional Moran scatter plots and the rose diagrams covering the full 20-year span. To deepen this analysis, the next section focuses on examining directional movements within five-year intervals, allowing for a more granular understanding of how spatial dependencies evolved over time.

5.5.2.1.b Directional LISA analysis (five-year blocks)

Having established the long-run patterns of directional movements in the full-period analysis (2001 through 2020), this section turns to a more granular view by examining standardised Directional LISA plots across five-year overlapping blocks. Figures 5.7 to 5.10 present the standardised Directional LISA plots for these subperiods. Again, in each Directional LISA plot, the length of the movement vector reflects the magnitude of change in a country's and its neighbours' EHB position, while the arrowhead shows the direction of the shift. The primary focus is on directionality across the four subperiods: 2001-2005; 2005-2010; 2010-2015; and, 2015-2020. The motivation here is to reveal the nature of spatial reconfigurations through standardised, five-year blocks of time (Rey and Montouri, 1999; Fratzscher, 2009; Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2012).

Breaking the analysis into five-year intervals allows directional shifts in EHB to be linked with major global and regional events that shaped investment patterns and global financial integration. For instance, the early 2000s (2001-2005) captures the post-dot.com bubble adjustment period (Akata, 2024), when risk perceptions and global equity linkages were reshaped. This period also coincides with the tragic events of 11 September 2001 (Fratzscher, 2009; Mun, 2004; Chen and Siems, 2004). The 2005-2010 block coincides with the lead-up to, and aftermath of, the GFC, an event that left a marked imprint on global capital flows (Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2012; Lane and Milesi-Ferretti, 2012; Claessens, Tong, and Wei, 2012). The 2010-2015 period reflects a phase of gradual recovery and renewed financial integration, alongside rising concerns about the Eurozone sovereign debt crisis (Lane, 2012; De Grauwe and Ji, 2013). Finally, the 2015-2020 block encompasses both the stabilisation of global markets in the mid-2010s and the disruptions toward the end of the decade, including heightened trade tensions (Amiti, Redding, and Weinstein, 2019; IMF, 2019) and the early effects of the COVID-19 pandemic (Goldstein, Koijen, and Mueller, 2021; Rajput, 2022). By anchoring directional movements of EHB in five-year historical contexts, the analysis shows that its persistence is not a statistical artefact but a path-dependent phenomenon, with trajectories conditioned by global shocks and regional influences.

Figure 5.7 Directional LISA plot 2001-2005 (standardised to the origin, 2001)



Note: The arrows are colour coded based on the MSCI ACWI country groups.

Table 5.15 Directional LISA significance test 2001-2005

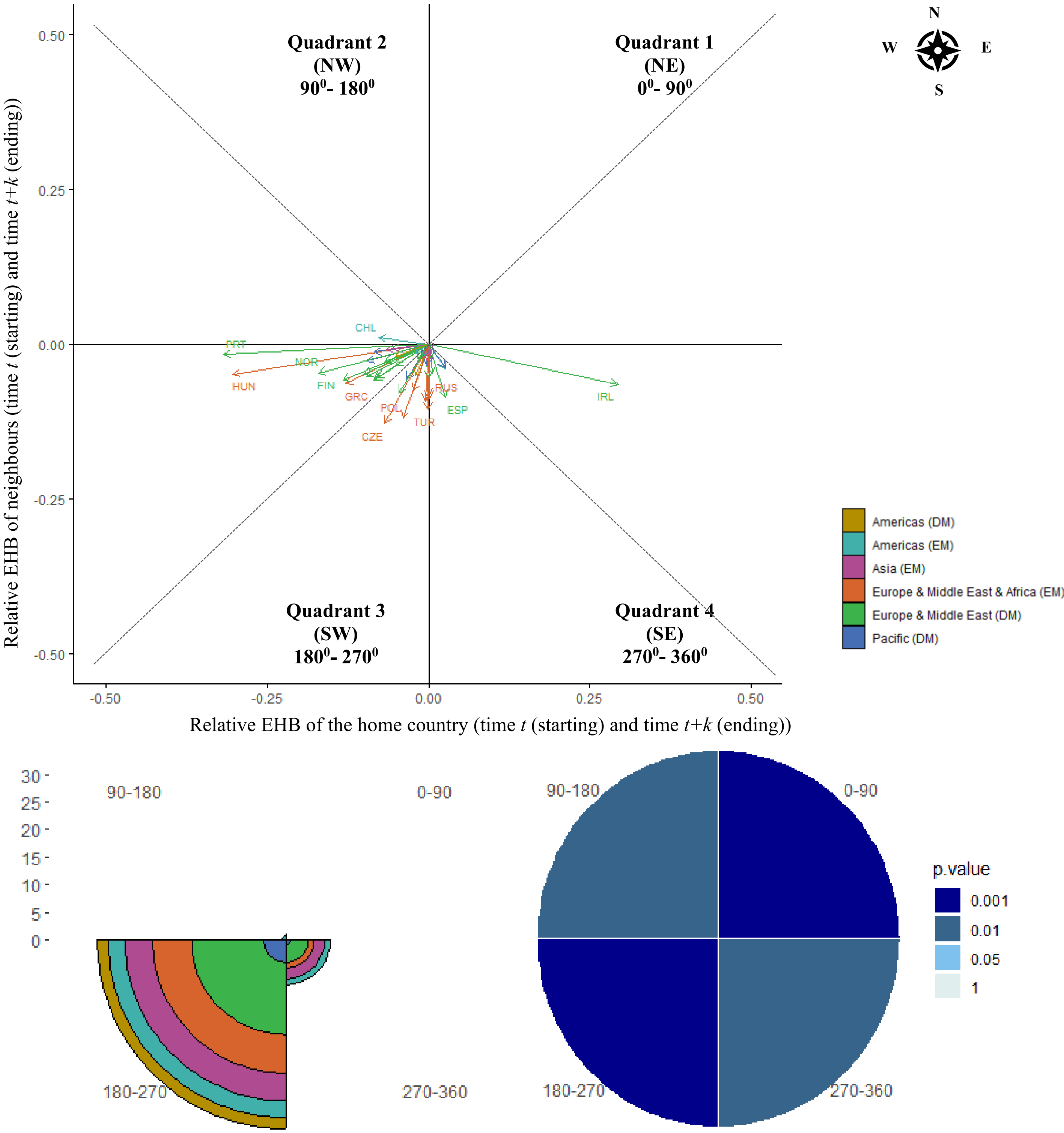
	NE 0^0- 90^0	NW 90^0- 180^0	SW 180^0- 270^0	SE 270^0- 360^0
Observed counts	0^{**}	4^{**}	22^{**}	17
Expected counts	3.931	9.622	14.818	14.628
p-values	0.001	0.010	0.050	1.000

Note: ** indicates significant at 5%; * indicates significant at 10%.

The majority of countries (22 of 43) in this five-year block (2001-2005) moved SW (Quadrant 3, joint downward convergence), and this pattern is statistically significant at the 5% level (Table 5.15). This indicates that both home countries and their neighbours reduced EHB simultaneously, consistent with strengthening global financial integration in the early 2000s (Rey and Montouri, 1999; Fratzscher, 2009). This period followed the dot.com bubble burst and the September 11 attacks, both of which contributed to heightened global risk aversion and a greater appetite for portfolio diversification (Chen and Siems, 2004; Mun, 2004). For many advanced economies, investors began reallocating capital toward international equities, reducing EHB (Bekaert and Harvey, 1995; Coeurdacier and Rey, 2013). At the same time, commodity-exporting emerging markets benefited from the early stages of the commodity super-cycle (2003-2005), which attracted substantial global investment inflows (Cashin, McDermott, and Scott, 2002; Erten and Ocampo, 2013).

Another group of countries (4 of 43: Chile, Hungary, Mexico, and the U.S.) exhibited movements toward the NW (Quadrant 2, neighbour-led divergence), implying declining EHB at the country-level but not in alignment with their neighbours. These shifts likely reflect idiosyncratic country-level dynamics, such as domestic capital market openness and/ or regulatory reforms that encouraged foreign equity participation (Henry, 2000; Chinn and Ito, 2006). Another set of countries (17 of 43) moved SE (Quadrant 4, home-led divergence), indicating rising EHB despite their neighbours exhibiting declining patterns. However, the lack of statistical significance suggests that these movements were neither strong nor consistent enough across spatial structures to reject the null hypothesis of randomness. In the U.S., heightened political and economic uncertainty following 9/11 may have reinforced investor reliance on domestic assets (Fuerst, 2006), contributing to a temporary retrenchment in favour of home markets. The statistical significance of this group indicates that their divergence was systematic rather than random, highlighting that even during periods of broad convergence, specific countries can move against global and regional trends.

Figure 5.8 Directional LISA plot 2005-2010 (standardised to the origin, 2005)



Note: The arrows are colour coded based on the MSCI ACWI country groups.

Table 5.16 Directional LISA significance test 2005-2010

	NE 0^0- 90^0	NW 90^0- 180^0	SW 180^0- 270^0	SE 270^0- 360^0
Observed counts	0^{**}	1^{**}	34^{**}	8^{**}
Expected counts	2.081	5.972	20.199	14.747
p-values	0.001	0.010	0.001	0.010

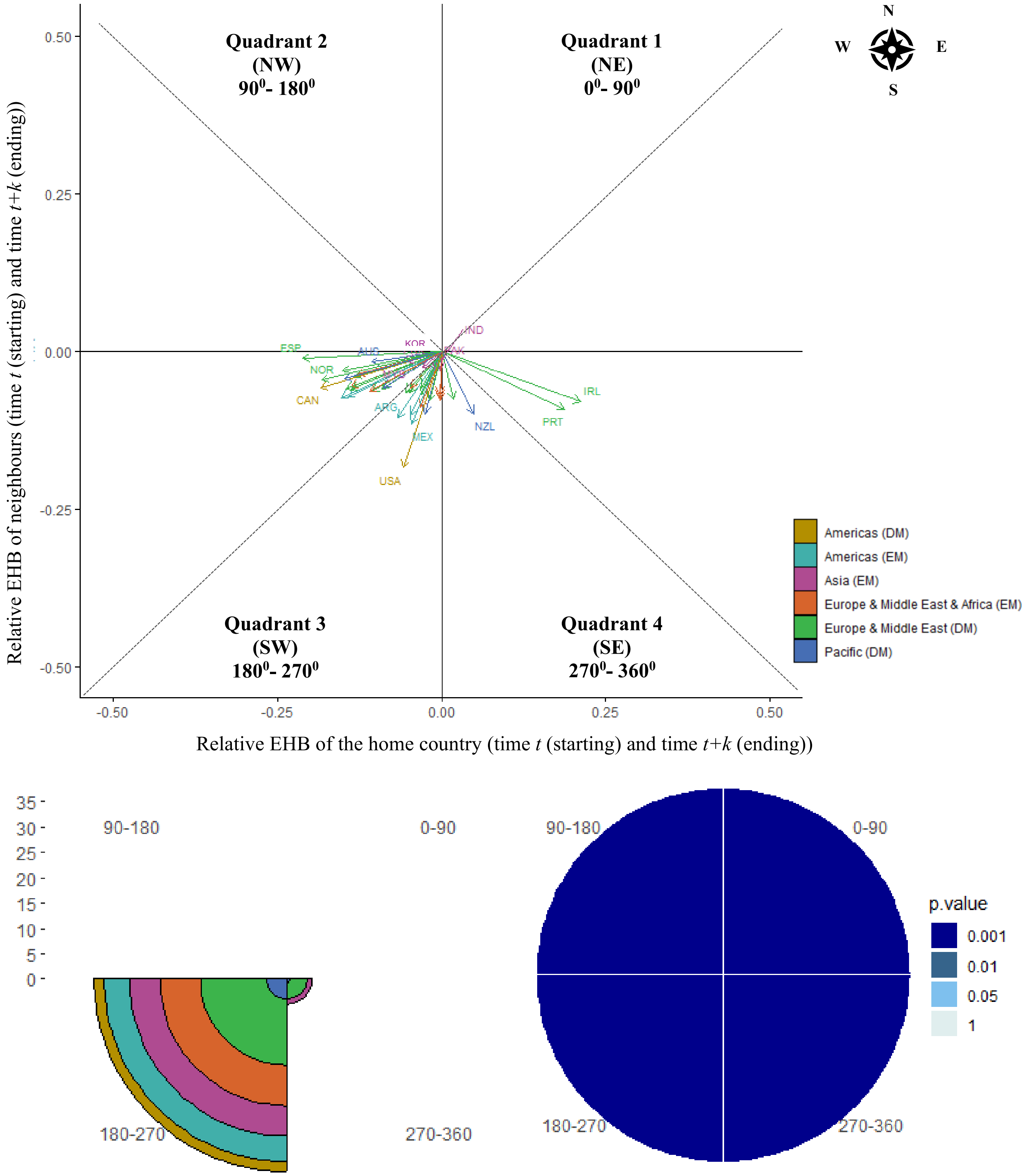
Note: ** indicates significant at 5%; * indicates significant at 10%.

For the 2005-2010 period (Figure 5.8), the highest frequency of movements is in the SW (Quadrant 3, joint downward convergence), with 34 of 43 neighbourhood structures moving in this direction. This indicates that both home countries and their neighbours reduced EHB simultaneously, consistent with a broad process of deleveraging and financial retrenchment during the GFC (Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2012). Several countries that had previously moved NW (Quadrant 2, neighbour-led divergence) in 2001-2005 shifted decisively to the SW, while nine countries that were previously in the SE (home-led divergence) also moved SW.

Strikingly, not a single country remained in the NE (Quadrant 1, joint upward convergence). This absence is significant: the NE quadrant represents rising EHB jointly with neighbours, yet its complete disappearance indicates that no country could sustain increasing EHB during this period. Instead, the systemic shock of the GFC seemingly pulled all neighbourhood structures away from the NE trajectory (Lane and Milesi-Ferretti, 2012; Claessens, Tong, and Wei, 2012). Several studies document that the GFC triggered structural breaks in stock market returns and correlations, notably altering long-run relationships and return dynamics across both developed and emerging markets (Choi, 2021, 2022; Kuo and Chiang, 2025).

Finally, the rose-diagram test results in Table 5.16 reject the null hypothesis of spatial randomness at the 1% level for NE, SW, and SE, and at the 5% level for NW, with *p-values* of 0.001 (NE, SW) and 0.010 (NW, SE). These very low values confirm that the observed dominance of SW movements, together with the disappearance of NE trajectories, is highly unlikely to be due to chance. Instead, it reflects the impact of the GFC on directional patterns and (as will be discussed in the following sections) marks the beginning of an entrenched joint downward convergence through to the end of the sample period (2020).

Figure 5.9 Directional LISA plot 2010-2015 (standardised to the origin, 2010)



Note: The arrows are colour coded based on the MSCI ACWI country groups.

Table 5.17 Directional LISA significance test 2010-2015

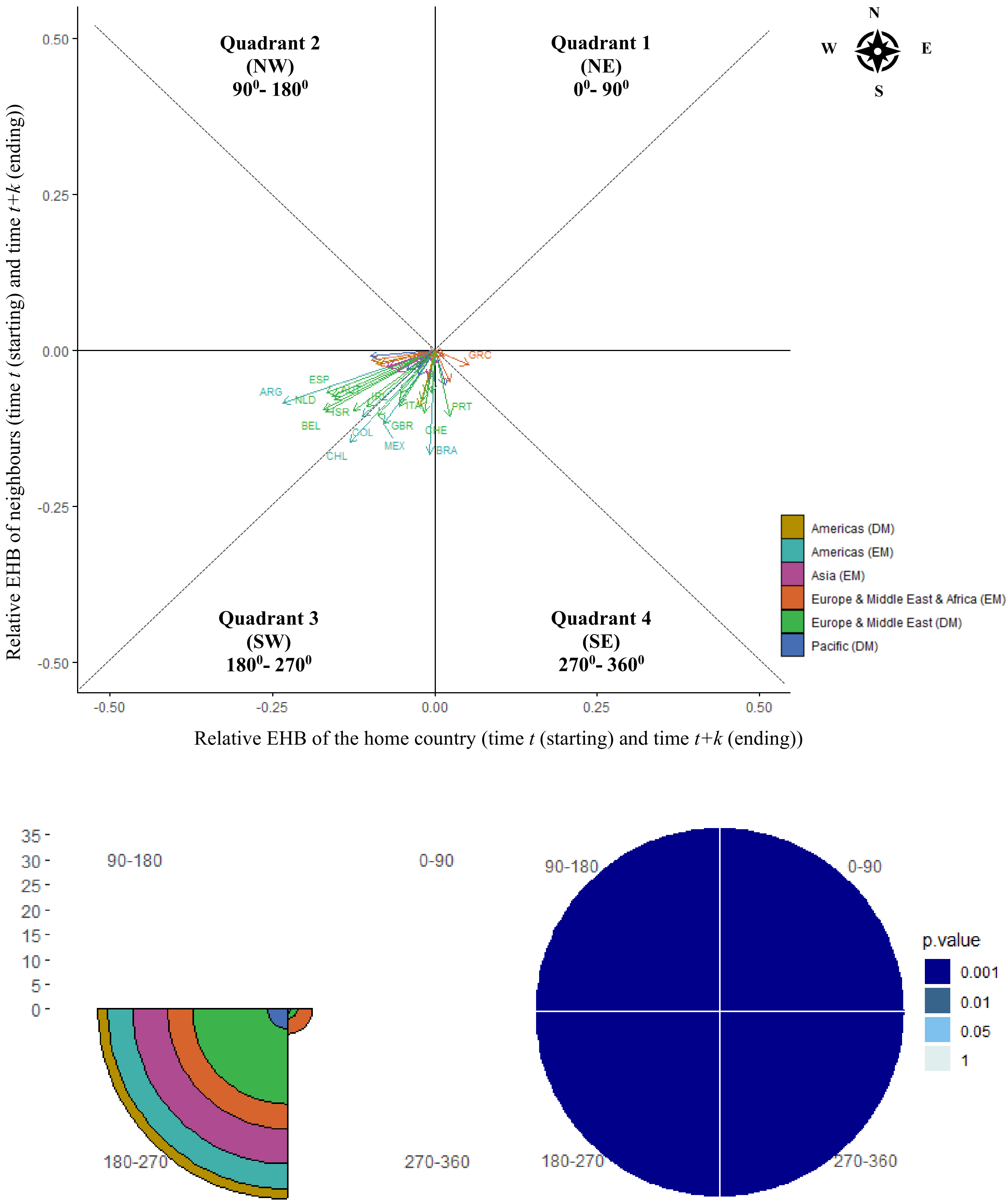
	NE 0^0- 90^0	NW 90^0- 180^0	SW 180^0- 270^0	SE 270^0- 360^0
Observed counts	0^{**}	0^{**}	38^{**}	5^{**}
Expected counts	1.418	5.726	20.879	14.977
p-values	0.001	0.001	0.001	0.001

Note: ** indicates significant at 5%; * indicates significant at 10%.

The results reported in Figure 5.9 and Table 5.17 indicate that 38 of 43 neighbourhood structures move SW (Quadrant 3: joint downward convergence), while only five move SE (Quadrant 4: home-led divergence) and none remain in NE or NW quadrants. The rose-diagram test rejects the null of spatial randomness at conventional levels in all quadrants ($p = 0.001$), confirming that directional co-movements are systematic rather than random and that declines in EHB are occurring jointly for many countries and their neighbours over 2010-2015 (Rey, Murray, and Anselin, 2011).

The dominance of the SW quadrant seems consistent with the post-GFC portfolio rebalancing and lower risk premia supported renewed international diversification, especially in advanced markets (Lane and Milesi-Ferretti, 2005, 2008; Milesi-Ferretti and Tille, 2011; Forbes and Warnock, 2012). Within Europe, policy interventions associated with the sovereign-debt crisis (including European Central Bank commitments) reduced tail risks and helped compress dispersion in risk pricing, a backdrop consistent with joint downward convergence in EHB for many European neighbourhood structures (Lane, 2012; De Grauwe and Ji, 2013). In summary, the absence of NE and NW, the strong SW pattern, and significant test results again indicate that persistence and change in EHB over 2010-2015 were jointly structured across space and time, rather than being isolated country-by-country phenomena (Rey and Montouri, 1999; Rey, 2014).

Figure 5.10 Directional LISA plot 2015-2020 (standardised to the origin, 2015)



Note: The arrows are colour coded based on the MSCI ACWI country groups.

Table 5.18 Directional LISA significance test 2015-2020

	NE 0^0- 90^0	NW 90^0- 180^0	SW 180^0- 270^0	SE 270^0- 360^0
Counts	0^{**}	0^{**}	38^{**}	5^{**}
Expected value	2.115	6.259	19.728	14.898
p-values	0.001	0.010	0.001	0.001

Note: ** indicates significant at 5%; * indicates significant at 10%.

The results presented in Figure 5.10 and Table 5.18 show that 38 of 43 neighbourhood structures move SW (Quadrant 3: joint downward convergence), while five move SE (Quadrant 4: home-led divergence). As per the previous block (2010-2015), there were no observed movements in the NE or NW quadrants. Again, the rose-diagram test rejects the null of spatial randomness at the 1% level in all quadrants, confirming that the dominance of SW movements is highly systematic rather than random (Rey, Murray, and Anselin, 2011).

The overwhelming SW pattern indicates that between 2015 through 2020, both home countries and their neighbours continued to reduce EHB in tandem. This coincides with a period of relative financial market stabilisation in the mid-2010s, supported by monetary accommodation and declining risk premia (Lane and Milesi-Ferretti, 2005, 2008; IMF, 2019). However, toward the end of the decade, trade tensions (Amiti, Redding, and Weinstein, 2019; IMF, 2019) and the onset of the COVID-19 pandemic (Choi, 2021, 2022; Goldstein, Koijen, and Mueller, 2021; Li, Zhuang, Wang, and Dong, 2021; Bissoondoyal-Bheenick, Do, Hu, and Zhong, 2021; Rajput, 2022). For the 2015 through 2020 block, the rose-diagram significance test rejects the null of spatial randomness in all quadrants at the 1% level. The very low *p-values* confirm that the observed dominance of SW movements, together with the absence of NE and NW trajectories, reflects systematic spatial structuring of EHB dynamics rather than random variation. The small number of SE (home-led divergence) cases, five in total, indicates that idiosyncratic retrenchment did occur, but only at the margin.

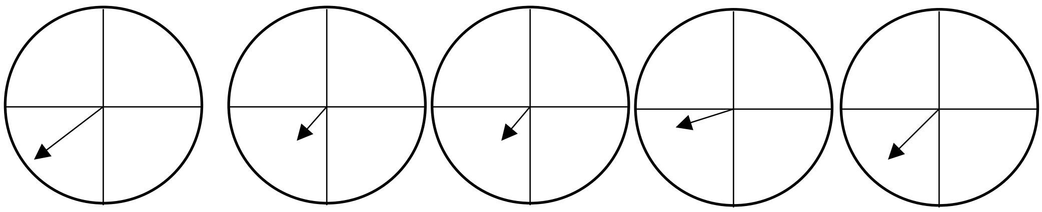
Finally, across all four sub-periods, the directional LISA analysis by five-year overlapping blocks shows that *persistence* and change in EHB are not random country-by-country phenomena but deeply embedded in global and regional processes. Periods of crisis accelerated joint downward convergence by eliminating upward paths, while recovery phases reinforced spatial clustering. By 2020, entrenched joint downward convergence toward lower EHB (SW) had become the prevailing global condition, with divergence limited to a handful of marginal cases, and joint upward convergence (NE) eliminated.

5.5.2.1.c Directional LISA example (Australia)

While the five-year block analysis reveals systematic global patterns, a closer look at individual countries helps to illustrate how these aggregate dynamics play out in specific regional contexts across the five-year overlapping blocks. Australia is classified as a developed market in the Pacific region (Pacific DM) and is examined as a case study to contrast its trajectory with those of its regional peers (New Zealand, Singapore, Hong Kong, and Japan).

Figure 5.11 Directional LISA plots 2001-2020

	2001-2020	2001-2005	2005-2010	2010-2015	2015-2020
Angle degree	224.54^0	267.78^0	239.42^0	189.30^0	217.42^0
Length	0.27	0.06	0.07	0.11	0.05
Change in EHB home	-0.19	-0.01	-0.03	-0.11	-0.04
Change in EHB neighbours	-0.19	-0.06	-0.06	-0.02	-0.03



Australia's neighbourhood structure exhibited a consistent SW-oriented movement in directional LISA space, corresponding to the 180°-270° sector of the rose diagram. Consistent with the previous analysis, in polar coordinate terms, 0° represents east (X-axis), 90° north (Y-axis), 180° west, and 270° south; thus, the 180°-270° sector corresponds to the SW quadrant (joint downward convergence). Australia's initial displacement vector from 2001 to 2005 had a modest magnitude of 0.06 and pointed at 267.78°, indicating a movement predominantly southward with a slight westward component. This suggests that early changes in Australia's EHB were largely influenced by regional neighbour effects rather than strong domestic shifts (Rey and Le Gallo, 2009; Rey and Sastré Gutiérrez, 2010). Across subsequent five-year blocks, Australia continued to move steadily in the SW direction, with small but consistent shifts (0.05-0.11) and a single larger adjustment of 0.27 when measured across the full 2001 through 2020 period. This trajectory indicates entrenched downward convergence in EHB, moving in close alignment with Pacific DM neighbours. New Zealand and Singapore exhibited similar SW movements, reflecting capital market openness, while

Hong Kong, already highly integrated, showed relatively shorter vector lengths, indicating smaller marginal adjustments. Japan's movements were more muted and occasionally closer to the SE quadrant, reflecting persistent domestic structural features that limited full convergence (De Brouwer, 1999).

In summary, these contrasts show that Australia's trajectory was broadly representative of the Pacific DM group but that heterogeneity within the region remained, with Japan and Hong Kong adjusting more cautiously than the smaller Pacific markets. This reinforces the broader conclusion that directional LISA captures both systematic regional clustering and country-specific divergences, underscoring the structured but uneven nature of EHB dynamics (Clark and Wójcik, 2007; Rey, 2014).

5.6 Conclusion

Chapter 5 employs a spatio-temporal analytical framework to deepen understanding of *joint space-time interaction* and *directional spatial heterogeneity* in EHB, overcoming limitations in the field which largely disregards the impact of spatio-temporal effects (Rey and Montouri, 1999; Clark and Wójcik, 2007; Wójcik, Iliopoulos, Ioannou, Keenan, Migozzi, Monteath, Pažitka, Torrance, and Urban, 2024). An exploratory methodological design moved the analysis from static (Chapter 4) to dynamic space-time approaches (Anselin, 1995; Rey, Murray, and Anselin, 2011). This methodological step allowed the concepts of *persistence*, convergence, or divergence in spatial regimes to be formally tested and analysed.

The Transition LISA (Spatial Markov chain) framework shows that EHB clusters are highly persistent over time. Countries overwhelmingly remained within their initial spatial regimes, with very high probabilities of staying in Low-Low or High-High states and virtually no transitions across opposite clusters. Even during systemic shocks (such as the GFC), neighbourhood structures did not 'break out' of their entrenched positions, underscoring the path-dependent nature of EHB (Rey, 2001, 2014; Rey and Janikas, 2006).

The Directional LISA approach added further insight by showing the orientation and magnitude of co-movements between countries and their neighbours over both the full 20-year period, successive five-year blocks, and an Australia case study. The 20-year observation period spans multiple global shocks and recoveries, from the dot.com bubble and the September 11 terrorist attacks, through to the systemic dislocation of the GFC and the Eurozone sovereign debt crisis, to the trade tensions of the late 2010s and the onset of the COVID-19 pandemic, each leaving a distinct imprint on the spatio-temporal dynamics of

EHB. However, regardless of time block specification, the rose-diagram tests rejected the null of randomness with strikingly low *p-values*, confirming that these directional movements were not noise but systematic and highly structured spatio-temporal dynamics (Rey, Murray, and Anselin, 2011; Sastré Gutiérrez and Rey, 2013). By the end of the observation period, convergence had become entrenched: 38 of 43 structures moved SW, only five diverged SE, and no neighbourhood structure sustained NE or NW trajectories, even with the onset of COVID-19 (Goldstein, Koijen, and Mueller, 2021; Rajput, 2022). The Australia case study further illustrates how these dynamics played out at the country level. Classified as Pacific DM under the MSCI ACWI, Australia exhibited consistent SW orientation across all five-year blocks, with small but steady vector lengths and one larger adjustment over the full 20-year sample. Its trajectory was strongly correlated with its regional neighbours, New Zealand, Singapore, Hong Kong, and Japan. The contrast with Japan (more muted adjustments) and Hong Kong (smaller, marginal changes) underscores that while the regional tendency was consistent joint downward convergence (SW), heterogeneity in pace *and* intensity remained.

These findings set the stage for the broader conclusions reached in Chapter 6. By showing that the dynamics of EHB are not random but characterised by *joint space-time interaction* and *directional spatial heterogeneity*, Chapter 5 demonstrates that EHB should no longer be framed as a puzzle but as a persistent spatio-temporal phenomenon. The persistence of Low-Low and High-High clusters, the dominance of the SW orientation, and the disappearance of upward convergence paths after the GFC, all point to a structural shift that opens new directions for the field of financial geography. In this sense, the EHB debate exemplifies what Kuhn (1962) described as the breakdown of an old paradigm and the need for a new one to rise. This study posits that, rather than treating EHB as a deviation from equilibrium to be arbitraged away, it must be reconceptualised as an enduring outcome of spatio-temporal effects. Chapter 6 builds on this evidence to examine the implications for financial integration, the EHB puzzle, and future directions for financial geography.

6. Conclusion

6.1 Introduction

For more than half a century, equity home bias (EHB) has stood as one of the most enduring anomalies in international finance. The neoclassical finance tradition, led by the seminal contributions of Markowitz (1952), Sharpe (1964), and Solnik (1974), prescribes that rational investors hold the global market portfolio in proportion to each respective country's relative market capitalisation. Yet, in practice, investors are observed to overwhelmingly overweight domestic equities (home), sacrificing the risk-return benefits of diversification (French and Poterba, 1991; Lewis, 1999; Sercu and Vanpée, 2007; Coeurdacier and Rey, 2013; Mishra, 2015; Ardalan, 2019; Balasubramanian and Kumar, 2023). The presence and persistence of EHB amounts to more than an anomaly; it is what Kuhn (1970) would describe as a puzzle, a phenomenon that resists explanation within the prevailing paradigm (Obstfeld and Rogoff, 2000).

The EHB puzzle has been investigated from multiple perspectives. Transaction costs, information asymmetries, regulatory frictions, and behavioural biases (to name but a few) have all been proposed as potential explanations (Tesar and Werner, 1995; Coval and Moskowitz, 1999; Huberman, 2001; Chan, Covrig, and Ng, 2005; Ardalan, 2019). It is argued that the field is in a state of stasis (Lewis, 1999). The inability of the neoclassical finance tradition to account for EHB raise the possibility that finance itself may be ill-equipped to capture the spatial and temporal realities of international finance (Clark, 2005).

6.2 Contributions to knowledge

The study has undertaken a systematic treatment of the EHB puzzle, guided by four interrelated research questions. It first asks how EHB should be defined, examining the competing forms by which the puzzle is conceptualised (what is EHB?). It then considers how EHB can be measured, evaluating alternative approaches to estimation (How should EHB be measured?). The third question addresses whether EHB is systematically present across space and through time, with particular attention to clustering within neighbourhood structures (Is EHB systematically present across time and space?). Finally, the study investigates whether these patterns persist, consistent with the dynamics of path dependence (Does EHB persist across space and time?). These questions, first posed in Chapter 1, provide the scaffolding for the study. Unapologetically, the research design avoids the temptation to revisit well-worn arguments in the EHB debate (Ardalan, 2019). Rather than seeking resolution through incremental refinement, it is argued that progress requires novel approaches to the EHB puzzle's ontological, epistemological, and methodological foundations (Kuhn, 1970; Guba and Lincoln, 1994; Crotty, 1998). Questions regarding the ontological (*what is the nature of EHB?*; Bhaskar, 1978), epistemological (*what counts as valid knowledge about EHB?*; Popper, 1959; Guba and Lincoln, 1994; Chalmers, 1999), and methodological (*by what means can EHB be studied?*; Crotty, 1998; Blaikie, 2007) foundations of the EHB puzzle have been considered, with the key innovation being the consideration of EHB across space and through time.

The evidence in this study does not require an 'either-or' choice between neoclassical finance and financial geography. Rather, it motivates a 'both-and' reading in which neoclassical finance provides indispensable benchmark logic (optimal weights and equilibrium expectations), while financial geography helps explain why the empirical world repeatedly fails to converge cleanly on those benchmarks once the production of returns is understood as embedded in relational space and sequenced time (Markowitz, 1952; Sharpe, 1964; Solnik, 1974; Clark and Monk, 2017). It is argued that the present contribution is not to discard finance, but to re-specify the conditions under which its stylised predictions can reasonably be expected to hold, and to demonstrate that spatial clustering and temporal persistence are not peripheral noise terms but patterned features of the global system. As noted previously, this 'both-and' position is, however, in tension with a strict Kuhnian reading of paradigms as incommensurable (Kuhn, 1962). If paradigms were fully incommensurable, then the relationship between neoclassical finance and financial geography would be one of replacement rather than dialogue. Framed this way, the EHB puzzle is not resolved by declaring a paradigm victory, but by demonstrating how different conceptualisations of space and time illuminate different regularities in the same phenomenon.

6.2.1 Definition

The definitional problem has been well-documented in the literature (Cooper, Sercu, and Vanpée, 2018; Ardalan, 2019). The absence of an agreed, stable definition has led to fragmentation and stasis (Lewis, 1999). Chapter 2 approached this issue through a Systematic Literature Review (SLR) that classified the forms of EHB into three dominant categories: model-based, data-based, and hybrid. Model-based forms are derived from the International Capital Asset Pricing Model (I-CAPM) and prescribe that investors should hold equities from each country in proportion to its share of world market capitalisation (Solnik, 1974; Adler and Dumas, 1983). Data-based forms, by contrast, rely on mean-variance optimisation (Markowitz, 1952) and/ or minimum-variance optimisation (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015), deriving optimal weights from historical returns. Finally, hybrid approaches combine the two by allowing for scepticism toward model assumptions, incorporating Bayesian priors that shift optimal weights between model-based and data-based approaches (Pástor, 2000; Pástor and Stambaugh, 2000; Mishra, 2015).

The SLR showed that while these forms appear distinct, they are ultimately grounded in the same equilibrium framework that underpins the neoclassical finance tradition (Markowitz, 1952; Sharpe, 1964; Fama, 1970). Their differences do not lie in ontology (there is broad agreement on the nature of EHB) but in methodology: they reflect varying ways of estimating the optimal benchmark against which actual holdings are compared (French and Poterba, 1991; Tesar and Werner, 1995; Baele, Pungulescu, and Ter Horst, 2007; Pástor and Stambaugh, 2000; Mishra, 2015). The implications are twofold: first, definitional ambiguity has constrained progress by fostering parallel literatures, each claiming authority over what constitutes the 'true' form of EHB (Lewis, 1999; Karolyi and Stulz, 2002; Ardalan, 2019); second, all forms are derived from the neoclassical finance tradition that makes the same critical omission: treating space as domicile and time as a homogeneous sequence, thereby ignoring spatio-temporal effects (Clark and Monk, 2017; Wójcik, 2011; Haberly and Wójcik, 2022).

The silence on the dimensions of space and time is consequential. Assuming away spatio-temporal effects risks estimation bias and model misspecification (Pace and Calabrese, 2022). As the literature in financial geography emphasises, investment is not frictionless and placeless, but embedded in networks of space, institutions, and history (Clark, 1998, 2005, 2008; Leyshon and Thrift, 1998; Clark, Feldman, Gertler, and Wójcik, 2018). Both behavioural studies and portfolio evidence confirm this point: investors systematically overvalue proximate assets and undervalue distant ones, not because of rational optimisation, but because of familiarity bias and bounded rationality (Huberman, 2001; Baltzer, Stolper, and Walter, 2013). The implication is that EHB is not a definitional artefact: rather, the definitional silence on geography, particularly clustering across space and path dependence through time, has constrained explanatory progress and obscured the spatio-temporal effects that lie at the heart of the puzzle.

6.2.2 Measurement

Drawing on data from 43 MSCI ACWI countries over the period 2001 through 2020, Chapter 3 constructs a panel of EHB estimates across the three forms (model-based, data-based, and hybrid) and four accompanying measures. Using a non-parametric Quantile Shift Function approach, it was found that the distribution of EHB estimates was statistically indistinguishable at the 5% level (Figure 3.2). While scholars have debated the superiority of one form over another (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015), the evidence suggests that such debates are less consequential than perhaps assumed. Since all forms come from the neoclassical finance tradition, it is unsurprising (*ex-post*) that they yield convergent results. As such, the puzzle cannot be dismissed as a measurement artefact.

The more revealing finding from Chapter 3 is not the similarity among EHB measures, but their distributional behaviour. At an aggregate level, the reported mean values suggest a modest global decline in EHB occurred from 2001 through 2020, corroborating previous studies in the field (Sercu and Vanpée, 2007; Sørensen, Wu, Yosha, and Zhu, 2007; Coeurdacier and Rey, 2013; Mishra, 2015; Solnik and Zuo, 2017). However, the Sankey diagram illustration (Figure 3.5) revealed widening heterogeneity of EHB levels over time. Some countries, such as the Netherlands and Norway, converged towards negligible levels, with EHB_i approaching zero (investors hold international equities in proportion to the global market portfolio, that is, no EHB). Others, including India, the Philippines, and Turkey, remained locked at extreme levels, with EHB_i approaching one (that is, investors hold no foreign equities, that is, complete EHB). Others followed intermediate trajectories, reducing home exposure incrementally but never eliminating it. These findings underscore Savage and Markowitz's (2009) warning about the flaw of averages, that is, what appears as a gradual decline of EHB globally is, in fact, a composite of divergent trajectories.[85]

[85] The work of Balasubramanian and Kumar (2023) shows that, during the COVID-19 pandemic, EHB declined in several markets, contrary to the flight-to-familiarity hypothesis of Huberman (2001). Rather than confirming a universal behavioural response, the evidence suggested contextual variation in how investors embedded in different geographies react to systemic shocks (Balasubramanian and Kumar, 2023).

6.2.3 Presence

Chapter 4 tested whether EHB is spatially clustered or simply an aggregation of independent, country-level outcomes. Using the model-based measure for 43 MSCI ACWI countries from 2001-2020 across a range of exploratory neighbourhood structures, two complementary methods were applied. First, Global Moran's Index was used to detect whether EHB values were more similar among neighbours than would be expected under randomness. Across all years, the null of spatial randomness was decisively rejected. The reported Global Moran's Index was consistently positive and significant, showing that EHB is *not* dispersed evenly across the global system but systematically clustered.

Second, Local Indicators of Spatial Association (LISA) decomposed this global association into local clusters. The LISA analysis revealed striking and persistent results. Starting with the Low-Low clusters, developed markets in Europe and the Middle East (such as Belgium, Denmark, Germany, Netherlands, and Switzerland) mimic global benchmark weights (that is, MSCI ACWI). The High-High clusters were found in the emerging markets in Asia (including India, Indonesia, and Philippines, and Pakistan). These clusters reflect home investors (and their neighbours) holding portfolios concentrated in domestic (home) equities. These 'dual regimes' persisted across the full twenty-year period, surviving systemic shocks such as the GFC and the COVID-19 pandemic (Clark, Dixon, and Monk, 2009; Nguyen, Phan, and Nguyen, 2022).

The LISA results also highlighted the importance of neighbourhood specification. Distance-based definitions of neighbours (*k*-nearest neighbours weighted by spherical distance) captured geographic proximity, but boundary-based definitions (MSCI ACWI classifications) captured institutional proximity through benchmark logic. Strikingly, benchmark-based neighbourhoods produced stronger and more stable clustering results (over 60% significant clusters) than distance-based ones (around 40%). This finding reflects a practical reality: global benchmarks (such as MSCI ACWI) do not simply describe markets; they condition and shape capital flows in international finance (Bekaert and Harvey, 1995; Clark, 2005, 2018; Clark and Monk, 2017; Wójcik, Keenan, Pažitka, Urban, and Wu, 2022). Finally, it is important to note that such conclusions are made for a particular state (or point in time). Chapter 5 extends this analysis by examining dynamic trajectories of clusters.

6.2.4 Persistence

The analysis in Chapter 5 considered matters of persistence and dynamism. First, Transition LISA (spatial Markov chains) traced how countries move between cluster states over time (Rey, 2001, 2014). The results show strong path dependence: countries in High-High or Low-Low regimes tend to remain there, with limited evidence of transitions across categories. This finding highlights the role of institutional and structural factors that anchor countries within particular regimes, even in the face of shocks (Clark, Dixon, and Monk, 2009). Second, Directional LISA mapped the trajectories of neighbourhood structure movements (Anselin, 1995; Rey and Anselin, 2010; Rey, 2014; Elhorst, 2014). It was found that neighbourhood structures rarely move randomly but follow consistent directional paths, a hallmark of path dependency (Rey and Anselin, 2010; Elhorst, 2014).

The persistence of these regimes contradicts the expectations of the neoclassical finance tradition, which predicts that anomalies should be arbitraged away over time (Fama, 1970; Ross, 1976; Merton, 1980). Path dependence implies that once embedded, EHB appears to be self-reinforcing: investors learn, benchmark, and imitate within their neighbourhood structure (Arthur, 1989; North, 1990; Clark and Wójcik, 2007; Clark and Monk, 2017; Innocenti, Clark, and McGill, 2023; Clark, Hoefer, and Innocenti, 2024). This helps explain why EHB has survived over 50 years of financial integration (French and Poterba, 1991; Lewis, 1999; Karolyi and Stulz, 2002; Rogoff, 2025). It could be argued that social norms and financial literacy also anchor investment practices in local contexts (Gaar, Scherer, and Schiereck, 2022). The findings suggest that the persistence of EHB is not random or aspatial but structurally grounded in the geography of international finance.

6.3 Contributions to practice

The work of Wójcik (2007) reminds financial geographers that the field is guided by three questions: what; why; and, most importantly, *"so what?(p. 557)"* While the previous discussion canvassed the what and the why, this section considers the implications (the so what?) of the findings on how financial integration, portfolio diversification, and the production of returns are understood and practised.

6.3.1 Financial integration

The dominant narrative across the fields of finance, economics, and geography over the observation period of this study (2001 through 2020) has been one of deepening global financial integration (Bekaert and Harvey, 1995; Obstfeld and Rogoff, 2000; Karolyi and Stulz, 2002; Mishkin, 2006; Posen, 2025; Rogoff, 2025; World Economic Forum, 2025). Financial economists have reported that global equity returns and risk premia became increasingly integrated, as barriers such as capital controls and information asymmetries were reduced (Bekaert and Harvey, 1995; Karolyi and Stulz, 2002; Goldstein, Koijen, and Mueller, 2021; Rajput, 2022). On the other hand, financial geographers have debated whether reduced frictions would result in a seamless global financial system (Clark and Wójcik, 2007; Pike and Pollard, 2010). The financial press echoed this theme (The Economist, 2001), with O'Brien (1992) proclaiming that, *"location no longer matters in finance (p.1)."*

The results of this study suggest that deepening financial integration has not uniformly impacted the evolution of clustering and path dependence of EHB (North, 1990; Arthur, 1989; Clark, 2005; Clark and Wójcik, 2007; Haberly and Wójcik, 2022). Low EHB countries (such as the Netherlands and its neighbours) hold portfolios that are highly correlated with the world portfolio (proxied by the MSCI ACWI benchmark), while high EHB countries (such as India and its neighbours) remain segmented, generating returns primarily from domestic factors (French and Poterba, 1991; Sørensen, Wu, Yosha, and Zhu, 2007; Coeurdacier and Rey, 2013; Mishra, 2015).[86] The reported heterogeneity challenges the expectation that anomalies should 'vanish' with financial integration and instead highlights the structural nature of spatio-temporal effects in international finance (Clark, 2005, 2018; Haberly and Wójcik, 2022).

While general areas for future research will be considered (Section 6.4), one specific question that arises from these findings relates to the future of financial integration. Will the remainder of the twenty-first century see a retracement of financial integration (OECD, 2024)? Will the future reflect fragmentation and the re-Balkanisation of international finance (Posen, 2025; Rogoff, 2025; World Economic Forum, 2025)? Researchers, policymakers, and investors alike are increasingly warning that rising geopolitical tensions, economic nationalism, and regulatory divergence may reverse decades of financial integration (Rodrik, 2011; Tooze, 2018; Helleiner, 2019; IMF, 2023; OECD, 2024; Posen, 2025; Rogoff, 2025;

[86] Countries such as the U.S., Japan, and Australia are situated somewhere in between: their portfolios are shaped both by global cycles *and* domestic factors.

World Economic Forum, 2025). In this context, an important pursuit for future consideration is to test whether the 2001 through 2020 observation period examined in this study was the 'high-water mark' of global financial integration, rather than a permanent structural condition (Kotz, 2022; IMF, 2023).

Given the clustering and path dependence found in this study, future research may investigate how *fragmentation* processes (say, geopolitical, global pandemics, institutional and/ or climate-related) reshape the presence and persistence of EHB in the decades ahead (Posen, 2025; Rogoff, 2025).[87] Preliminary evidence suggests that geopolitical risk is associated with reduced cross-border portfolio allocations and heightened financial fragmentation (IMF, 2023; Alsadan, Alalmaee, Zehri, Chokri, and Youssef, 2025). Some studies suggest that the COVID-19 pandemic resulted in greater cointegration of stock markets around the world, thereby diminishing diversification opportunities for investors (Goldstein, Koijen, and Mueller, 2021; Rajput, 2022). Likewise, there is important work being undertaken on the future role of large asset owners (a key subset of investor types) under fragmentation scenarios (Clark and Monk, 2017; Glossner, Matos, Ramelli, and Wagner, 2022). Finally, and perhaps not unexpectedly, climate change and policy uncertainty are producing uneven resilience across geographies, potentially reinforcing localised investment practices and EHB (Dugbartey, 2025). The interplay of these dynamics will shape the trajectory of financial integration broadly, and the presence and persistence of EHB specifically, making this one of the defining questions for investors in the decades to come. Two aspects of this debate for practitioners, portfolio diversification and the production of returns, are addressed in turn.

6.3.2 Portfolio diversification

The findings on the EHB puzzle have implications for the practice of portfolio diversification (Markowitz, 1952). In Low-Low neighbourhood structures (such as the Netherlands and Norway), investor portfolios approximate the theoretical (or optimal) portfolio, consistent with the predictions of the I-CAPM (Solnik, 1974). At the other end of the spectrum, High-High neighbourhood structures (such as India and Pakistan) hold portfolios dominated (in

[87] Posen's (2025) makes a compelling case for a new economic geography, a world in which the changing role and posture of the U.S. will require countries to manage the risk of heightened financial fragmentation by forming blocks with selective partners rather relying on a multilateral approach. In this context of this study, walking back financial integration would, of course, further entrench clustering by space and path dependence through time.

some cases almost exclusively) by domestic equities (Mishra, 2015). By not diversifying, such portfolios are chronically exposed to idiosyncratic risk (Sharpe, 1964), making them more susceptible to geopolitical and economic shocks (Bridgewater Associates, LP, 2019), and to liquidity risk (Wójcik, 2011). Neighbourhood structures that fall in the middle of this Low-Low to High-High spectrum, such as the U.S., Japan, and Australia hold portfolios with varying combinations of expected global equity returns and risk (market beta or systematic risk) *and* idiosyncratic risk (Sharpe, 1964).

For practitioners, the implication is clear: portfolio diversification is inseparable from space and time. Different levels of portfolio diversification across countries expose home investor portfolios to differing systematic and idiosyncratic risk exposures. For investors, and their fiduciaries, the lesson is that benchmarking and performance evaluation cannot assume universality: the MSCI ACWI index may be an appropriate benchmark for Low-Low countries; but it has limited application for investors in High-High countries (Drew and Walk, 2019).

6.3.3 Production of returns

The study found evidence of clustering in Low-Low (Europe’s developed markets) and High-High (Asia’s emerging markets) neighbourhood structures (Chapter 4). Moreover, neighbourhood structures were found to be path-dependent, which means they rarely transition across regimes and, when they do, follow predictable directional paths (Chapter 5). It is argued that the observed trajectories of EHB through time, illustrated by the rose diagrams in Chapter 5, are illustrative of what Martin (2018) describe as, *“lock-in (p.857).”* It is hypothesised that EHB is sustained by institutional structures and historical patterns that are reinforced in the production of returns (Clark and Monk, 2017). Institutional reinforcement describes the mechanisms through which these trajectories are embedded and stabilised (Innocenti, Clark, and McGill, 2023). These can include the forces of regulation, benchmark construction, governance practices, and the social norms that shape investor behaviour (Clark and Monk, 2017).

For the practitioner, the key insight is that clustering and path dependence are seemingly reinforced by investment policy and practices (for example, the design, implementation, and evaluation of investment mandates, Drew and Walk, 2019). Benchmarks like MSCI ACWI not only measure markets but actively structure them, shaping how portfolios are constructed and how ‘performance’ is defined and evaluated (Clark and

Monk, 2017). Governance arrangements and fiduciary obligations frequently amplify EHB, as asset owners are assessed against domestic reference points, reinforcing proximity in allocation decisions (Clark and Monk, 2017; Drew and Walk, 2019). As a result, the production of returns is embedded in local contexts, clustering neighbourhood structures, and reinforcing path dependence (Clark and Monk, 2017; Gaar, Scherer, and Schiereck, 2022; Tao, Petrović, Kwan, and van Ham, 2025). Investment decisions are institutionally conditioned: what counts as value-added for a pension fund in Norway, India, or Japan is not universal but defined by the interaction of benchmarks, governance structures, and local expectations (Clark and Monk, 2017; Drew and Walk, 2019). The practical application of these ideas is provided by Clark and O'Neill (2023), illustrating how defined contribution (termed superannuation) funds in Australia are shaped by organisational design and regulatory frameworks (for instance, incentives regarding benchmark logics and relative investment performance).

6.4 Limitations and future directions

No study is without limitations and it is important to acknowledge the numerous constraints of this study. These relate to the scope of data employed, the specification of neighbourhood structures, the exploratory orientation of correlation-based methods, the temporal granularity of the analysis, the exclusive focus on listed equities, and the need for tests of behavioural factors. Finally, a short reflection on the future of financial geography and finance is considered.

The first limitation concerns the scope and structure of the data. The analysis relied on a dataset covering 43 of the 50 MSCI ACWI markets for the period 2001 through 2020. While this accounts for over 85% of global equity market capitalisation, it excludes several significant markets, including China, Taiwan, Saudi Arabia, and the United Arab Emirates, due to limitations in the availability and consistency of the IMF's CPIS data. While the decision to focus on a complete dataset aligns with best practice (Baele, Pungulescu, and Ter Horst, 2007; Mishra, 2015), it inevitably restricts the generalisability of findings. The empirical analysis relies on CPIS data and the MSCI country classification to construct consistent measures of EHB over time. These choices support comparability and long-horizon analysis, but they also delimit the kinds of questions that can be addressed. CPIS data reflect aggregate portfolio positions rather than the behaviour of specific investor types, and the use of a fixed country classification abstracts from changes in market categorisation and index construction. Examining EHB using alternative data sources (such as investor-level holdings, sector-specific portfolios, or classifications that vary over time) would therefore be a valuable extension of the present work.[88]

A second issue lies in the specification of neighbourhood structures. The analysis used both distance-based measures (*k*-nearest neighbours weighted by spherical distance) and benchmark-defined measures (MSCI ACWI classifications). Specifically, this study has focused on identifying spatial and temporal regularities in EHB using a staged approach that moves from topographical to topological measures of proximity, applied to internationally comparable portfolio holdings data. While this approach provides a transparent and tractable framework for analysing clustering and persistence across countries, it also implies a deliberate progression in the conception of space. Proximity is initially operationalised in physical terms, consistent with standard practice in spatial analysis (Cliff and Ord, 1981), providing a parsimonious baseline against which more relational conceptions can be assessed. The analysis then extends beyond purely physical distance, recognising that financial relationships may be structured through institutional and market-based connections that are not reducible to geography alone. Accordingly, topological conceptions of proximity are implemented through benchmark-defined neighbourhood structures, which capture shared inclusion within global equity benchmarks and hence common institutional, informational, and investment linkages (Morse and Shive, 2011; Coe, Lai, and Wójcik, 2014; Clark and Monk, 2017; Drew and Walk, 2019). Although benchmark-based neighbourhoods capture clustering more effectively in this study, they represent only one possible topological construction of financial space (MSCI ACWI). Alternative neighbourhood structures (structured by trade linkages, cultural similarity, legal systems, or regional integration agreements) may capture other dimensions of financial connectedness that lie beyond the scope of the present analysis (Frankel and Rose, 1998; Florax and Nijkamp, 2003; Campos and Kim, 2017). As Florax and Nijkamp (2003) emphasise, the choice of spatial weight matrices in spatio-temporal analysis is never neutral; it conditions both the results obtained and the inferences drawn. Future research could therefore extend this framework by

[88] Moreover, the analysis abstracts from explicit consideration of who the investors are and how ownership structures and economic sectors shape portfolio allocation decisions. These issues are, of course, closely related to the prevalence and persistence of EHB but fall outside the scope of the present study. Future research that integrates investor identity, ownership forms, and sectoral composition with spatial and temporal frameworks would further deepen understanding of how EHB is produced and maintained across the global financial system (Clark and Monk, 2017).

exploring alternative topological specifications to assess the robustness of observed EHB clustering and persistence across different relational conceptions of space.

A third limitation concerns the methodological orientation and temporal resolution of the analysis. By prioritising correlation-based spatio-temporal approaches (such as Global Moran's Index, LISA, Transition LISA, and Directional LISA), the study moved deliberately away from causal inference. These methods are appropriate for uncovering clustering and path dependence, but do not establish causal mechanisms (Arthur, 1989; North, 1990; David, 1994; Leyshon and Thrift, 1998; Clark, 1998; Martin, 1999, 2010; Clark, Mansfield, and Tickell, 2001; Martin and Sunley, 2006, 2010). The results should, therefore, be interpreted as exploratory, mapping the spatio-temporal effects of the EHB puzzle (Anselin, 1995; Rey and Le Gallo, 2009). While the annual intervals considered in this study allowed for the detection of long-run clustering and persistence (including across shocks such as the GFC and the onset of COVID-19), this obscures higher-frequency adjustments that characterise international finance. Studies using higher-frequency data suggest that EHB can shift rapidly in response to shocks, even if long-term persistence remains (Balasubramanian and Kumar, 2023; Hu, 2023). Subject to data availability, further investigation of short-run dynamics of EHB would make for an important contribution to the field.

A fourth limitation is the study's exclusive focus on listed (public) equities. Equities remain the most widely analysed asset class in the EHB literature (French and Poterba, 1991; Lewis, 1999). However, proximity bias manifests in other asset classes as well. Studies on home bias in hedge funds, bonds, and real estate (Sialm, Sun, and Zheng, 2020; Krebbers, Marshall, McColgan, and Neupane, 2023; Singh, Kumar, Goel, and Johri, 2023), raise the possibility that clustering and persistence differ across asset classes due to variations in liquidity, regulation, and/ or liability structures. By focusing on listed equities, the study has clearly traded depth for breadth. A fuller understanding of the geography of home bias will require comparative studies across asset classes, integrated causal designs that test the determinants of observed clusters, and data extensions as they become available.

Fifth, the field of behavioural finance has identified familiarity bias as a driver of EHB (Huberman, 2001; Coval and Moskowitz, 1999; Gaar, Scherer, and Schiereck, 2020). Experimental studies confirm that investors systematically perceive proximate assets as less risky, even when fundamentals are equivalent (Baltzer, Stolper, and Walter, 2013). This study has not attempted the important task of testing behavioural mechanisms related to EHB in spatio-temporal frameworks. Again, this seems an important direction for future research.

Finally, this study has successfully prosecuted the argument that the neoclassical finance tradition and the field of financial geography reflect a paradigmatic divide in the Kuhnian (1970) sense. The central tenets of the neoclassical finance tradition assume universality of information efficiency, optimisation, linearity, and equilibrium, abstracting investors into rational actors whose portfolios converge on the global market portfolio (Markowitz, 1952; Sharpe, 1964; Fama, 1970). In this tradition, space is reduced to domicile, and time to an ordinal sequence, conceived as an aspatial time-series in which arbitrage progressively eliminates anomalies. In sharp contrast, financial geography emphasises that finance is spatially clustered and temporally path-dependent, shaped by the uneven geographies of markets, the institutional arrangements that govern them, and the historical trajectories through which they evolve (Clark, 2005, 2018; Wójcik, 2020). From this perspective, EHB is not an anomaly awaiting arbitrage but a structural feature of international finance. In Kuhn's (1970) terms, the two fields operate with different problem framings, different criteria of validity, and different logics of explanation.

It is important to critically reflect on how the disciplines of financial geography and finance might move forward. Perhaps optimistically, it is posited that a rejoinder, based on the principle of complementarity, provides a path forward. Rather than treating the paradigms of financial geography and finance as mutually exclusive (Kuhn, 1970), it is time to move from an *'either-or'* framing, to a *'both-and'* perspective. For the field of financial geography, this means bringing the central tenets of clustering and path dependence directly to the puzzles of international finance. For the field of finance, innovations in theory and method that move beyond reductionist assumptions of space and time can provide novel insights.[89] This will be left to the next generation of scholars to discover the complementarity of both financial geography and finance, as this study has sought to demonstrate.

[89] This argument is supported by Wójcik (2007) who opines that, *"If financial economics … dealt with the spatiality of finance effectively, we would not need financial geography. In reality, however, … financial economics … fails to consider space in finance (p.557)"*

6.5 Concluding remarks

The central claim of this study is that EHB is a structural feature of international finance, sustained by clustering across space and path dependence through time. By addressing the EHB puzzle through its definition, measurement, presence, and persistence, the study provides novel insights into portfolio diversification and the production of returns. The effects of financial integration on EHB in recent decades have not been uniform. Spatial clustering and temporal path dependence are associated with negligible EHB in developed European markets, while reinforcing persistently high EHB in emerging Asian markets. These patterns indicate that portfolio allocation decisions are embedded in spatially structured environments and evolve through historically contingent trajectories. In short, investing is inherently geographical, structured through the intersection of space and time.

7. Reference list

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8. Appendices

- Appendix 1 Reviewed studies for the systematic literature review (N = 60)
- Appendix 2 Equity home bias estimates for China
- Appendix 3 Actual weights (w^A) of equity home bias by country
- Appendix 4 Equity home bias estimates for given optimal weights (w^O) by country
- Appendix 5 Model-based, I-CAPM validity test
- Appendix 6 Quantile shift function results for all pair-wise combinations
- Appendix 7 ISO3 codes by country
- Appendix 8 Home and neighbour chain computation example (2001 to 2002)

Appendix 1 Reviewed papers for the systematic literature review (N =60)

ID	Author	Year	Title	Journal name	Home bias definition			Form of measure			
					F	E	G	Model-based	Data-based	Hybrid	Remarks
1	JD Coval TJ Moskowitz	1999	Home bias at home: Local equity preference in domestic portfolios	The Journal of Finance	Yes		Yes	Yes			This study uses Capital Asset Pricing model (CAPM) as the benchmark and compute distance adjusted portfolio shares and compare with actual portfolio weights
2	KR French JM Poterba	1991	Investor diversification and international equity markets	National Bureau of Economic Research	Yes				Yes		
3	M Obstfeld K Rogoff	2000	The six major puzzles in international macroeconomics: Is there a common cause?	NBER Macroeconomics Annual	Yes	Yes					Trade costs and home bias in trade
4	KK Lewis	1999	Trying to explain home bias in equities and consumption	Journal of Economic Literature	Yes	Yes		Yes	Yes		
5	A Ahearne W Griever F Warnock	2004	Information costs and home bias: an analysis of US holdings of foreign equities	Journal of International Economics	Yes	Yes		Yes			Derivative of I-CAPM. Home bias is computed as the proportion of the portfolio weight of country i in the portfolio of U.S. investors, with the portfolio weight of country i in the world market portfolio.
6	I Cooper E Kaplanis	1994	Home bias in equity portfolios, inflation hedging, and international capital market equilibrium	The Review of Financial Studies	Yes	Yes			Yes		
7	L Pástor	2000	Portfolio selection and asset pricing models	The Journal of Finance	Yes					Yes	

8	R Uppal T Wang	2003	Model misspecification and under-diversification	Journal of Finance	Yes			Yes		Yes	
9	G Bekaert XS Wang	2009	Home bias revisited	Working paper	Yes			Yes			This study uses CAPM as the benchmark
10	M Fidora M Fratzscher C Thimann	2007	Home bias in global bond and equity markets: the role of real exchange rate volatility	Journal of International Money and Finance	Yes			Yes			
11	K Jeske	2001	Equity home bias: Can information cost explain the puzzle?	Economic Review-Federal Reserve Bank of Atlanta (Industry article)	Yes				Yes		
12	B Sørensen Y Wu O Yosha Y Zhu	2007	Home bias and international risk sharing: Twin puzzles separated at birth	Journal of International Money and Finance	Yes			Yes			
13	F Cai F Warnock	2006	International diversification at home and abroad	National Bureau of Economic Research	Yes		Yes	Yes			Derivative of I-CAPM framework Relative weight of domestic market and global equity market in multi-national firms
14	B Kho R Stulz F Warnock	2009	Financial globalization, governance, and the evolution of the home bias	Journal of Accounting Research	Yes	Yes		Yes			Derivative of I-CAPM. Home bias is computed as the proportion of the portfolio weight of country i in the portfolio of U.S. investors, with the portfolio weight of country i in the world market portfolio. Refer to Eq. [22] in (Kho *et al.,* 2009, p. 614)
15	N Coeurdacier H Rey	2013	Home Bias in Open Economy Financial Macroeconomics	Journal of Economic Literature	Yes	Yes		Yes			

16	F Warnock	2002	Home bias and high turnover reconsidered	Journal of International Money and Finance	Yes	Yes		Yes			Derivative of I-CAPM. Home bias is computed as the proportion of the portfolio weight of country i in the portfolio of U.S. investors, with the portfolio weight of country i in the world market portfolio. Refer to Eq. [22] in (Warnock 2002, p. 796)
17	P Boyle L Garlappi R Uppal T Wang	2012	Keynes Meets Markowitz: The Trade-Off Between Familiarity and Diversification	Management Science	Yes	Yes			Yes		
18	A Morse S Shive	2011	Patriotism in your portfolio	Journal of Financial Markets	Yes			Yes			This study uses CAPM as the benchmark
19	L Baele C Pungulescu J T Horst	2007	Model uncertainty, financial market integration and the home bias puzzle	Journal of International Money and Finance	Yes			Yes	Yes	Yes	
20	M Grote M Umber	2006	Home biased? A spatial analysis of the domestic merging behaviour of US firms	Working paper	Yes		Yes				Home bias is presented as partial proximity for every M&A transaction. Refer to equation in (Grote and Umber, 2006, p. 21)
21	AA Amadi	2004	Does familiarity breed investment? An empirical analysis of foreign equity holdings	Working paper	Yes		Yes	Yes			
22	G Georgopoulos W Hejazi	2009	The Feldstein–Horioka puzzle revisited: Is the home-bias much less?	International Economic Review of Economics and Finance	Yes		Yes				Refer to equation 2 in (Georgopoulos and Hejazi, 2009, p. 343) for correlation adjusted home bias measure
23	B Solnik L Zuo	2012	A global equilibrium asset pricing model with home preference	Management Science	Yes	Yes		Yes			

24	A Mishra	2011	Australia's equity home bias and real exchange rate volatility	Review of Quantitative Finance and Accounting	Yes			Yes		
25	H Levy M Levy	2014	The home bias is here to stay	Journal of Banking and Finance	Yes				Yes	
26	E Wincoop F Warnock	2010	Can trade costs in goods explain home bias in assets?	Journal of International Money and Finance	Yes	Yes	Yes	Yes		Derivative of CAPM. Refer to equations 8 and 9 in (Wincoop and Warnock, 2010, p. 1112)
27	P Sercu R Vanpée	2012	The home bias puzzle in equity portfolios	International Finance: A Survey (Book)	Yes			Yes		Derivative of I-CAPM and scaling methods Sercu and Vanpée, (2012, p.7)
28	A Mishra	2008	Australia's equity home bias	Australian Economic Papers	Yes			Yes		Float adjusted home bias using I-CAPM framework
29	A Mishra R Ratti	2013	Home bias and cross border taxation	Journal of International Money and Finance	Yes			Yes		Float adjusted home bias using I-CAPM framework
30	G Bekaert C Harvey A Kiguel X Wang	2016	Globalization and asset returns	Annual Review of Financial Economics	Yes		Yes			Correlation study with several controls for geography considers I-CAPM framework as well
31	S Eichler	2012	Equity home bias and corporate disclosure	Journal of International Money and Finance	Yes	Yes	Yes	Yes		Derivative of I-CAPM. Home bias is computed as the proportion of the portfolio weight of country i in the portfolio of U.S. investors, with the portfolio weight of country i in the world market portfolio. Refer to Eq. [22] in (Eichler, 2012, p. 1017)
32	L Moor R Vanpée	2013	What drives international equity and bond holdings? An empirical study	Applied Financial Economics	Yes	Yes		Yes		Derivative of I-CAPM and scaling methods discussed by Sercu and Vanpée, (2012)

33	D Schoenmaker T Bosch	2008	Is the home bias in equities and bonds declining in Europe?	Investment Management and Financial Innovations	Yes		Yes	Yes			
34	AV Mishra	2015	Measures of equity home bias puzzle	Journal of Empirical Finance	Yes			Yes	Yes	Yes	
35	H Asgharian B Hansson	2006	Home bias among European investors from a Bayesian perspective	Journal of International Financial Markets, Institutions and Money	Yes	Yes	Yes	Yes	Yes	Yes	
36	M Ferreira A Miguel	2007	Home equity bias and industry concentration	Working paper	Yes			Yes			
37	J Mondria T Wu	2013	Imperfect financial integration and asymmetric information: competing explanations of the home bias puzzle?	Canadian Journal of Economics	Yes	Yes		Yes			Derivative of I-CAPM. Home bias is computed as the proportion of the portfolio weight of country i in theportfolio of U.S. investors, with the portfolio weight of country i in the world market portfolio. Refer to Eq. [9] in (Mondria and Wu, 2013, p. 317)
38	M Baltzer O Stolper A Walter	2013	Is local bias a cross-border phenomenon? Evidence from individual investors' international asset allocation	Journal of Banking and Finance			Yes	Yes			
39	H Foad	2011	Immigration and equity home bias	Journal of International Money and Finance	Yes		Yes	Yes			Derivative of I-CAPM. Refer to Eq. [11] in (Foad, 2011, p. 987). EHB is computed as a function of I-CAPM benchmark, control variables and vector of return characteristics relating to equities issued by countries. Two sub home bias measures are derived as: immigration and emigration home bias
40	A Mishra	2014	Australia's home bias and cross border taxation	Global Finance Journal	Yes			Yes			Float adjusted home bias using I-CAPM framework

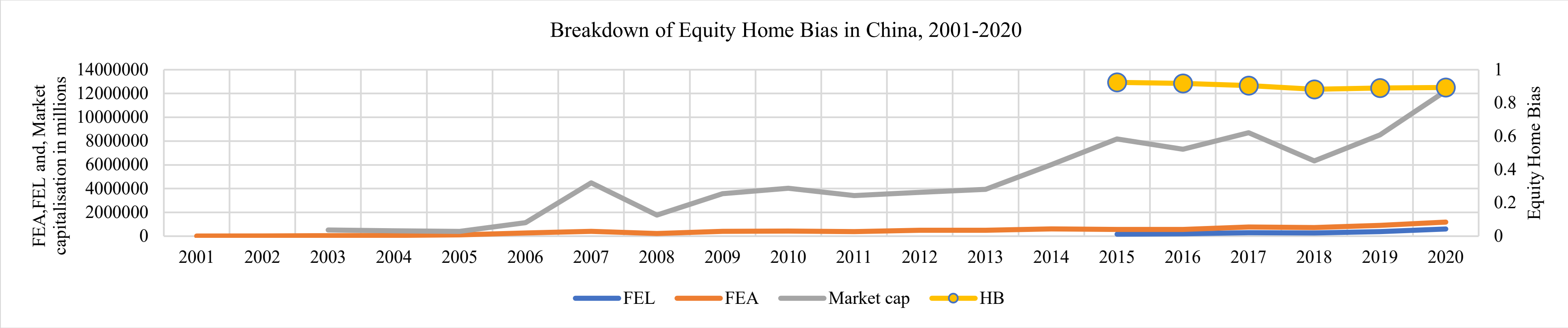
41	M Wynter	2019	Why Did the Equity Home Bias Fall During the Financial Panic of 2008	The World Economy	Yes	Yes		Yes			
42	W Wu Y Gau	2017	Home bias in portfolio choices: social learning among partially informed agents	Review of Quantitative Finance and Accounting	Yes	Yes			Yes	Yes	
43	B Solnik L Zuo	2017	Relative optimism and the home bias puzzle	Review of Finance	Yes			Yes			
44	C Pungulescu	2015	Real effects of financial market integration: does lower home bias lead to welfare benefits?	The European Journal of Finance		Yes		Yes		Yes	
45	F Kwabi C Thapa K Paudyal E Adegbite	2017	Biases in international portfolio allocation and investor protection standards	International Review of Financial Analysis	Yes			Yes			
46	T Lindblom T Mavruk S Sjögren	2017	Proximity Bias in Investors' Portfolio Choice	Springer International Publishing (Book)	Yes			Yes	Yes		
47	F Lundtofte	2009	Endogenous Acquisition of Information and the Equity Home Bias	Economica	Yes				Yes		
48	B Kim Y Yun B Cin YKim	2014	Home bias in emerging bond and stock markets	Emerging Markets Finance and Trade	Yes	Yes		Yes			
49	H Foad	2012	Equity home bias and the Euro	Quarterly Journal of Finance	Yes	Yes	Yes	Yes			Derivative of I-CAPM framework
50	R Mukherjee S Paul S Shankar	2018	Equity home bias—A global perspective from the shrunk frontier	Economic Analysis and Policy	Yes					Yes	
51	H Levy	2017	What is the Economic Cost of the Investment Home Bias?	Journal of Money, Credit and Banking	Yes	Yes			Yes		Investment home bias and economic home bias
52	D Su X Li	2016	Equity Home Bias Puzzle Revisited	Working paper	Yes			Yes	Yes		
53	Y Chen J Huang S Xiao Z Zhao	2020	The "home bias" of corporate subsidiary locations	Journal of Corporate Finance			Yes				Subsidiary location study with control variables
54	A Mishra	2017	Foreign bias in Australia's international equity holdings	Review of Financial Economics	Yes			Yes	Yes	Yes	
55	E Benos M Jochec	2009	Liberalism and home equity bias	Working paper	Yes			Yes			Derivative of I-CAPM framework

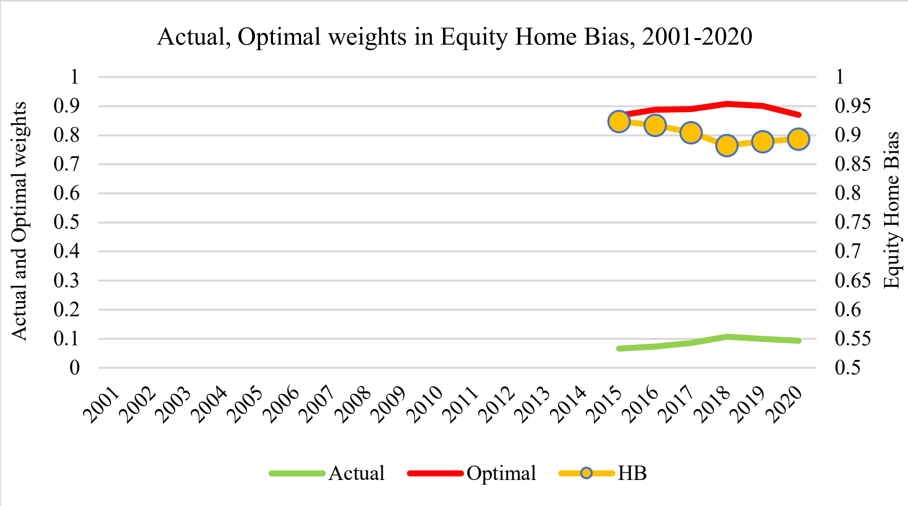
56	R Carpio M Gu Y Liu J Pyun	2021	Wealth heterogeneity, information acquisition and equity home bias: Evidence from U.S. household surveys of consumer finance	Journal of Banking and Finance	Yes	Yes		Yes
57	K Kyounghun H Kim	2021	Explaining equity home bias using hedging motives against real exchange rate and wage risks	International Review of Economics and Finance	Yes	Yes		Yes
58	C Hu	2020	Industrial specialization matters: A new angle on equity home Bias	Journal of International Economics	Yes	Yes		Yes
59	S Blank M Hoffmann M Roth	2020	Foreign direct investment and the equity home bias puzzle	Working paper	Yes			Yes
60	A Mesa-Toro A Moreno M Julieta Sammartino T Trani	2021	Equity Home Bias when Firms are Indebted	Working paper	Yes	Yes		Yes

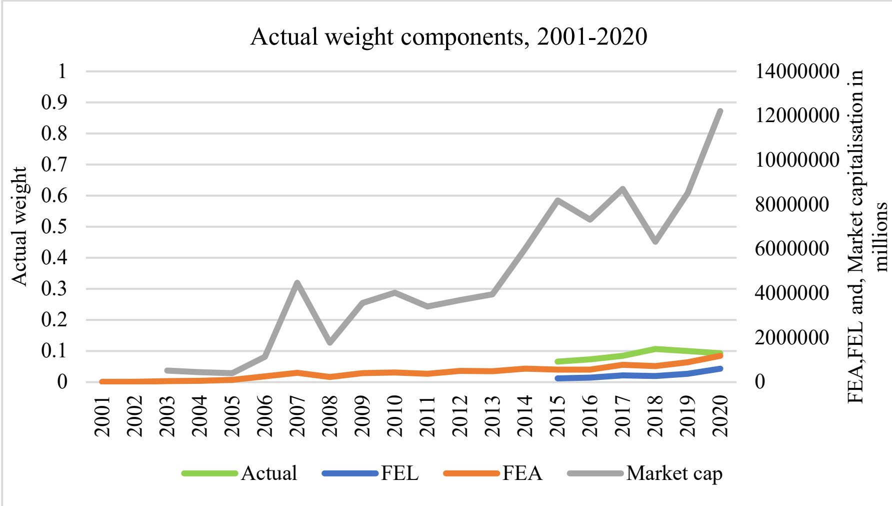
Note: Regarding the fifth column named "home bias definition", acronym "F" stands for Finance related definitions/ concepts such as unequal wealth allocation in home market/ empirical estimation of incomplete diversification (optimal weights, actual weight) etc. Acronym "E" stands for an Economic related concepts of home bias such as economic trade barriers, currency regimes, bi-lateral trade flows, investor preference (behaviour), scarcity of resources, etc. Acronym "G" stands for Geography, with related concepts such as proximity bias, studies on head quarter locations, mergers and acquisitions, globalisation, etc. The common forms of EHB measures are categorised as: model-based, data-based, hybrid, and other related to various one-off measures. The articles presented are in descending order based on their number of citations.

Appendix 2 Equity home bias estimates for China

Country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
China	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.924	0.917	0.905	0.883	0.890	0.894







Appendix 3 Actual weights (w^A) of equity home bias by country

Country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Argentina	0.182	0.306	0.185	0.180	0.173	0.194	0.222	0.173	0.203	0.146	0.208	0.262	0.223	0.210	0.212	0.207	0.166	0.311	0.379	0.441
Australia	0.172	0.186	0.164	0.150	0.173	0.176	0.208	0.229	0.199	0.204	0.245	0.248	0.277	0.301	0.311	0.320	0.330	0.362	0.375	0.361
Austria	0.618	0.529	0.510	0.486	0.421	0.408	0.381	0.543	0.507	0.518	0.581	0.574	0.599	0.660	0.656	0.592	0.636	0.668	0.703	0.750
Belgium	0.449	0.529	0.529	0.453	0.501	0.498	0.565	0.657	0.599	0.569	0.584	0.559	0.578	0.576	0.551	0.624	0.656	0.701	0.677	0.793
Brazil	0.019	0.022	0.013	0.008	0.007	0.006	0.006	0.010	0.008	0.012	0.017	0.013	0.021	0.034	0.059	0.038	0.043	0.043	0.041	0.046
Canada	0.308	0.204	0.272	0.247	0.244	0.271	0.260	0.311	0.272	0.262	0.288	0.309	0.351	0.376	0.447	0.420	0.452	0.486	0.507	0.509
Chile	0.069	0.088	0.114	0.121	0.150	0.210	0.241	0.214	0.247	0.225	0.233	0.245	0.297	0.336	0.369	0.360	0.342	0.357	0.444	0.491
Colombia	0.025	0.039	0.074	0.024	0.020	0.028	0.022	0.018	0.032	0.028	0.036	0.028	0.066	0.111	0.181	0.160	0.181	0.193	0.175	0.272
Czech Republic	0.217	0.253	0.135	0.140	0.176	0.215	0.200	0.234	0.216	0.244	0.223	0.251	0.317	0.355	0.382	0.442	0.434	0.462	0.472	0.527
Denmark	0.416	0.381	0.357	0.363	0.381	0.422	0.418	0.470	0.478	0.466	0.516	0.521	0.515	0.513	0.495	0.531	0.535	0.577	0.575	0.551
Egypt	0.021	0.017	0.043	0.032	0.014	0.010	0.008	0.011	0.011	0.013	0.018	0.013	0.012	0.012	0.016	0.025	0.026	0.010	0.010	0.011
Finland	0.203	0.282	0.331	0.389	0.402	0.429	0.461	0.523	0.514	0.534	0.593	0.615	0.565	0.605	0.626	0.625	0.629	0.672	0.667	0.638
France	0.204	0.228	0.266	0.299	0.313	0.323	0.317	0.337	0.333	0.364	0.354	0.378	0.389	0.403	0.394	0.407	0.415	0.411	0.409	0.533
Germany	0.322	0.403	0.371	0.405	0.434	0.483	0.460	0.503	0.531	0.512	0.520	0.504	0.484	0.526	0.560	0.577	0.557	0.601	0.606	0.631
Greece	0.017	0.040	0.048	0.055	0.066	0.079	0.096	0.190	0.142	0.195	0.315	0.177	0.091	0.166	0.323	0.315	0.243	0.261	0.237	0.263
Hong Kong	0.181	0.191	0.198	0.209	0.197	0.184	0.180	0.190	0.193	0.194	0.192	0.194	0.200	0.203	0.218	0.236	0.239	0.230	0.213	0.217
Hungary	0.025	0.029	0.033	0.063	0.094	0.182	0.228	0.345	0.344	0.397	0.368	0.345	0.396	0.484	0.428	0.377	0.354	0.364	0.366	0.474
India	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002
Indonesia	0.000	0.003	0.000	0.000	0.001	0.003	0.005	0.006	0.004	0.003	0.003	0.004	0.008	0.009	0.012	0.011	0.013	0.017	0.018	0.021
Ireland	1.187	1.493	1.436	1.474	1.542	1.641	1.684	1.775	2.378	2.832	3.169	5.736	7.012	-22.8	-7.06	-5.97	-8.75	-5.22	-3.18	-3.66
Israel	0.047	0.056	0.056	0.060	0.087	0.090	0.088	0.163	0.166	0.170	0.249	0.295	0.285	0.325	0.276	0.297	0.329	0.390	0.379	0.452
Italy	0.369	0.403	0.419	0.398	0.431	0.442	0.446	0.470	0.467	0.534	0.577	0.602	0.629	0.666	0.679	0.736	0.727	0.756	0.754	0.791
Japan	0.105	0.106	0.100	0.112	0.101	0.127	0.149	0.137	0.185	0.184	0.202	0.203	0.173	0.270	0.264	0.282	0.272	0.299	0.300	0.307
Korea	0.007	0.009	0.014	0.029	0.026	0.056	0.109	0.118	0.101	0.090	0.086	0.101	0.118	0.135	0.142	0.160	0.163	0.203	0.258	0.229
Malaysia	0.012	0.015	0.005	0.006	0.009	0.018	0.033	0.066	0.073	0.065	0.072	0.075	0.085	0.103	0.124	0.136	0.127	0.146	0.191	0.211
Mexico	0.004	0.006	0.004	0.022	0.018	0.021	0.022	0.029	0.038	0.037	0.044	0.057	0.069	0.079	0.084	0.088	0.117	0.115	0.126	0.166
Netherlands	0.523	0.569	0.681	0.732	0.675	0.640	0.552	0.697	0.694	0.671	0.668	0.702	0.724	0.757	0.803	0.806	0.769	1.224	1.121	0.978
New Zealand	0.345	0.347	0.356	0.357	0.421	0.412	0.435	0.507	0.501	0.516	0.492	0.481	0.469	0.469	0.467	0.493	0.467	0.522	0.520	0.518
Norway	0.436	0.531	0.509	0.480	0.482	0.475	0.516	0.654	0.700	0.650	0.738	0.758	0.782	0.815	0.834	0.809	0.812	0.812	0.833	0.862
Pakistan	0.005	0.002	0.003	0.002	0.008	0.005	0.004	0.004	0.003	0.003	0.003	0.003	0.003	0.002	0.002	0.001	0.002	0.002	0.003	0.003
Philippines	0.006	0.007	0.008	0.007	0.003	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.003	0.002	0.005	0.004	0.009	0.012
Poland	0.005	0.007	0.007	0.012	0.020	0.039	0.061	0.053	0.052	0.060	0.059	0.060	0.062	0.084	0.170	0.130	0.119	0.141	0.159	0.107
Portugal	0.192	0.211	0.200	0.249	0.370	0.444	0.476	0.806	0.573	0.687	1.008	0.373	0.393	0.493	0.500	0.506	0.482	0.530	0.508	0.483
Russia	0.002	0.000	0.000	0.000	0.000	0.000	0.003	0.007	0.003	0.005	0.008	0.007	0.005	0.014	0.008	0.006	0.009	0.012	0.013	0.037
Singapore	0.297	0.389	0.453	0.388	0.393	0.381	0.386	0.465	0.356	0.364	0.386	0.405	0.441	0.450	0.512	0.538	0.560	0.542	0.594	0.638
South Africa	0.174	0.144	0.142	0.098	0.111	0.093	0.086	0.120	0.112	0.133	0.152	0.157	0.157	0.152	0.180	0.149	0.140	0.159	0.155	0.153
Spain	0.141	0.127	0.120	0.126	0.138	0.141	0.117	0.104	0.090	0.112	0.105	0.126	0.182	0.230	0.322	0.364	0.411	0.438	0.463	0.531
Sweden	0.394	0.431	0.409	0.491	0.409	0.389	0.443	0.504	0.464	0.454	0.479	0.472	0.459	0.475	0.472	0.471	0.493	0.500	0.491	0.475
Switzerland	0.427	0.348	0.397	0.400	0.402	0.391	0.433	0.408	0.444	0.402	0.437	0.444	0.448	0.456	0.455	0.512	0.515	0.535	0.514	0.527
Thailand	0.002	0.002	0.004	0.007	0.010	0.016	0.021	0.026	0.023	0.021	0.026	0.023	0.025	0.033	0.048	0.044	0.056	0.058	0.075	0.101
Turkey	0.001	0.001	0.000	0.001	0.000	0.001	0.000	0.000	0.001	0.001	0.001	0.001	0.002	0.002	0.003	0.003	0.002	0.003	0.003	0.004
United Kingdom	0.279	0.291	0.303	0.332	0.369	0.379	0.410	0.468	0.393	0.389	0.399	0.414	0.443	0.501	0.537	0.573	0.606	0.626	0.632	0.665
United States	0.110	0.120	0.138	0.147	0.178	0.199	0.230	0.214	0.234	0.237	0.253	0.250	0.240	0.232	0.248	0.241	0.260	0.242	0.257	0.248

Appendix 4 Equity home bias estimates for given optimal weights (w^O) by country

EHB estimates for the model-based, I-CAPM approach (2001 through 2020)

Country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Argentina	0.817	0.693	0.814	0.819	0.826	0.804	0.777	0.825	0.796	0.853	0.791	0.737	0.775	0.788	0.787	0.792	0.832	0.688	0.620	0.558
Australia	0.825	0.809	0.832	0.845	0.823	0.820	0.786	0.765	0.794	0.789	0.747	0.744	0.716	0.692	0.682	0.673	0.663	0.630	0.617	0.631
Austria	0.380	0.470	0.488	0.512	0.576	0.589	0.617	0.455	0.490	0.480	0.417	0.423	0.399	0.338	0.342	0.406	0.361	0.330	0.295	0.248
Belgium	0.547	0.467	0.467	0.543	0.495	0.497	0.431	0.338	0.396	0.427	0.412	0.437	0.418	0.420	0.445	0.372	0.339	0.295	0.319	0.203
Brazil	0.980	0.977	0.986	0.991	0.992	0.993	0.993	0.989	0.991	0.987	0.981	0.985	0.978	0.964	0.939	0.961	0.956	0.955	0.958	0.953
Canada	0.684	0.787	0.719	0.744	0.746	0.718	0.729	0.678	0.717	0.725	0.698	0.676	0.636	0.610	0.540	0.566	0.533	0.499	0.478	0.475
Chile	0.930	0.911	0.884	0.877	0.849	0.788	0.757	0.785	0.751	0.772	0.764	0.752	0.701	0.662	0.629	0.638	0.656	0.641	0.554	0.507
Colombia	0.975	0.961	0.925	0.975	0.979	0.971	0.977	0.981	0.967	0.971	0.963	0.971	0.933	0.887	0.817	0.838	0.818	0.805	0.824	0.727
Czech Republic	0.782	0.746	0.864	0.859	0.823	0.784	0.799	0.765	0.783	0.755	0.776	0.747	0.682	0.644	0.617	0.557	0.565	0.537	0.527	0.472
Denmark	0.582	0.617	0.641	0.634	0.616	0.575	0.579	0.527	0.519	0.531	0.480	0.475	0.482	0.483	0.501	0.465	0.461	0.418	0.421	0.444
Egypt	0.949	0.998	0.956	0.967	0.985	0.989	0.991	0.988	0.988	0.986	0.981	0.986	0.987	0.987	0.983	0.974	0.973	0.989	0.989	0.988
Finland	0.795	0.715	0.667	0.608	0.595	0.568	0.535	0.474	0.483	0.462	0.404	0.382	0.432	0.392	0.371	0.372	0.368	0.324	0.330	0.358
France	0.786	0.761	0.721	0.686	0.672	0.660	0.667	0.646	0.651	0.621	0.632	0.607	0.594	0.582	0.591	0.578	0.569	0.574	0.576	0.452
Germany	0.663	0.584	0.615	0.581	0.552	0.499	0.522	0.478	0.452	0.473	0.465	0.480	0.499	0.458	0.423	0.407	0.425	0.382	0.378	0.352
Greece	0.982	0.959	0.951	0.944	0.933	0.920	0.903	0.808	0.857	0.804	0.684	0.822	0.908	0.833	0.676	0.684	0.756	0.738	0.762	0.736
Hong Kong	0.814	0.804	0.796	0.785	0.797	0.808	0.811	0.801	0.795	0.794	0.796	0.794	0.788	0.785	0.769	0.751	0.746	0.755	0.773	0.767
Hungary	0.975	0.970	0.966	0.936	0.905	0.817	0.771	0.654	0.655	0.602	0.631	0.654	0.603	0.515	0.571	0.622	0.644	0.635	0.632	0.524
India	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.998	0.998	0.999	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.998	0.997
Indonesia	0.999	0.996	0.999	0.999	0.998	0.996	0.994	0.993	0.995	0.996	0.996	0.995	0.991	0.990	0.987	0.988	0.986	0.982	0.981	0.978
Ireland	0.160	0.332	0.305	0.323	0.353	0.392	0.407	0.437	0.580	0.647	0.685	0.826	0.857	0.956	0.858	0.833	0.886	0.808	0.686	0.727
Israel	0.852	0.943	0.943	0.939	0.912	0.909	0.910	0.835	0.833	0.828	0.750	0.703	0.713	0.673	0.722	0.701	0.669	0.608	0.619	0.546
Italy	0.522	0.587	0.571	0.593	0.560	0.548	0.544	0.521	0.524	0.459	0.415	0.391	0.364	0.327	0.314	0.257	0.265	0.236	0.239	0.203
Japan	0.885	0.882	0.888	0.875	0.885	0.859	0.839	0.847	0.799	0.800	0.780	0.781	0.812	0.708	0.712	0.694	0.704	0.675	0.676	0.668
Korea	0.992	0.990	0.985	0.970	0.973	0.942	0.888	0.880	0.896	0.907	0.911	0.896	0.878	0.861	0.854	0.835	0.832	0.792	0.736	0.765
Malaysia	0.987	0.984	0.994	0.993	0.990	0.981	0.966	0.933	0.925	0.933	0.927	0.924	0.913	0.896	0.874	0.863	0.871	0.852	0.807	0.787
Mexico	0.900	0.994	0.995	0.977	0.981	0.978	0.977	0.969	0.961	0.961	0.954	0.941	0.929	0.920	0.915	0.910	0.882	0.883	0.872	0.832
Netherlands	0.466	0.420	0.307	0.256	0.314	0.348	0.439	0.294	0.296	0.320	0.322	0.287	0.265	0.232	0.187	0.183	0.219	0.188	0.115	0.011
New Zealand	0.564	0.652	0.643	0.642	0.577	0.586	0.564	0.491	0.497	0.482	0.506	0.518	0.529	0.530	0.531	0.505	0.531	0.477	0.478	0.480
Norway	0.562	0.466	0.488	0.518	0.515	0.521	0.480	0.342	0.295	0.345	0.257	0.237	0.213	0.181	0.162	0.187	0.184	0.184	0.163	0.134
Pakistan	0.994	0.997	0.996	0.997	0.991	0.994	0.995	0.995	0.996	0.996	0.996	0.996	0.996	0.997	0.997	0.998	0.997	0.997	0.996	0.996
Philippines	0.993	0.992	0.991	0.992	0.996	0.997	0.997	0.999	0.999	0.999	0.999	0.999	0.998	0.998	0.996	0.997	0.994	0.995	0.990	0.987
Poland	0.800	0.892	0.992	0.987	0.979	0.960	0.938	0.945	0.947	0.939	0.940	0.939	0.937	0.914	0.829	0.869	0.879	0.858	0.839	0.892
Portugal	0.807	0.788	0.799	0.750	0.628	0.554	0.522	0.191	0.425	0.311	0.010	0.625	0.605	0.505	0.499	0.492	0.517	0.469	0.491	0.515
Russia	0.998	0.996	0.999	0.999	0.999	0.999	0.996	0.992	0.996	0.994	0.991	0.992	0.994	0.985	0.991	0.993	0.990	0.987	0.986	0.962
Singapore	0.601	0.608	0.544	0.609	0.603	0.615	0.610	0.530	0.639	0.630	0.607	0.588	0.552	0.543	0.482	0.456	0.433	0.452	0.400	0.357
South Africa	0.824	0.854	0.856	0.899	0.887	0.905	0.912	0.877	0.885	0.864	0.844	0.840	0.840	0.844	0.817	0.848	0.856	0.838	0.842	0.844
Spain	0.855	0.869	0.877	0.870	0.857	0.854	0.878	0.892	0.906	0.884	0.892	0.870	0.813	0.765	0.672	0.631	0.583	0.556	0.532	0.463
Sweden	0.602	0.565	0.586	0.504	0.585	0.605	0.552	0.491	0.530	0.540	0.514	0.522	0.534	0.519	0.522	0.523	0.501	0.494	0.503	0.518
Switzerland	0.563	0.642	0.593	0.590	0.587	0.598	0.556	0.580	0.543	0.587	0.551	0.544	0.539	0.532	0.533	0.476	0.473	0.452	0.474	0.460
Thailand	0.997	0.997	0.995	0.992	0.989	0.983	0.978	0.973	0.976	0.978	0.973	0.976	0.974	0.966	0.950	0.955	0.943	0.941	0.924	0.897
Turkey	0.998	0.998	0.999	0.998	0.999	0.998	0.999	0.999	0.998	0.998	0.998	0.998	0.997	0.997	0.996	0.996	0.997	0.996	0.996	0.995
United Kingdom	0.695	0.682	0.671	0.640	0.600	0.589	0.561	0.502	0.577	0.583	0.570	0.555	0.524	0.467	0.431	0.398	0.363	0.344	0.340	0.310
United States	0.768	0.766	0.745	0.734	0.692	0.672	0.655	0.665	0.643	0.640	0.606	0.603	0.597	0.600	0.582	0.582	0.561	0.564	0.571	0.559

EHB estimates for the data-based, mean-variance approach (2001 through 2020)

Country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Argentina	0.824	0.683	0.799	0.808	0.798	0.787	0.952	0.824	0.788	0.839	0.760	0.678	0.762	0.782	0.769	0.800	0.814	0.665	0.653	0.559
Australia	0.865	0.851	0.784	0.805	0.747	0.788	0.762	0.767	0.783	0.788	0.744	0.725	0.742	0.825	0.595	0.661	0.652	0.343	0.574	0.634
Austria	0.404	0.805	0.292	0.247	0.465	0.556	0.775	0.443	0.492	0.498	0.360	0.426	0.385	0.167	0.134	0.389	0.200	0.187	0.413	0.273
Belgium	0.562	0.516	0.471	0.282	0.385	0.400	0.753	0.324	0.375	0.551	0.367	0.185	0.375	0.319	0.118	0.949	0.333	0.122	0.346	0.278
Brazil	0.981	0.977	0.984	0.990	0.991	0.993	0.992	0.989	0.991	0.989	0.980	0.989	0.989	0.942	0.929	0.959	0.957	0.957	0.958	0.960
Canada	0.664	0.830	0.574	0.715	0.589	0.740	0.640	0.684	0.718	0.693	0.650	0.728	0.705	0.715	0.321	0.446	0.581	0.126	0.330	0.514
Chile	0.930	0.903	0.866	0.854	0.788	0.750	0.714	0.784	0.706	0.703	0.738	0.778	0.930	0.800	0.398	0.571	0.614	0.564	0.749	0.520
Colombia	0.976	0.998	0.913	0.973	0.976	0.972	0.974	0.981	0.965	0.963	0.964	0.964	0.993	0.781	0.800	0.825	0.785	0.798	0.826	0.743
Czech Republic	0.658	0.592	0.838	0.822	0.801	0.775	0.745	0.765	0.784	0.841	0.790	0.772	0.735	0.693	0.398	0.638	0.142	0.611	0.609	0.491
Denmark	0.544	0.628	0.571	0.455	0.416	0.511	0.473	0.522	0.511	0.439	0.407	0.327	0.401	0.384	0.177	0.547	0.127	0.316	0.353	0.373
Egypt	0.981	0.964	0.953	0.964	0.984	0.989	0.988	0.988	0.987	0.985	0.978	0.985	0.987	0.985	0.981	0.974	0.975	0.987	0.987	0.993
Finland	0.793	0.726	0.683	0.616	0.515	0.538	0.414	0.463	0.510	0.465	0.350	0.391	0.348	0.527	0.166	0.677	0.332	0.388	0.463	0.330
France	0.778	0.783	0.733	0.641	0.636	0.620	0.652	0.656	0.670	0.743	0.619	0.607	0.572	0.996	0.625	0.688	0.419	0.493	0.560	0.485
Germany	0.674	0.596	0.617	0.572	0.512	0.451	0.299	0.488	0.483	0.515	0.445	0.443	0.441	0.941	0.810	0.579	0.248	0.153	0.494	0.369
Greece	0.981	0.955	0.944	0.931	0.924	0.914	0.862	0.805	0.859	0.756	0.666	0.825	0.903	0.811	0.671	0.701	0.753	0.716	0.757	0.861
Hong Kong	0.817	0.792	0.784	0.755	0.754	0.747	0.776	0.801	0.790	0.753	0.787	0.758	0.791	0.774	0.908	0.791	0.546	0.757	0.842	0.777
Hungary	0.976	0.964	0.962	0.924	0.901	0.814	0.754	0.652	0.652	0.710	0.611	0.663	0.656	0.334	0.492	0.544	0.617	0.647	0.646	0.558
India	0.998	0.998	0.981	0.999	0.999	0.999	0.999	0.998	0.998	0.999	0.998	0.998	0.998	0.998	0.998	0.999	0.998	0.998	0.998	0.997
Indonesia	0.999	0.995	0.999	0.999	0.998	0.996	0.994	0.993	0.994	0.996	0.992	0.995	0.995	0.989	0.984	0.987	0.979	0.981	0.982	0.979
Ireland	0.006	0.342	0.408	0.530	0.144	0.504	0.644	0.448	0.575	0.501	0.787	0.810	0.879	0.954	0.914	0.265	0.881	0.875	0.713	0.732
Israel	0.952	0.939	0.939	0.934	0.869	0.924	0.861	0.831	0.793	0.831	0.691	0.836	0.668	0.407	0.559	0.754	0.771	0.639	0.710	0.543
Italy	0.563	0.685	0.541	0.392	0.720	0.430	0.642	0.517	0.545	0.867	0.380	0.417	0.366	0.913	0.220	0.811	0.145	0.102	0.292	0.265
Japan	0.880	0.896	0.892	0.886	0.829	0.897	0.982	0.861	0.824	0.770	0.752	0.806	0.803	0.822	0.524	0.742	0.615	0.590	0.536	0.668
Korea	0.991	0.984	0.985	0.969	0.964	0.946	0.878	0.881	0.894	0.900	0.911	0.895	0.879	0.936	0.808	0.824	0.811	0.747	0.771	0.753
Malaysia	0.987	0.985	0.992	0.991	0.993	0.970	0.957	0.929	0.912	0.903	0.933	0.891	0.915	0.970	0.828	0.921	0.861	0.841	0.899	0.789
Mexico	0.976	0.998	0.995	0.964	0.976	0.977	0.976	0.970	0.960	0.950	0.947	0.932	0.943	0.978	0.872	0.965	0.886	0.880	0.888	0.842
Netherlands	0.419	0.468	0.364	0.275	0.115	0.264	0.282	0.280	0.295	0.457	0.289	0.224	0.162	0.342	0.156	0.426	0.311	0.365	0.327	0.045
New Zealand	0.714	0.899	0.484	0.519	0.552	0.530	0.542	0.466	0.467	0.482	0.476	0.423	0.523	0.390	0.333	0.430	0.514	0.518	0.327	0.450
Norway	0.521	0.523	0.413	0.279	0.453	0.489	0.415	0.340	0.274	0.372	0.275	0.187	0.235	0.038	0.020	0.134	0.035	0.170	0.381	0.180
Pakistan	0.976	0.996	0.996	0.997	0.990	0.994	0.994	0.995	0.996	0.995	0.995	0.994	0.995	0.996	0.996	0.997	0.998	0.996	0.996	0.997
Philippines	0.993	0.991	0.991	0.991	0.996	0.997	0.997	0.999	0.999	0.999	0.999	0.999	0.998	0.997	0.995	0.998	0.993	0.994	0.991	0.988
Poland	0.994	0.993	0.992	0.984	0.977	0.958	0.930	0.945	0.947	0.939	0.936	0.936	0.939	0.940	0.773	0.888	0.872	0.856	0.913	0.913
Portugal	0.792	0.788	0.751	0.670	0.803	0.276	0.316	0.169	0.394	0.587	0.135	0.661	0.611	0.268	0.297	0.531	0.305	0.397	0.379	0.503
Russia	0.976	0.981	0.999	0.999	0.999	0.999	0.996	0.992	0.996	0.993	0.991	0.992	0.995	0.983	0.988	0.992	0.991	0.988	0.983	0.967
Singapore	0.677	0.607	0.514	0.452	0.314	0.459	0.542	0.522	0.622	0.544	0.552	0.457	0.653	0.283	0.005	0.513	0.086	0.394	0.520	0.452
South Africa	0.824	0.891	0.825	0.883	0.873	0.908	0.909	0.881	0.884	0.840	0.835	0.838	0.881	0.839	0.764	0.844	0.859	0.835	0.870	0.853
Spain	0.868	0.883	0.867	0.844	0.890	0.809	0.848	0.894	0.908	0.938	0.891	0.881	0.810	0.883	0.545	0.727	0.517	0.465	0.648	0.519
Sweden	0.597	0.583	0.564	0.426	0.550	0.546	0.691	0.486	0.523	0.466	0.489	0.503	0.510	0.734	0.393	0.634	0.458	0.378	0.550	0.498
Switzerland	0.535	0.701	0.595	0.517	0.440	0.527	0.724	0.583	0.563	0.557	0.527	0.424	0.435	0.683	0.751	0.828	0.304	0.359	0.179	0.447
Thailand	0.997	0.997	0.995	0.993	0.988	0.984	0.976	0.972	0.974	0.976	0.976	0.972	0.979	0.954	0.902	0.946	0.899	0.942	0.944	0.913
Turkey	0.998	0.998	0.999	0.998	0.999	0.998	0.999	0.999	0.998	0.998	0.998	0.998	0.998	0.996	0.995	0.999	0.997	0.996	0.996	0.995
United Kingdom	0.721	0.714	0.689	0.458	0.654	0.474	0.633	0.511	0.598	0.620	0.638	0.555	0.502	0.851	0.148	0.659	0.108	0.002	0.434	0.465
United States	0.895	0.875	0.877	0.880	0.879	0.804	0.849	0.774	0.767	0.722	0.871	0.700	0.611	0.790	0.929	0.575	0.662	0.797	0.529	0.731

EHB estimates for the data-based, minimum-variance approach (2001 through 2020)

Country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Argentina	0.810	0.659	0.791	0.807	0.850	0.824	0.789	0.808	0.765	0.843	0.728	0.747	0.782	0.800	0.799	0.787	0.828	0.699	0.637	0.626
Australia	0.681	0.701	0.720	0.820	0.764	0.792	0.797	0.729	0.823	0.818	0.707	0.721	0.665	0.630	0.686	0.679	0.644	0.563	0.467	0.469
Austria	0.094	0.033	0.115	0.386	0.577	0.634	0.605	0.472	0.581	0.591	0.457	0.548	0.301	0.399	0.384	0.502	0.357	0.119	0.402	0.390
Belgium	0.178	0.538	0.514	0.395	0.321	0.558	0.518	0.208	0.458	0.370	0.170	0.435	0.359	0.402	0.448	0.309	0.309	0.232	0.288	0.209
Brazil	0.979	0.974	0.987	0.992	0.993	0.994	0.995	0.991	0.992	0.990	0.979	0.988	0.979	0.965	0.948	0.962	0.957	0.948	0.960	0.962
Canada	0.607	0.653	0.491	0.757	0.747	0.733	0.773	0.617	0.787	0.719	0.557	0.709	0.516	0.689	0.566	0.648	0.503	0.237	0.235	0.554
Chile	0.867	0.828	0.869	0.859	0.805	0.793	0.792	0.705	0.591	0.615	0.725	0.720	0.662	0.655	0.656	0.479	0.649	0.432	0.548	0.488
Colombia	0.948	0.988	0.902	0.974	0.979	0.973	0.972	0.968	0.953	0.950	0.940	0.962	0.916	0.894	0.829	0.838	0.793	0.771	0.839	0.781
Czech Republic	0.757	0.683	0.813	0.834	0.824	0.784	0.759	0.733	0.784	0.767	0.691	0.736	0.624	0.598	0.505	0.485	0.448	0.135	0.126	0.457
Denmark	0.215	0.536	0.546	0.444	0.511	0.601	0.625	0.380	0.441	0.442	0.263	0.371	0.313	0.489	0.395	0.376	0.392	0.212	0.244	0.142
Egypt	0.955	0.956	0.951	0.965	0.984	0.989	0.986	0.985	0.986	0.978	0.971	0.984	0.985	0.985	0.981	0.972	0.973	0.983	0.986	0.983
Finland	0.794	0.760	0.682	0.600	0.574	0.591	0.577	0.338	0.559	0.459	0.441	0.493	0.383	0.473	0.381	0.431	0.354	0.018	0.275	0.171
France	0.748	0.812	0.770	0.623	0.633	0.705	0.677	0.481	0.706	0.705	0.658	0.706	0.542	0.586	0.625	0.676	0.546	0.313	0.548	0.525
Germany	0.713	0.691	0.684	0.565	0.520	0.577	0.473	0.322	0.547	0.456	0.500	0.605	0.419	0.527	0.446	0.540	0.405	0.075	0.372	0.424
Greece	0.979	0.935	0.939	0.933	0.927	0.924	0.896	0.780	0.878	0.828	0.644	0.834	0.900	0.843	0.678	0.727	0.759	0.716	0.776	0.785
Hong Kong	0.774	0.664	0.750	0.755	0.692	0.725	0.816	0.669	0.710	0.657	0.722	0.730	0.701	0.762	0.780	0.552	0.705	0.587	0.816	0.697
Hungary	0.968	0.963	0.955	0.929	0.908	0.824	0.760	0.668	0.705	0.682	0.610	0.696	0.572	0.478	0.552	0.551	0.646	0.550	0.577	0.552
India	0.999	0.999	0.999	0.999	0.999	0.999	0.999	0.997	0.998	0.998	0.997	0.998	0.998	0.998	0.998	0.997	0.998	0.997	0.998	0.995
Indonesia	0.998	0.995	0.999	0.999	0.998	0.997	0.995	0.993	0.994	0.994	0.993	0.992	0.990	0.990	0.988	0.983	0.983	0.977	0.978	0.973
Ireland	0.524	0.329	0.503	0.487	0.427	0.418	0.353	0.456	0.566	0.629	0.661	0.816	0.876	0.952	0.864	0.797	0.889	0.872	0.679	0.740
Israel	0.952	0.926	0.941	0.935	0.894	0.884	0.855	0.780	0.793	0.742	0.573	0.629	0.562	0.573	0.663	0.528	0.695	0.465	0.540	0.547
Italy	0.441	0.590	0.490	0.436	0.453	0.489	0.450	0.303	0.630	0.599	0.441	0.485	0.340	0.374	0.341	0.401	0.243	0.102	0.364	0.280
Japan	0.831	0.851	0.886	0.878	0.862	0.871	0.725	0.738	0.724	0.706	0.621	0.758	0.785	0.625	0.660	0.654	0.666	0.432	0.508	0.644
Korea	0.992	0.989	0.984	0.971	0.972	0.944	0.884	0.874	0.896	0.879	0.897	0.900	0.852	0.828	0.840	0.772	0.841	0.727	0.750	0.670
Malaysia	0.981	0.973	0.989	0.989	0.982	0.971	0.961	0.888	0.904	0.899	0.894	0.897	0.885	0.840	0.874	0.759	0.777	0.749	0.702	0.664
Mexico	0.994	0.994	0.994	0.979	0.981	0.981	0.982	0.967	0.967	0.959	0.929	0.941	0.928	0.914	0.913	0.913	0.877	0.870	0.878	0.806
Netherlands	0.276	0.528	0.429	0.199	0.099	0.393	0.455	0.124	0.380	0.325	0.254	0.314	0.114	0.164	0.220	0.347	0.113	0.548	0.336	0.267
New Zealand	0.441	0.400	0.347	0.517	0.439	0.449	0.485	0.002	0.425	0.322	0.076	0.477	0.417	0.330	0.343	0.341	0.470	0.138	0.244	0.058
Norway	0.162	0.367	0.344	0.460	0.500	0.523	0.519	0.386	0.356	0.488	0.258	0.272	0.046	0.265	0.280	0.260	0.090	0.168	0.182	0.057
Pakistan	0.977	0.996	0.995	0.996	0.990	0.994	0.993	0.993	0.995	0.993	0.993	0.993	0.995	0.996	0.997	0.997	0.997	0.996	0.996	0.994
Philippines	0.992	0.987	0.990	0.991	0.996	0.997	0.997	0.998	0.999	0.999	0.999	0.999	0.998	0.998	0.995	0.995	0.994	0.992	0.986	0.979
Poland	0.994	0.990	0.992	0.987	0.980	0.960	0.936	0.943	0.951	0.954	0.935	0.947	0.930	0.901	0.817	0.870	0.892	0.851	0.843	0.882
Portugal	0.701	0.711	0.685	0.660	0.435	0.361	0.273	0.175	0.209	0.402	0.344	0.675	0.573	0.534	0.554	0.549	0.422	0.156	0.193	0.320
Russia	0.999	0.999	0.999	0.999	0.999	0.999	0.996	0.993	0.996	0.994	0.991	0.993	0.994	0.985	0.992	0.994	0.990	0.984	0.984	0.969
Singapore	0.581	0.291	0.473	0.391	0.355	0.528	0.611	0.299	0.626	0.271	0.394	0.450	0.366	0.211	0.356	0.199	0.292	0.138	0.307	0.072
South Africa	0.746	0.791	0.797	0.894	0.892	0.915	0.919	0.882	0.909	0.874	0.828	0.838	0.840	0.859	0.843	0.867	0.866	0.854	0.868	0.834
Spain	0.830	0.879	0.878	0.859	0.835	0.864	0.843	0.853	0.921	0.912	0.886	0.890	0.817	0.760	0.712	0.685	0.562	0.324	0.499	0.470
Sweden	0.621	0.654	0.649	0.523	0.526	0.651	0.605	0.394	0.604	0.602	0.547	0.589	0.480	0.537	0.511	0.584	0.462	0.238	0.590	0.339
Switzerland	0.263	0.676	0.595	0.407	0.521	0.568	0.455	0.486	0.188	0.263	0.161	0.426	0.329	0.241	0.412	0.020	0.373	0.365	0.318	0.456
Thailand	0.996	0.996	0.994	0.991	0.987	0.985	0.979	0.964	0.968	0.969	0.962	0.973	0.971	0.957	0.940	0.934	0.928	0.909	0.877	0.864
Turkey	0.998	0.998	0.999	0.998	0.999	0.998	0.999	0.999	0.998	0.998	0.997	0.998	0.997	0.997	0.996	0.996	0.997	0.996	0.996	0.993
United Kingdom	0.587	0.651	0.676	0.348	0.503	0.546	0.565	0.135	0.625	0.537	0.447	0.508	0.362	0.541	0.562	0.566	0.193	0.161	0.248	0.147
United States	0.873	0.880	0.871	0.801	0.672	0.772	0.602	0.777	0.548	0.622	0.545	0.561	0.586	0.754	0.608	0.786	0.584	0.582	0.554	0.587

EHB estimates for the hybrid, Bayesian approach (2001 through 2020)

Country	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Argentina	0.812	0.679	0.810	0.647	0.812	0.807	0.786	0.852	0.673	0.851	0.705	0.695	0.771	0.844	0.915	0.963	0.813	0.665	0.669	0.551
Australia	0.868	0.811	0.881	0.773	0.830	0.717	0.758	0.856	0.831	0.778	0.734	0.867	0.747	0.797	0.837	0.837	0.725	0.656	0.541	0.671
Austria	0.122	0.399	0.526	0.380	0.563	0.744	0.593	0.629	0.146	0.423	0.033	0.412	0.367	0.368	0.289	0.226	0.641	0.214	0.327	0.260
Belgium	0.596	0.479	0.530	0.642	0.558	0.351	0.445	0.399	0.310	0.405	0.516	0.529	0.386	0.375	0.533	0.820	0.254	0.300	0.538	0.257
Brazil	0.977	0.978	0.986	0.989	0.992	0.992	0.994	0.991	0.991	0.987	0.978	0.985	0.979	0.951	0.973	0.972	0.957	0.960	0.965	0.953
Canada	0.441	0.792	0.836	0.865	0.776	0.863	0.685	0.397	0.734	0.747	0.765	0.434	0.633	0.324	0.883	0.666	0.483	0.503	0.484	0.422
Chile	0.919	0.905	0.802	0.909	0.875	0.829	0.721	0.668	0.777	0.795	0.533	0.772	0.671	0.700	0.936	0.427	0.724	0.664	0.596	0.461
Colombia	0.944	0.985	0.930	0.985	0.980	0.982	0.975	0.985	0.975	0.966	0.970	0.969	0.935	0.903	0.680	0.816	0.717	0.822	0.838	0.745
Czech Republic	0.687	0.751	0.856	0.749	0.821	0.780	0.806	0.696	0.760	0.751	0.773	0.795	0.669	0.678	0.541	0.750	0.520	0.495	0.607	0.431
Denmark	0.697	0.594	0.483	0.723	0.563	0.693	0.532	0.543	0.416	0.557	0.530	0.735	0.354	0.612	0.899	0.938	0.041	0.365	0.383	0.556
Egypt	0.945	0.943	0.957	0.939	0.985	0.983	0.990	0.977	0.987	0.987	0.981	0.987	0.986	0.984	0.986	0.993	0.968	0.989	0.989	0.987
Finland	0.818	0.685	0.607	0.440	0.533	0.451	0.519	0.249	0.504	0.454	0.145	0.222	0.470	0.420	0.651	0.934	0.540	0.294	0.534	0.105
France	0.798	0.775	0.735	0.684	0.675	0.817	0.707	0.695	0.681	0.623	0.668	0.577	0.564	0.649	0.344	0.812	0.648	0.591	0.629	0.420
Germany	0.655	0.524	0.490	0.460	0.501	0.056	0.585	0.257	0.351	0.517	0.568	0.607	0.513	0.463	0.845	0.098	0.343	0.425	0.211	0.329
Greece	0.978	0.958	0.954	0.945	0.931	0.948	0.903	0.719	0.875	0.782	0.753	0.835	0.908	0.822	0.717	0.765	0.706	0.741	0.808	0.766
Hong Kong	0.794	0.801	0.886	0.845	0.775	0.889	0.789	0.827	0.858	0.767	0.783	0.860	0.785	0.695	0.857	0.901	0.819	0.747	0.701	0.785
Hungary	0.954	0.968	0.966	0.918	0.908	0.753	0.773	0.662	0.693	0.634	0.664	0.386	0.607	0.522	0.396	0.921	0.640	0.603	0.637	0.460
India	0.997	0.998	0.999	0.999	0.999	0.999	0.999	0.998	0.998	0.999	0.998	0.999	0.997	0.998	0.999	0.998	0.998	0.998	0.998	0.997
Indonesia	0.999	0.996	0.999	0.999	0.998	0.996	0.994	0.993	0.995	0.996	0.996	0.994	0.991	0.990	0.991	0.977	0.986	0.982	0.983	0.979
Ireland	0.265	0.281	0.471	0.549	0.355	0.033	0.411	0.711	0.647	0.676	0.748	0.887	0.852	0.948	0.767	0.549	0.895	0.785	0.684	0.692
Israel	0.971	0.941	0.952	0.956	0.912	0.918	0.907	0.827	0.876	0.832	0.654	0.623	0.730	0.700	0.911	0.828	0.569	0.589	0.293	0.594
Italy	0.635	0.515	0.633	0.674	0.631	0.340	0.592	0.348	0.336	0.313	0.078	0.609	0.410	0.210	0.744	0.878	0.408	0.228	0.099	0.220
Japan	0.922	0.885	0.879	0.870	0.896	0.912	0.834	0.804	0.710	0.838	0.668	0.710	0.836	0.748	0.889	0.770	0.717	0.646	0.680	0.620
Korea	0.993	0.990	0.986	0.973	0.972	0.951	0.891	0.871	0.900	0.903	0.905	0.892	0.880	0.862	0.802	0.841	0.855	0.808	0.721	0.762
Malaysia	0.986	0.984	0.995	0.993	0.990	0.983	0.966	0.939	0.927	0.935	0.933	0.931	0.914	0.891	0.956	0.912	0.871	0.854	0.817	0.796
Mexico	0.995	0.983	0.996	0.975	0.976	0.978	0.977	0.963	0.964	0.964	0.945	0.921	0.925	0.909	0.927	0.964	0.904	0.890	0.879	0.804
Netherlands	0.370	0.372	0.299	0.485	0.391	0.606	0.470	0.268	0.492	0.369	0.400	0.024	0.280	0.265	0.262	0.227	0.181	0.281	0.247	0.082
New Zealand	0.561	0.654	0.721	0.772	0.433	0.849	0.604	0.559	0.595	0.516	0.683	0.303	0.513	0.525	0.675	0.676	0.120	0.438	0.494	0.538
Norway	0.571	0.478	0.009	0.242	0.462	0.489	0.434	0.240	0.467	0.341	0.390	0.246	0.171	0.048	0.745	0.760	0.046	0.065	0.153	0.105
Pakistan	0.998	0.997	0.996	0.997	0.990	0.994	0.995	0.995	0.996	0.996	0.996	0.996	0.995	0.997	0.996	0.998	0.996	0.997	0.996	0.996
Philippines	0.993	0.992	0.992	0.992	0.996	0.998	0.997	0.999	0.999	0.999	0.999	0.999	0.998	0.998	0.998	0.997	0.993	0.994	0.988	0.986
Poland	0.994	0.991	0.989	0.985	0.981	0.928	0.933	0.926	0.947	0.932	0.932	0.916	0.934	0.913	0.907	0.929	0.903	0.854	0.847	0.901
Portugal	0.747	0.811	0.805	0.798	0.693	0.712	0.518	0.006	0.353	0.258	0.220	0.589	0.583	0.417	0.508	0.770	0.631	0.397	0.364	0.474
Russia	0.988	0.989	0.999	0.999	0.999	0.999	0.996	0.992	0.995	0.994	0.990	0.991	0.994	0.986	0.990	0.995	0.991	0.987	0.986	0.961
Singapore	0.610	0.621	0.490	0.253	0.462	0.268	0.594	0.592	0.707	0.663	0.629	0.693	0.564	0.489	0.423	0.600	0.362	0.433	0.366	0.334
South Africa	0.815	0.841	0.839	0.944	0.867	0.918	0.914	0.903	0.826	0.849	0.847	0.719	0.829	0.733	0.946	0.971	0.832	0.833	0.822	0.857
Spain	0.906	0.861	0.887	0.920	0.840	0.868	0.877	0.924	0.837	0.885	0.866	0.901	0.791	0.732	0.828	0.530	0.577	0.559	0.315	0.405
Sweden	0.538	0.557	0.538	0.044	0.550	0.526	0.545	0.587	0.490	0.325	0.500	0.360	0.460	0.202	0.716	0.728	0.612	0.482	0.627	0.494
Switzerland	0.775	0.662	0.373	0.586	0.548	0.542	0.381	0.371	0.515	0.455	0.625	0.246	0.549	0.578	0.730	0.779	0.265	0.375	0.178	0.197
Thailand	0.997	0.997	0.995	0.992	0.988	0.986	0.978	0.975	0.974	0.979	0.969	0.979	0.973	0.965	0.916	0.980	0.932	0.943	0.914	0.901
Turkey	0.998	0.998	0.999	0.998	0.999	0.998	0.999	0.999	0.998	0.998	0.998	0.998	0.997	0.997	0.997	0.992	0.997	0.996	0.996	0.994
United Kingdom	0.702	0.706	0.684	0.644	0.620	0.731	0.580	0.497	0.596	0.585	0.590	0.611	0.561	0.537	0.264	0.530	0.411	0.377	0.256	0.349
United States	0.877	0.879	0.859	0.856	0.818	0.831	0.766	0.793	0.761	0.763	0.749	0.765	0.763	0.763	0.624	0.769	0.723	0.752	0.731	0.755

Appendix 5 Model-based, I-CAPM validity test

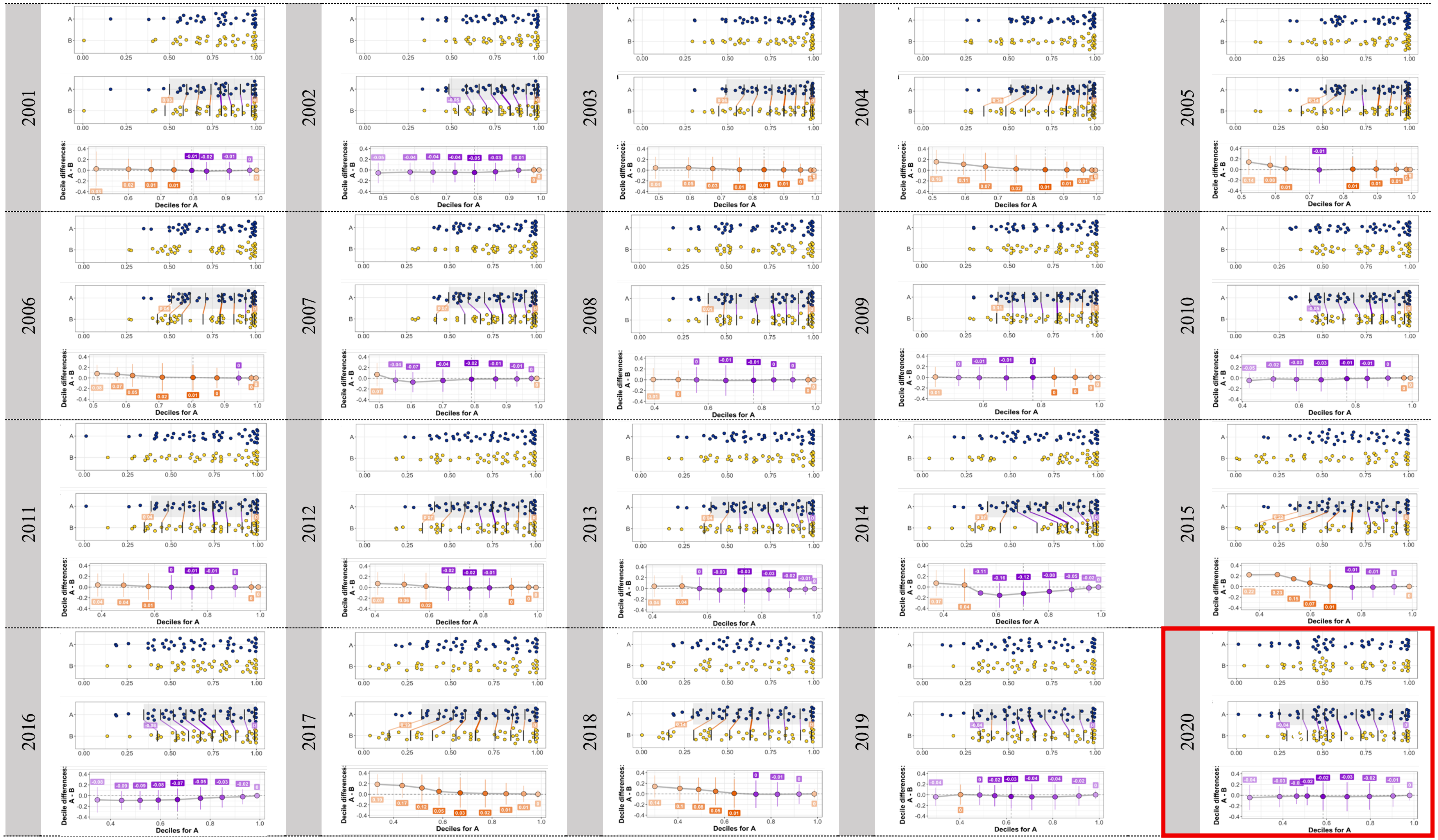
The table reports the ordinary least squares regressions results for the constant term (intercept β) in the I-CAPM equation for the sample period 2001 through 2020 ($R_D - R_F = \beta + \beta_D(R_W\text{-}\ R_F) + \varepsilon$). The intercept ($\beta$) for 38 of the 43 countries has a reported t-statistic with absolute value below the 5% critical threshold (≈ ±1.96), and the corresponding p-values are greater than 0.05. The five remaining countries (Columbia, Denmark, Indonesia, New Zealand, and, Thailand) reject the null hypothesis. The results show that the I-CAPM equilibrium hypothesis is not rejected for 90% of the sample, supporting model's validity over the period examined.

Country	Intercept (β)	St. error	t-statistic	p-value	Slope (β_D)	St. error	t-statistic	p-value
Argentina	0.081	0.154	0.524	0.600	0.967**	0.064	15.138	0.0000
Australia	0.113	0.082	1.386	0.166	0.767**	0.034	22.618	0.0000
Austria	0.029	0.100	0.293	0.769	1.050**	0.041	25.344	0.0000
Belgium	0.003	0.083	0.036	0.971	0.906**	0.034	26.411	0.0000
Brazil	0.117	0.122	0.956	0.339	1.192**	0.051	23.556	0.0000
Canada	0.027	0.062	0.435	0.664	0.947**	0.026	36.705	0.0000
Chile	0.061	0.090	0.672	0.501	0.697**	0.037	18.617	0.0000
Colombia	0.273*	0.118	2.320	0.021	0.765**	0.049	15.643	0.0000
Czech Republic	0.192	0.101	1.895	0.058	0.758**	0.042	18.030	0.0000
Denmark	0.150*	0.075	2.00	0.046	0.741**	0.031	23.832	0.0000
Egypt	0.198	0.129	1.537	0.125	0.402**	0.054	7.504	0.0000
Finland	-0.027	0.104	-0.263	0.793	1.022**	0.043	23.668	0.0000
France	-0.001	0.072	-0.008	0.993	1.008**	0.03	33.922	0.0000
Germany	0.011	0.075	0.146	0.884	1.043**	0.031	33.326	0.0000
Greece	-0.246	0.155	-1.589	0.112	1.060**	0.064	16.483	0.0000
Hong Kong	0.082	0.075	1.087	0.277	0.606**	0.031	19.345	0.0000
Hungary	0.137	0.129	1.063	0.288	1.012**	0.054	18.854	0.0000
India	0.159	0.103	1.541	0.124	0.628**	0.043	14.641	0.0000
Indonesia	0.269*	0.130	2.060	0.040	0.547**	0.054	10.089	0.0000
Ireland	-0.045	0.097	-0.464	0.643	0.969**	0.04	24.161	0.0000
Israel	-0.001	0.078	-0.013	0.989	0.643**	0.032	19.838	0.0000
Italy	-0.055	0.083	-0.661	0.509	0.982**	0.034	28.462	0.0000
Japan	0.012	0.073	0.166	0.868	0.496**	0.03	16.276	0.0000
Korea	0.196	0.114	1.725	0.085	0.776**	0.047	16.401	0.0000
Malaysia	0.080	0.071	1.139	0.255	0.343**	0.029	11.701	0.0000
Mexico	0.069	0.086	0.797	0.426	0.930**	0.036	25.893	0.0000
Netherlands	0.034	0.071	0.484	0.629	0.932**	0.029	31.689	0.0000
New Zealand	0.180*	0.08	2.245	0.025	0.480**	0.033	14.407	0.0000
Norway	0.074	0.099	0.743	0.458	0.984**	0.041	23.839	0.0000
Pakistan	0.199	0.122	1.633	0.103	0.201**	0.051	3.978	0.0000
Philippines	0.155	0.102	1.510	0.131	0.424**	0.043	9.955	0.0000
Poland	0.033	0.114	0.286	0.775	0.971**	0.047	20.536	0.0000
Portugal	-0.025	0.088	-0.288	0.774	0.738**	0.037	20.166	0.0000
Russia	0.179	0.137	1.305	0.192	1.085**	0.057	19.070	0.0000
South Africa	0.048	0.074	0.652	0.515	0.663**	0.031	21.516	0.0000
Singapore	0.101	0.101	1.001	0.317	0.999**	0.042	23.812	0.0000
Spain	0.011	0.088	0.125	0.900	0.963**	0.036	26.416	0.0000
Sweden	0.052	0.086	0.603	0.547	1.063**	0.036	29.744	0.0000
Switzerland	0.065	0.058	1.120	0.263	0.688**	0.024	28.722	0.0000
Thailand	0.213*	0.106	1.998	0.046	0.558**	0.044	12.621	0.0000
Turkey	0.076	0.164	0.462	0.644	0.955**	0.068	13.985	0.0000
United Kingdom	-0.025	0.062	-0.397	0.691	0.853**	0.026	32.877	0.0000
United States	0.039	0.043	0.904	0.366	0.804**	0.018	45.114	0.0000

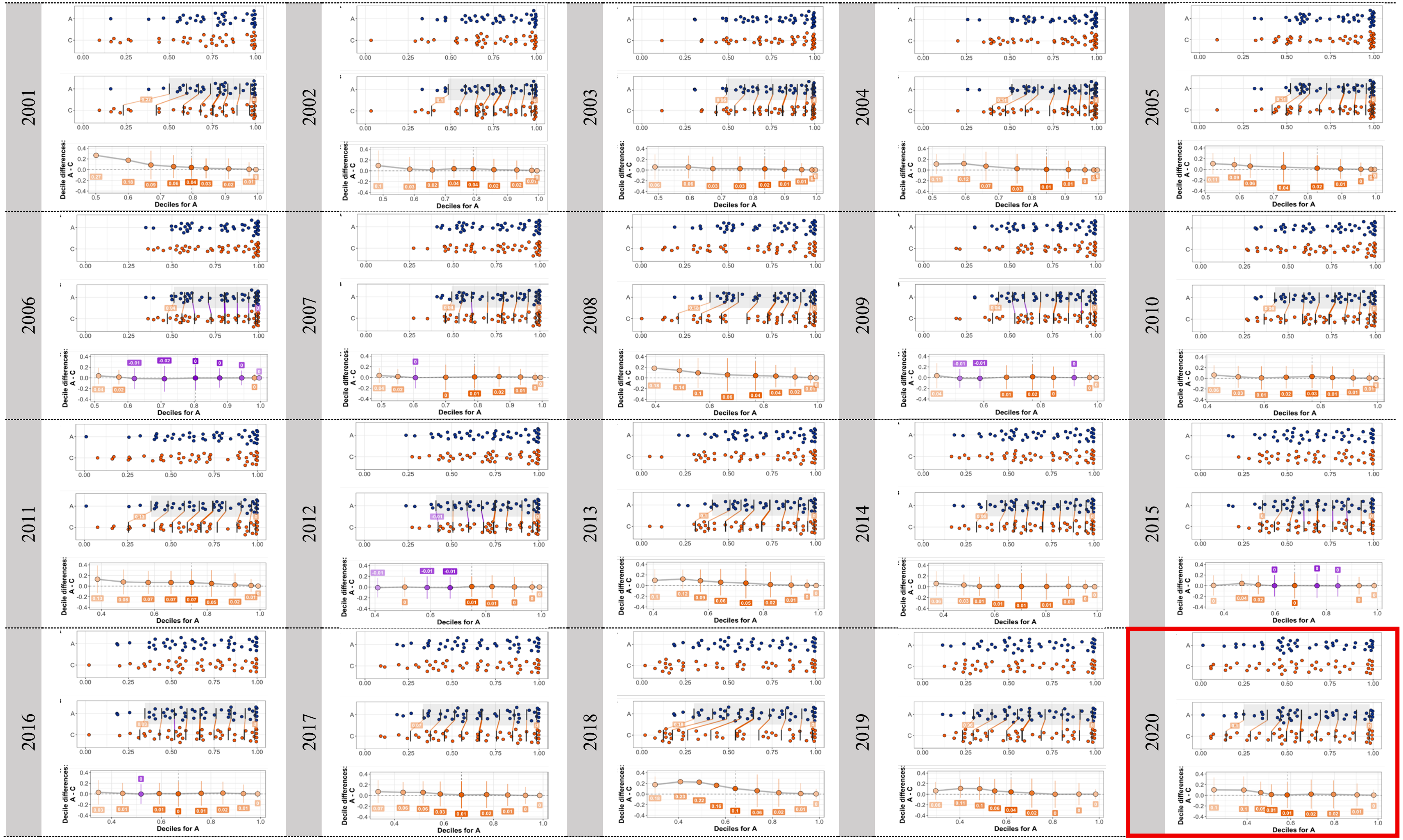
Note: The sample period commences from January 2001 through December 2020 using weekly data. Given the small sample size, Newey West (1987) standard errors (St. error) are reported; * indicates 5% significance level, and ** indicates 1% significance level.

Appendix 6 Quantile shift function results for all pair-wise combinations

Pair-wise comparison of (1) model-based & data-based (mean-variance), annually

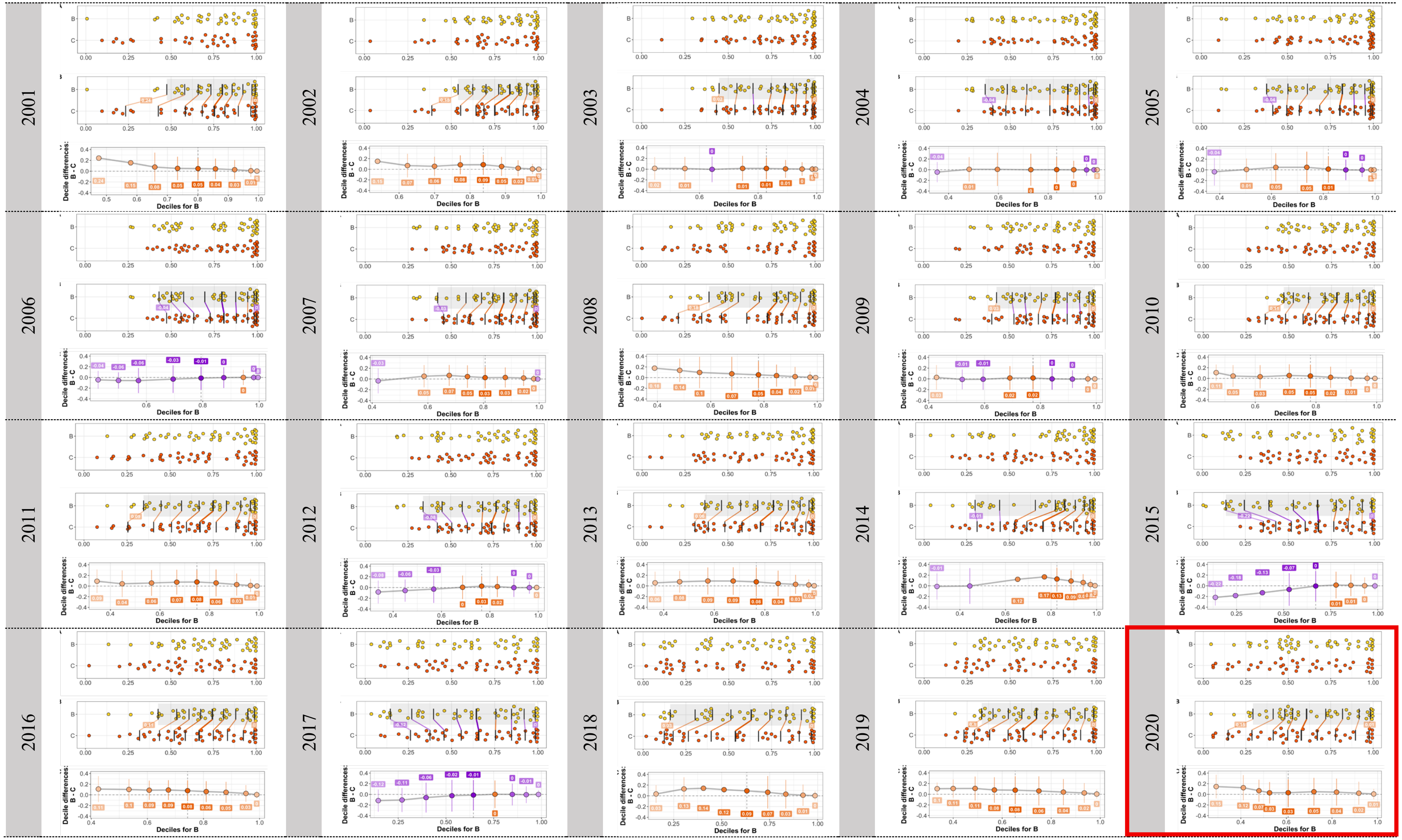


Pair-wise comparison of (2) model-based & data-based (min–variance) , annually

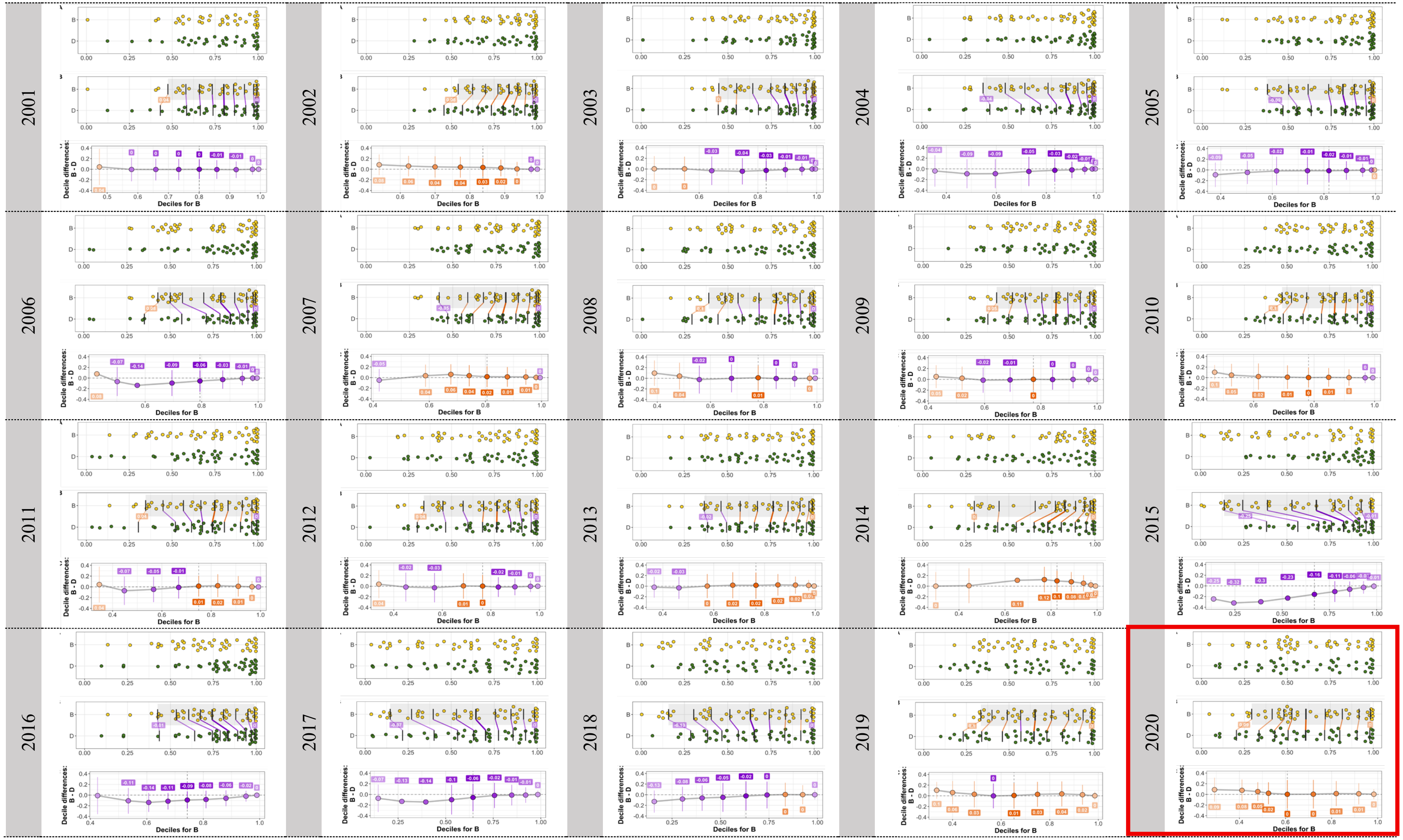


Pair-wise comparison of (3) model-based & hybrid, annually

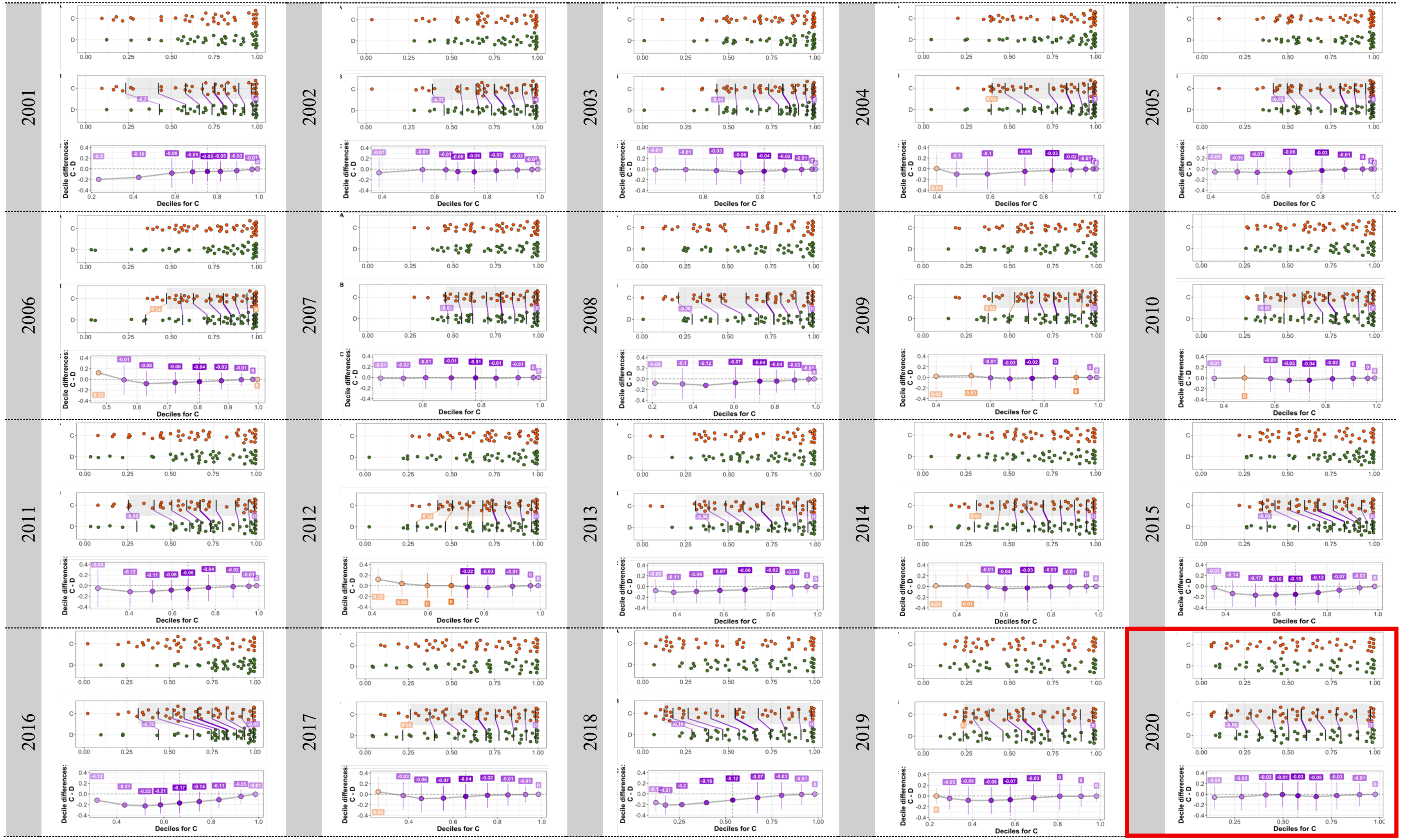
Pair-wise comparison of (4) data-based (mean–variance) & data-based (min–variance) , annually



Pair-wise comparison of (5) data-based (mean-variance) & hybrid, annually



Pair-wise comparison of (5) data-based (mean-variance) & hybrid, annually

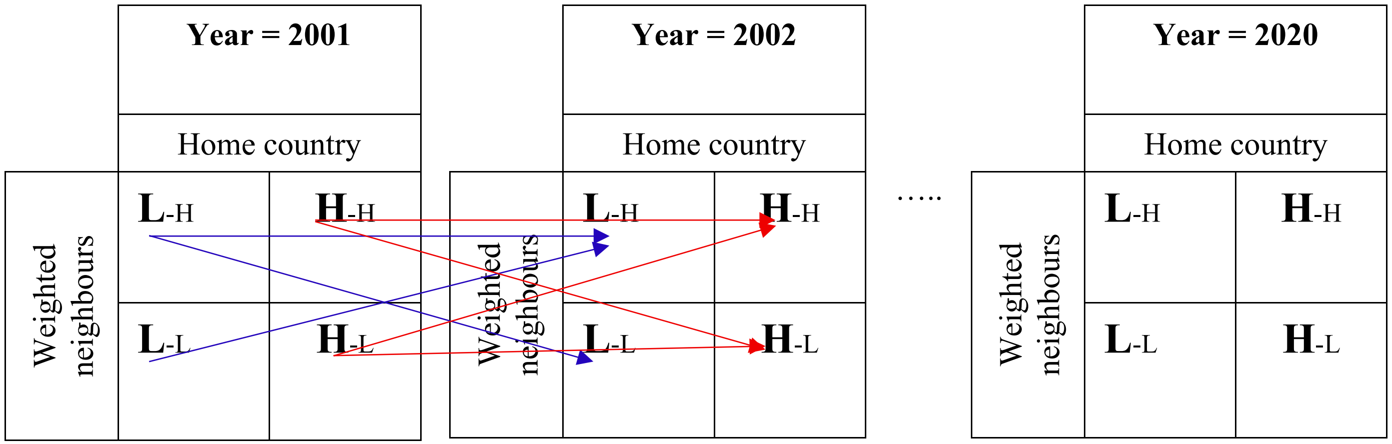


Appendix 7 ISO3 codes by country

Country	ISO3 code	Financial centre	Longitude	Latitude	Group	
Argentina	ARG	Buenos Aires	-58.37	-34.61	AM_EM	
Australia	AUS	Sydney	151.21	-33.87	PAC_DM	
Austria	AUT	Vienna	16.37	48.22	EME_DM	
Belgium	BEL	Brussels	4.33	50.83	EME_DM	
Brazil	BRA	Sao Paulo	-46.63	-23.53	AM_EM	
Canada	CAN	Toronto	-79.38	43.65	AM_DM	
Chile	CHL	Santiago	-70.64	-33.46	AM_EM	
Colombia	COL	Bogota	-74.09	4.63	AM_EM	
Czech Republic	CZE	Prague	14.43	50.08	EMEA_EM	
Denmark	DNK	Copenhagen	12.57	55.68	EME_DM	
Egypt	EGY	Cairo	31.25	30.06	EMEA_EM	
Finland	FIN	Helsinki	24.94	60.17	EME_DM	
France	FRA	Paris	2.34	48.86	EME_DM	
Germany	DEU	Berlin	13.38	52.52	EME_DM	
Greece	GRC	Athens	23.73	37.98	EMEA_EM	
Hong Kong	HKG	Hong Kong	114.15	22.285	PAC_DM	
Hungary	HUN	Budapest	19.08	47.51	EMEA_EM	
India	IND	Bombay	72.82	18.96	AS_EM	
Indonesia	IDN	Jakarta	106.83	-6.18	AS_EM	
Ireland	IRL	Dublin	-6.25	53.33	EME_DM	
Israel	ISR	Jerusalem	35.22	31.78	EME_DM	
Italy	ITA	Rome	12.50	41.89	EME_DM	
Japan	JPN	Tokyo	139.77	35.67	PAC_DM	
Korea	KOR	Seoul	126.97	37.56	AS_EM	
Malaysia	MYS	Kuala Lumpur	101.71	3.16	AS_EM	
Mexico	MEX	Mexico City	-99.14	19.43	AM_EM	
Netherlands	NLD	Amsterdam	4.89	52.37	EME_DM	
New Zealand	NZL	Auckland	174.76	-36.85	PAC_DM	
Norway	NOR	Oslo	10.75	59.91	EME_DM	
Pakistan	PAK	Karachi	67.01	24.86	AS_EM	
Philippines	PHL	Manila	120.97	14.62	AS_EM	
Poland	POL	Warsaw	21.02	52.26	EMEA_EM	
Portugal	PRT	Lisbon	-9.14	38.72	EME_DM	
Russia	RUS	Moscow	37.62	55.75	EMEA_EM	
Singapore	SGP	Singapore	103.85	1.30	PAC_DM	
South Africa	ZAF	Johannesburg	28.05	-26.20	EMEA_EM	
Spain	ESP	Madrid	-3.71	40.42	EME_DM	
Sweden	SWE	Stockholm	18.07	59.33	EME_DM	
Switzerland	CHE	Zurich	8.54	47.38	EME_DM	
Thailand	THA	Bangkok	100.5	13.73	AS_EM	
Turkey	TUR	Istanbul	29.00	41.10	EMEA_EM	
United Kingdom	GBR	London	-0.13	51.51	EME_DM	
United States	USA	New York	-73.94	40.67	AM_DM	

Notes: AM_DM refers to Americas developed markets, EME_DM refers to Europe & Middle East, PAC_DM refers to Pacific developed markets, AM_EM refers to Americas emerging markets, EMEA_EM refers to Europe, Middle East & Africa emerging markets, AS_EM refers to Asia emerging markets.
Sources: International Organization for Standardization (ISO). (2020). *ISO 3166-1:2020 Codes for the representation of names of countries and their subdivisions – Part 1: Country codes*. ISO. Group classifications are from MSCI ACWI benchmark, MSCI (2020).

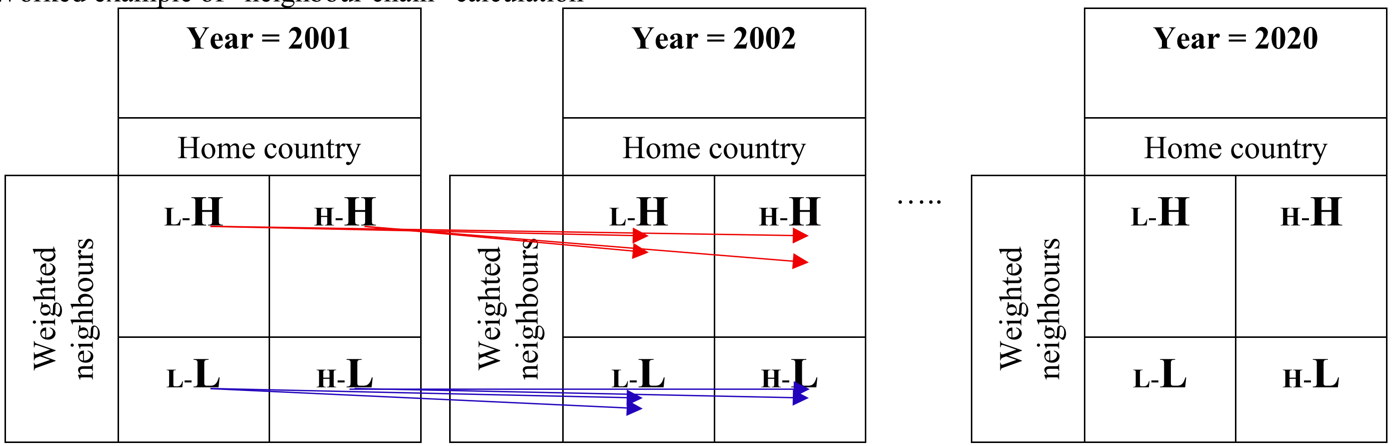
Appendix 8 Home and neighbour chain computation example (2001 to 2002)



Total movements

	Low	High
Low	L-H to L-H = 61 L-H to L-L = 3 L-L to L-H = 3 L-L to L-L = 303 **Total = 370**	L-H to H-H = 5 L-H to H-L = 0 L-L to H-H = 0 L-L to H-L = 6 **Total = 11**
High	H-H to L-H = 8 H-H to L-L = 0 H-L to L-H = 0 H-L to L-L = 8 **Total = 16**	H-H to H-H = 339 H-H to H-L = 0 H-L to H-H = 1 H-L to H-L = 80 **Total = 420**

Worked example of "neighbour chain" calculation



Total movements

	Low	High
Low	H-L to H-L = 80 H-L to L-L = 8 L-L to H-L = 6 L-L to L-L = 303 **Total = 397**	H-L to H-H = 1 H-L to L-H = 0 L-L to H-H = 0 L-L to L-H = 3 **Total = 4**
High	H-H to H-L = 0 H-H to L-L = 0 L-H to H-L = 0 L-H to L-L = 3 **Total = 3**	L-H to H-H = 5 L-H to L-H = 61 H-H to L-H = 8 H-H to H-H = 339 **Total = 413**

Note: Low is denoted as "L", and *High* is denoted as "H".