Essays on Business Cycle Synchronisation and Environmental, Social and Governance Activities

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Abstract

This thesis presents empirical applications of panel data models with a factor structure regarding business cycle synchronisation (BCS) and environmental, social, and governance (ESG) activities.

Chapter 1 assesses the relationship between BCS and trade/finance intensities in a simultaneous equation panel data model that jointly accommodates simultaneity, spatial spillovers, global shocks and parameter heterogeneity. Individual CCEX-2SLS estimation results of 136 country-pairs (1995Q1-2019Q4) suggest explicitly considering parameter heterogeneity. In the spatial network analysis, most samples exhibit the opposite signs of direct and indirect effects of trade/finance intensities on BCS. Total effects of trade intensity and spillovers of trade/financial intensities on BCS are negative, suggesting that EU economies encourage smarter trade/financial intensity facilitation for improved BCS.

Chapter 2 analyses systematic components of ESG ratings using multilevel factor model. We adopt generalised canonical correlation method to MSCI and Refinitiv datasets across legal origins (English, French, German, Scandinavian). In ESG and E/S/G ratings, we find one global factor, implying ESG globalisation, whereas varying number of local factors across legal origins and subcomponents. The global (local) factor dominates in Refinitiv (MSCI) data in explaining variance of ESG. Mixed evidence on impacts of legal origin on ESG performance indicates ESG divergence among raters, suggesting enhancing relative importance ratios of global factor to better predict overall ESG performance, which can be achieved by enforcing global mandatory reporting standards.

Chapter 3 explores the relationship between ESG and SDG across legal origins using integrated panel data model that jointly accommodates local spillovers, global shocks and parameter heterogeneity. Combining CCEX-IV approach and GCM network analysis, we find that civil (common) legal origin achieves higher direct (spill-in) effects of ESG on SDG, supporting the first and second generations of legal origin theory. But network analysis of ESG and E/S/G ratings suggests higher direct effect in common legal origin. Significant heterogeneity found within civil legal origins, with German legal origin being the most influential shock transmitter, challenges the monolithic view of civil law countries, suggesting considering sub-categorisation in legal origin theory.

Declaration

I declare that this thesis is a presentation of original work and I am the sole author. This work has not previously been presented for an award at this or any other University. Where individual chapters were coauthored with other researchers, this is indicated with the necessary specifications in this declaration. I am the sole author of Chapter 1. Chapters 2 and 3 are coauthored papers with Dr. Han Jin, Prof. Kausik Chaudhuri and my supervisor, Prof. Yongcheol Shin. I contributed to every part of the research, and my co-authors contributed at various points with revisions and comments. All sources are acknowledged as references.

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Introduction

The global economic integration has been accelerating through the rise in international trade flows and financial market integration over the past decades. The sustainability of the EMU crucially rely on the business cycle synchronisation (BCS) among the member countries, as they experience economic shocks simultaneously, resulting in a more effective single monetary policy. This growing mutual reliance between partner countries is also related to the contact with a third country which leads to systemic interconnectivity through the trade and financial linkages.

Both trade intensity and financial integration are acknowledged as the chief means for business cycle propagation, though considerable debate has surrounded the impacts of real and financial integration on international business cycles. This mechanism will involve a confluence of four key aspects, such as simultaneity (e.g., Frankel & Rose (1998) and Imbs (2004)), local spatial effect (e.g., Fiaschi et al. (2017) and Cainelli et al. (2021)), global cross-section dependence (e.g., Kose et al. (2003*a*) and Servén & Abate (2020)) and parameter heterogeneity (e.g., Ando et al. (2022)). Most of existing studies assess how BCS changes with trade/financial intensities, while accommodating one or two of these aspects only. Mixed results have been found in the current literature, which can be attributed to the differences in economic structures, institutional development, market integration level and the nature of shocks. Homogeneous parameters are largely imposed in most studies, which is considered to be restrictive as the direction and effect of spatial spillovers between regions may vary over space. The predominant pooled estimation results document that business cycle comovement is positively associated with BCS in neighbouring countries and to bilateral trade intensity while negatively associated with financial market integration, though these results are likely to obscure the important individual-specific information. In this regard, most of exiting literature may lead to an incomplete conclusion.

There has been an increased attention on research related to sustainable finance since the United Nation report "Who Cares Wins" in 2004. Although no clear consensus exists on the definition of sustainable finance and various terms have been toyed with it such as environmental, social, and governance (ESG) indicator, socially or sustainably responsible investing, and corporate social responsibility (CSR), a plethora of work mainly focuses on ESG issues and financial markets.

However, existing literature fail to reach a consensus on the impact of ESG on financial, environmental and social performance, mainly because ESG data can be noisy and uncertain due to data quality, measurement, metrics, time lag, industry/country regulations and aggregation. Berg, Koelbel & Rigobon (2022) document that the ESG disagreement is fundamentally driven by the divergence in measurement, scope and weighting, stemming from the lack of standardised ESG rating approach. We must carefully navigate this noise to make informed decisions, since discrepancies in ratings yield diverging performances (Billio et al. 2021). Furthermore, ESG regulations are multifaceted and can vary by region based on their legal origins (Liang & Renneboog 2017). It is challenging to navigate all these complexities while aligning with the different ESG disclosure reporting standards. Therefore, it is important to investigate the role of legal origins in shaping ESG practices using either the first generation legal origin theory that emphasises investor protection and financial development (La Porta et al. 1998) or the second generation theory with extended focuses on labour regulation, property rights, contract enforcement, and government intervention (Djankov et al. 2003, La Porta et al. 2008).

While ESG mainly focuses on risks and opportunities related to environmental performance, social responsibility, and corporate governance by businesses, SDG (Sustainable Development Goal) set by the United Nations, on the other hand is a comprehensive blueprint for addressing global challenges mainly related to economic, environmental and social dimensions. The adoption of ESG principles by businesses and investors can directly contribute to the achievement of the SDGs and therefore understanding the interplay between these two metrics is important for developing effective practices and strategies from three aspects: (i) corporates' contributions in achieving the SDGs; (ii) increasing expectations from investors and stakeholders regarding alignment of ESG efforts towards SDGs and (iii) linking corporate ESG disclosures to national SDG commitments by the regulators. Therefore, mapping ESG scores against SDGs is important in guiding companies to comply and track their sustainability strategies with sustainable growth.

Although ESG can be generally regraded as a sustainable input mechanism designed for promoting SDG outputs (e.g., Zhao et al. (2021)), the existing literature has largely neglected the spatial dynamics, cross-section dependence and the parameter heterogeneity while modelling their relationship. Given the variations in ESG/SDG strategies due to cultural, economic, and regulatory differences subject to the country's legal origin (Kock & Min 2016, Liang & Renneboog 2017), it is imperative to conduct a spatial analysis to capture these nuances based on legal origin, leading to a more accurate representation of what drives the performance of the overall ESG-SDG nexus. Moreover, it is crucial to allow for cross-sectional dependence in examining the relationship between ESG and SDG. Although countries with different legal origins may share common trends in SDG/ESG performance influenced by similar legal or economic forces, they may differ depending on economic development, regulatory framework and/or institutional quality even belonging to the same legal origin. Furthermore, allowance for heterogeneity of parameters can be essential in capturing local variations reflecting the complexities of real-world phenomena, leading to more robust insights and better-informed decision-making. In this regard, the existing findings with respect to the causal relationship from ESG inputs to SDG outcomes can be deficient.

Chapter 1

We investigate the fundamental relationship between trade/finance intensities and BCS by developing an integrated panel data model that accommodates the four key elements, such as simultaneity, spatial spillovers, global interactive effects and the parameter heterogeneity. We follow Chen et al. (2022) and propose the individual CCEX-2SLS estimator to consistently estimate the spillover effect and the endogeneous effects of bilateral trade and finance intensities on BCS for the 136 pairs of the 17 OECD countries from 1995Q1 to 2019Q4. The results demonstrate that it is important to explicitly take heterogeneity into account, showing that the proportion of positive and negative effects of trade/financial intensities on BCS are similar whilst their mean group estimates become small and insignificant, but they are also significantly affected by the outlying results. A pooled or mean group estimator subject to such netting off has the potential to produce a misleading global picture, which provides some explanations for the mixed findings in existing studies.

Next, we conduct a spatial network analysis to investigate the direct effects from the trade and financial channels and the indirect (spillover) effects from neighbouring country pairs' trade and financial linkages, respectively. By doing so, we address the important issue of which country-pairs contribute to boost or inhibit BCS through trade/financial intensities, using the two network measures, heterogeneous direct effect and heterogeneous spill-out effect, and find that signs of their direct and indirect effects on BCS tend to be opposite. These results provide some support for mixed theoretical predictions in the literature. Direct and indirect effects of trade intensity depend on the nature of trade (intra-industry and inter-industry) and spillovers from neighbouring country pairs (Duval et al. 2014), whereas the impacts of financial intensity can be explained from the perspective of balance sheet effects (Davis 2014) and wealth effects (Dees et al. 2007).

Finally, we conduct the GCM analysis by Greenwood-Nimmo et al. (2021) and Shin & Thornton (2021), using an intermediate level of aggregation by dividing 17 countries into the 3 groups as EU core (EC), EU periphery (EP) and non-EU (NEU) countries and constructing the 6 clusters (EC-EC, EC-EP, EC-NEU, EP-EP, EP-NEU and NEU-NEU). We observe the surprisingly negative aggregate total effect of trade intensity on BSC, which may stem from unbalanced integration, not integration itself; although the advanced country-pairs are influential transmitters of trade intensity for cycle alignment (e.g., the EC-EC cluster standing out as a direct and indirect BCS booster), they receive adverse spill-in impacts, mostly from the clusters associated with EP, leading to cycle misalignment. Next, we should address negative spillovers of financial intensities mainly from EU country-pairs due to fundamental imbalance. Furthermore, the EC-EC cluster stands out as the BCS inhibitor both directly and indirectly, implying that its high volume of transactions can amplify the negative impact of financial intensity on BCS. This may suggest that the EU are not fully integrated yet for fulfilling the optimal currency area (OCA) criteria (Krugman 2009), while policy recommendations should focus on improving the quality of integration (e.g., risk-sharing, diversified trade) rather than just increasing it. To progress towards this goal and help policymakers to coordinate across borders and mitigate adverse economic fluctuations, relevant policy implications are provided, such as enhancing trade policies, promoting financial integration and coordination of macroeconomic policies.

Chapter 2

We address the aforementioned challenging issues of noisy ESG data while aligning with the different ESG disclosure reporting standards between common and civil legal origins by identifying and analysing systematic and noisy components of ESG ratings. We apply the generalised canonical correlation (GCC) approach advanced by Choi et al. (2023) and Lin & Shin (2023) to estimate the multilevel factor model and characterise the systematic global and local factors across the four legal origins (English, French, German and Scandinavian), using monthly observations of IVA rating and its three E/S/G pillars for $3,911$ companies during January 2014 and December 2023 from the MSCI dataset as well as annual observations of ESG rating and its three components for $2,306$ companies over 2002–2023 from the Refinitiv/LSEG dataset. The respective estimation results share some similarities and differences. First, we find one global factor in both datasets, which confirms the presence of ESG trend/globalisation. The time-varying patterns of global common components of ESG ratings closely resemble the raw data, with Scandinavian origin as the top performer. On the other hand the number of local factors varies and the time-varying patterns of local common components are significantly heterogeneous across legal origins and sub-components of ESG, which reflects the presence of multiple local factors driving the ESG practices across legal origins with different goals subject to varying cultures, economies, environments and political systems. Second, although the time-varying patterns of the ESG data and global common components of both raters are qualitatively similar to each other, global factor dominates in explaining the variance of Refinitiv

ESG data whereas local factors dominate in that of MSCI ESG data. This finding potentially indicates the priorities on universal ESG standards and international benchmarks for the former rater, while more emphasises on local regulations and cultural norms in ESG assessment for the latter.

Next, following ‘doing well doing good’ literature (Martiny et al. 2024), we explore the associations of the ESG data and their global and local common components with country-specific macro (GDP growth, inflation) and firm-specific variables (size, ROE, leverage ratio) along with Covid pandemic and legal origin dummies. Although the estimation results are qualitatively different between MSCI and Refinitiv datasets (e.g., the impacts of GDP growth and inflation are mostly positive for MSCI data, but mostly negative for Refinitiv data), the sign and significance associated with these determinants for the systematic components of ESG match in almost all cases with those of raw data. Furthermore, systematic global components can be well predicted by these determinants while the raw data and local components are harder to predict. Together with much higher relative importance of idiosyncratic components estimated in MSCI data, we conjecture that the MSCI data is likely to be subject to more noises and uncertainties related to ESG disclosures. Finally, we find the mixed evidence on the impacts of legal origin on the ESG performance. The MSCI results are generally inconsistent with the existing studies (Kock & Min 2016, Liang & Renneboog 2017, Kim et al. 2017) whereas the Refinitiv results provide some support for the second generation legal origin theory.

Given the data-driven characteristic of GCC-based approach, such different findings point towards the raters’ ESG divergence as postulated in the literature (Avramov et al. 2022, Christensen et al. 2022, Berg, Koelbel, Pavlova & Rigobon 2022). Hence, it is still complex to uncover the fundamental relationship between ESG factors and firm characteristics/macro variables/legal origins. We suggest that the relative importance ratios of the global factor be greatly improved relative to local factors and idiosyncratic components so as to better predict overall ESG performance. Given that the standards of ESG disclosure reporting are currently quite different across civil and common law countries, this goal can be achieved through enforcement of global mandatory reporting standards, e.g., active implementation of international ESG training programs.

Chapter 3

In Chapter 2, we explore how macro variables, firm financial characteristics, and legal origins shape the systematic components of ESG performance, focusing on 'doing well' (financial benefits) from 'doing good' (ESG practices) on the firm level. In Chapter 3, we extend this logic to the societal level by investigating whether firms that 'do good' also contribute to 'doing well' at a broader scale by advancing SDGs. While Chapter 2 examines the determinants of ESG performance, Chapter 3 evaluates its real-world impact, thus bridging firm-level incentives with global sustainability outcomes. This progression aligns with the 'doing well doing good' paradigm by showing how corporate sustainability efforts can translate into measurable societal benefits, moderated by legal origins.

In Chapter 3, we uncover the network causal effect of ESG on SDG across legal origins through developing an integrated panel data model that simultaneously accommodates the three key elements such as spatial spillovers, global shocks and the parameter heterogeneity. We propose the use of the CCEX-IV estimator by Chen et al. (2022) to consistently estimate all heterogeneous parameters using annual SDG Index collected from the SDG Transformation Center and IVA from MSCI Database for 41 countries over 2007-2023. Next, we conduct the GCM network analysis advanced by Greenwood-Nimmo et al. (2021) and Shin & Thornton (2021), and analyse the network multipliers of SDG with respect to ESG by distinguishing the direct and indirect spillover effects across legal origins where direct effects mostly capture *ex ante* effect, while indirect spillover effects capture network feedback and economic interactions. By investigating the relative role/position of each legal origin in terms of respective direct and indirect effects within the system, we find that direct effect of ESG on SDG in civil legal origin is significantly larger than in common legal origin while spill-in effect is higher in common legal origin. These results support both the first and second generations of legal origin theory. The pronounced heterogeneous spillover patterns are observed within civil legal origins. In particular, spill-out effects from German legal origin dominate while its spill-in effects are almost negligible, leading to its role as the most influential ESG shock transmitter in the system. On the other hand, French legal origin takes an opposite pattern while Scandinavian legal origin takes an intermediate position. Finally, the four legal origins lay along a line from north-west to south-east in the (EM, SI) coordinate where EM refers to external factors often subject to social, economic, political or global impacts and SI discloses the relationship within the spatial system. This pattern vividly reveals their relative position in the ESG-SDG network, and suggests that English and French legal origins are the main beneficiaries of ESG shocks, mainly from German legal origin. We also develop and test the validity of hypotheses on the predictions of legal origin theories.

As a robustness check, we investigate the determinants of aggregate IVA using the individual E/S/G pillars across legal origins by employing the extended monthly data from MSCI Database for 54 countries over the period January 2014-December 2023. We find that the highest direct effect of E/S/G pillars on IVA is achieved by English legal origin while the direct effect ranking of civil legal origins varies across the individual pillar. Direct effect within civil legal origin is outperformed by common legal origin, which does not provide support to the second generation of legal origin theory. Spill-in to common legal origin remains higher than that to civil legal origin. Taken together, English legal origin obtains the highest total effects of all E/S/G pillars on IVA. The spillover patterns maintain heterogeneous across civil legal origins while German legal origin is shown to be systemically most influential.

These findings challenge the presumption of the binary classification within legal origin theory that one legal origin universally holds superiority over another, which may oversimplify the complex interplay between law systems and socio-economic relationships (Acemoglu & Johnson 2005). The prominent spill-out from German civil legal origin implies its systematic role as an influential contributor and exporter of superior ESG practices whereas the pronounced spill-in to common legal origin indicates that they tend to import global ESG standards owing to the flexible and market-driven governance and global supply chain integration. Moreover, both ESG-SDG and E/S/G-ESG nexuses provide additional evidence of the nuanced divergences in how different civil legal origins process E/S/G integration and propagate shocks from ESG to SDG. The heterogeneity within civil legal origins can challenge the monolithic view of civil law countries, thereby raising the importance of accommodating sub-categorisation in legal origin theory.

Chapter 1

Network Analysis of Business Cycle Synchronisation

Abstract To investigate the fundamental relationship between business cycle synchronisation (BCS) and trade/finance intensities, we develop the simultaneous equation panel data model that accommodates all the key elements: simultaneity, spatial spillovers, global shocks and parameter heterogeneity. We propose the consistent CCEX-2SLS estimator, and conduct a spatial network analysis to investigate the direct and indirect impacts of trade/finance intensities on the BCS across country-pairs or the selected clusters. We apply the proposed approach to the dataset consisting of the 136 pairs of the 17 OECD countries over 1995Q1-2019Q4, and convincingly unveil: (i) the individual CCEX-2SLS estimation results demonstrate the importance of explicitly taking parameter heterogeneity into account; (ii) almost 90% of the sample belong to cases where the direct and indirect effects of trade/finance intensities on BCS display opposite signs; (iii) we observe the surprisingly negative total effect of trade intensity on BCS and negative spillovers of trade and financial intensities on BCS. This suggests that EU economies promote the policies to facilitate trade/financial intensities for improved BCS.

Keywords: Business Cycle Synchronisation, Simultaneous Equations Panel Data Model with Spatial/Factor Dependence and Parameter Heterogeneity, CCEX-2SLS estimator, Network Multipliers of Trade and Financial Intensities.

JEL Classification: C33, C38, F44.

1.1 Introduction

Over the past decades the global economic integration has been accelerating through the rise in international trade flows and financial market integration. This transformation has been manifested in the adoption of the euro as a single currency. The sustainability of the EMU depends crucially upon the business cycle synchronisation (BCS) among the member countries, because they experience economic ups and downs at the same time, making a single monetary policy more effective. The increasing interdependence between partner countries is also associated with the exposure of a third country which can result in systemic connections through the trade and financial linkages.

The focus on trade and financial intensities as the primary determinants for BCS is motivated by their well-documented theoretical and empirical prominence in the literature. In terms of the theoretical foundations, trade intensity directly influences BCS through demand and supply linkages (Frankel & Rose 1998), while financial integration facilitates risk-sharing and cross-border capital flows, affecting co-movement (Imbs 2004, Kalemli-Ozcan, Papaioannou & Perri 2013). These channels are central to canonical models of international macroeconomics. By isolating these variables, we aim to rigorously test their distinct and combined effects, avoiding potential multicollinearity or over-specification issues that could arise from including broader structural similarities, e.g., political integration and industry structure. In terms of empirical applications, prior meta-analyses consistently rank trade and financial linkages as the primary drivers of BCS. For instance, Frankel & Rose (1998), Clark & Van Wincoop (2001) and Baxter & Kouparitsas (2005) show that trade significantly explains more variance than industrial structure, while Darvas et al. (2005) and Kalemli-Ozcan, Papaioannou & Perri (2013) highlight financial integration's dominance, especially banking integration, over fiscal or monetary policy alignment in the EU. While we acknowledge the role of institutional or industrial similarities, their omission aligns with our study's focus on cross-border interaction mechanisms rather than structural homophily.

Trade intensity and financial integration are identified as primary channels for business cycle propagation, though considerable debate has surrounded the effects of real and financial integration on international business cycles. Although this mechanism will involve a confluence of simultaneity (e.g., Frankel & Rose (1998) and Imbs (2004)), local spatial neighbour effect (e.g., Fiaschi et al. (2017) and Cainelli et al. (2021)), global cross-section dependence (e.g., Kose et al. (2003*a*) and Servén & Abate (2020)) and parameter heterogeneity (e.g., Ando et al. (2022)), most of existing studies, thoroughly reviewed in Section 2, focus on one or two of these aspects only.

In sum the existing literature examine how BCS changes with trade/financial intensities, while incorporating simultaneity, local spillovers and global shocks, separately. They tend to produce the mixed findings due to the differences in various respects such as economic structures, institutional development, market integration level and the nature of shocks. However, most studies impose the parameter homogeneity that is restrictive in a data-rich environment, since the strength and direction of spatial dependence between regions may vary over space. The predominant pooled estimation results reveal that business cycle comovement is positively related to BCS in neighbouring countries and to bilateral trade intensity while negatively related to financial market integration, though these results are likely to obscure an important individual-specific information. In this regard, most of existing studies may lead to an incomplete conclusion.

We aim to investigate the fundamental relationship between trade/finance intensities and BCS. In this paper, as a main contribution, we develop an integrated panel data model that accommodates all the key elements: simultaneity, spatial spillovers, global interactive effects and the parameter heterogeneity. We follow Chen et al. (2022) and propose the CCEX-2SLS estimator to consistently estimate the spillover effect and the (endogenous) effects of bilateral trade and finance intensities on BCS for the 136 pairs of the 17 OECD countries over 1995Q1-2019Q4. Next, as a complete modelling package, we conduct a spatial network analysis to investigate the direct effects from the trade and financial channels and the indirect effects from neighbouring country pairs' trade and financial linkages, respectively.

The main empirical findings are summarised as follows: The individual CCEX-2SLS estimation results clearly demonstrate the importance of explicitly taking heterogeneity into account, showing that the proportion of positive and negative effects of trade/financial intensities on BCS are similar whilst their mean group (MG) estimates become small and insignificant, but they are also significantly affected by the outlying samples. A pooled or mean group estimator subject to such netting off has the potential to produce a misleading global picture. This could provide some explanations behind the mixed findings reported in the existing studies, indicating that they conceal essential heterogeneous information.

Next, we conduct a diffusion network analysis to investigate the direct and indirect (spillover) effects from the trade and financial channels, and address the important issue of which country-pairs contribute to boost or inhibit BCS through trade/financial intensities, using the two network measures, heterogeneous direct effect (HDE) and heterogeneous spill-out effect (HSO), and assigning the individual country pair to the following four cases: (i) they boost BCS directly through HDE and indirectly through HSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly. We observe quite interesting patterns: almost 90% of the sample belong to cases (ii) and (iii), which implies that signs of their direct and indirect effects on BCS tend to be opposite. These results are more or less in line with mixed theoretical predictions in the literature. Duval et al. (2014)

suggest that the direct and indirect effects of trade intensity depend on the nature of trade and spatial spillovers from the neighbouring country pairs. When different economies engage in intra-industry trade, they become more interconnected (Fidrmuc 2004), directly boosting BCS through trade integration. Nevertheless, the negative spatial spillovers can be present when more trade between two countries comes at the cost of a decline in trade with the neighbour countries. On the other hand, when different countries engage in inter-industry trade, Calderon et al. (2007) find that economies with more asymmetric structures of production tend to have a low degree of BCS. Nonetheless, neighbouring countries can benefit from the positive spillovers through enhanced trade opportunities (Ponnusamy 2022), boosting BCS indirectly. For financial intensity, enhanced financial linkages account for the alignment of business cycles through balance sheet effects and risk sharing, whilst leading to the misalignment through wealth effects (Davis 2014). From the perspective of balance sheet effects, intensive cross-border financial transactions enhance regional financial integration and risk mitigation, boosting BCS while negative indirect impacts of financial intensity may spill out to neighbouring country pairs (Claessens et al. 2012). With respect to wealth effects, higher financial intensities introduce larger volatilities in asset prices, driving economic activities out of sync whereas the positive indirect effects can occur when financial linkages can reduce risks and enhance financial stability in neighbouring countries, synchronising the business cycles (Dees et al. 2007).

Finally, we conduct the GCM analysis advanced by Greenwood-Nimmo et al. (2021) and Shin & Thornton (2021), using an intermediate level of aggregation by dividing 17 countries into the 3 groups as EU core (EC), EU periphery (EP) and non-EU (NEU) countries and constructing the 6 clusters (EC-EC, EC-EP, EC-NEU, EP-EP, EP-NEU and NEU-NEU). We observe the surprisingly negative aggregate total effect of trade intensity on BSC which may stem from unbalanced integration, instead of integration itself; although the advanced country-pairs are influential transmitters of trade intensity for cycle alignment (e.g., the EC-EC cluster standing out as a direct and indirect BCS booster), they receive (larger) adverse spill-in impacts, mostly from the clusters associated with EP, that leads to cycle misalignment. Next, we should address negative spillovers of financial intensities mainly from EU country-pairs due to fundamental imbalance. Furthermore, the EC-EC cluster stands out as the BCS inhibitor both directly and indirectly, implying that its high volume of transactions can amplify the negative impact of financial intensity on BCS. This may suggest that the EU are not fully integrated yet for fulfilling the optimal currency area (OCA) criteria (Krugman 2009), and policy recommendations should focus on improving the quality of integration (e.g., risk-sharing, diversified trade) rather than just increasing it. To progress towards this goal and help policymakers to coordinate across borders and mitigate adverse economic fluctuations, relevant policy implications are provided, such as enhancing trade policies, promoting financial integration and coordination of macroeconomic policies, improving the monitoring of risk management, and supporting structural reforms.

The rest of the paper is organised as follows. Section 1.2 reviews the related literature. Section 1.3 develops the model, proposes the CCEX-2SLS estimator and describes the spatial network analysis. Section 1.4 presents the main empirical results with policy implications. Section 1.5 concludes. The detailed variable construction, the construction of the spatial weights matrix, the additional empirical results, the sketch of the proof, and the Monte Carlo simulation exercises are relegated to the Appendix.

1.2 Related Literature

Trade intensity and financial integration are commonly identified as primary channels for business cycle propagation in the literature. Although this mechanism will involve a confluence of simultaneity, (local) spatial neighbour effect, (global) cross-section dependence and parameter heterogeneity, existing studies focus on one or two of these aspects only. We review the related works in the three groups.

The first group aims to investigate the relationship between trade/finance intensity and BCS using a panel data model that accommodates simultaneity, where BCS is typically measured by the absolute differential or a bilateral correlation of GDP growth rates. Frankel & Rose (1998) explore a crucial condition for an optimum currency area (OCA) with the focus on the relationship between trade intensity and BCS. They suggest it to be bidirectional due to the endogenous nature between various OCA criteria; while more international trade can lead to higher business cycle correlations, countries already with aligned cycles tend to have closer ties with their trading partners. This simultaneity prompts to employ the instrumental variable (IV) method and the generalised method of moments (GMM), e.g., Baxter & Kouparitsas (2005). With the increasing globalisation, Ng (2010) documents that bilateral production fragmentation, capturing the positive impact exerted by trade in complements, is crucial in uncovering the positive responses of BCS to trade. Liao & Santacreu (2015) employ the volume of goods transactions between trading partners as a proxy for the trade intensity, showing that trade effects are positive for industrialised and developing economies over 1959-2016. When decomposing cross-border trades, BCS is shown to be driven more by intra-industry trade than total trade, e.g., Calderon et al. (2007) and Shin & Wang (2003). Intra-industry trade linkages can lead to stronger spillovers through demand and supply channels across economies, amplifying their output correlations. However, when the trade intensity is linked to greater specialisation between industries across countries, the dominance of industry-specific shocks is likely to inhibit BCS.

Mixed estimation results have been reported for the effect of financial intensity on BCS, where financial intensity is usually measured by banking linkages and FDI flow intensity. Lee (2010) emphasises that the effect of FDI intensity on coherent cycles tends to be positive within regional US economies during 1990 and 2005. Such a positive finance-comovement is commonly observed in domestic integration, see the regional studies of China (Lei & Yao 2008). Otto et al. (2001) find that though cross-border trade and financial integration can boost BCS, the similarity of economic characteristics and institutions are shown to be the main driver of the strong business cycle correlations between Australia and the US. On the other hand, some studies conversely claim that financial intensity can inhibit BCS. Heathcote & Perri (2004) show that a decrease in the BCS of US-OECD has been witnessed while the financial integration has levelled up during 1972–1986. Zouri (2020) documents a similar finding for the Economic Community of West African States over the period 1980–2015. Moreover, Kalemli-Ozcan, Papaioannou & Perri (2013) document evidence that the divergent output cycles of advanced economies are associated with enhanced bilateral banking linkages in the tranquil times while financially integrated nations tend to experience greater comovement during financial crises.

An increasing number of studies analyse the causalities among BCS, trade- and financial-intensities using the system of simultaneous equations to disentangle direct from indirect channels. A feasible generalized least squares (FGLS) method (Antonakakis & Tondl 2014) and a two-stage least squares (2SLS) or three-stage least squares (3SLS) method (Imbs 2004, Kalemli-Ozcan, Papaioannou & Peydro 2013) are typically applied. Using 3SLS and GMM approaches, Imbs (2004) obtains a robust result that financial intensity has a positive direct effect on BCS, though its indirect effect can be adverse through facilitating specialisation. Imbs (2006) explains the dual impacts of financial intensity on BCS through risk-sharing mechanisms. Financially integrated economies have more enhanced BCS due to greater exposure to global shocks and effective shock propagation, while simultaneously becoming less sensitive to country-specific shocks, which inhibits those regions' BCS. Financial intensity can boost BCS via the wealth effects,[1] but it can also inhibit BCS via capital reallocation that facilitates production specialisation aligned with countries' comparative edge (Kalemli-Ozcan et al. 2003). Moreover, Gong & Kim (2018) document that regional financial integration directly inhibit BCS, but indirectly boosts BCS through the enhanced regional

[1] According to Kalemli-Ozcan et al. (2003), financially integrated markets enable individuals and firms to diversify their portfolios globally, decreasing the dependence of income and wealth on local regions. Consequently, the consumption patterns become increasingly synchronised across economies, leading to improved BCS due to international risk-sharing.

trade integration.[2] For 30 OECD countries over 1993–2007, Dées & Zorell (2012) find the positive indirect effect of financial intensity on BCS via increasing the similarity in specialisation, but no evidence of the direct effect. Antonakakis & Tondl (2014) discover the pronounced positive direct and indirect effects (through stimulating trade) of financial intensity on business cycle correlations between incumbent and new EU members over 1995–2012, while documenting strong evidence that poor fiscal regulation is the biggest obstacle of boosting BCS among EU members.

The second group highlights the important issue of controlling the spatial spillover in studying the relationship among BCS, trade- and finance-intensities. The neoclassical growth theory, that claims economies to be entirely independent, was disproved, the increasing trade volume and financial links can enhance the interactions of output growth indirectly through spatial spillovers, e.g., Chari et al. (2005) and Kehoe & Ruhl (2009). Spatially binding trade and monetary policies are implemented to promote cross-border economic activities (Harvey 2009). In this regard, GDP growth comovement within a country pair may be connected with the economic activities in the neighbouring countries (pairs) through trade interdependence and financial integration. The spatial spillover of economic growth is largely found to be positive, leading to an increase in output growth convergence (Ho et al. 2013). Li & Han (2019) adopt a generalised spatial Durbin model for analysing the spillover of treaty ports on prefecture population and long-term economic growth in China in the 19th century, demonstrating the important role of positive economic growth spillover based on geographical proximity. Fiaschi et al. (2017) investigate the determinants of the macroeconomic volatility (MV) (measured by the standard deviation of per capita GDP growth) in the EU over 1992-2008, and find a significantly positive spatial dependence of MV, mainly from the spillover from neighbouring regions. Notice, however, that the measurements of BCS used in most spatial applications are different from those in the first group.

To identify the regional determinants of pairwise business cycle synchronisation across 49 US states during the period 2002–11, Cainelli et al. (2021) adopt a spatial Durbin model in the cross-section, where the dependent variable is measured as the time average of the synchronisation index between state pairs. Applying the QML estimation with a contiguity-based spatial weights matrix (see Appendix A.3 for details), they find that local business cycles are more synchronised in those states in close proximity, and multiple channels can lead to aligned economic activities directly and indirectly through spillover effects of the neighbouring state pairs on the BCS. Given technology development and enhanced communication efficiency, it is possible for countries being widely separated from each other while maintaining a robust economic partnership to experience

[2] Gong & Kim (2018) show that global financial linkages exhibit the most significant effect in East Asia and Latin America while regional trade integrations reveal the most significant effect in Central and Eastern Europe.

a high degree of BCS (Baxter & Kouparitsas 2005, Clark & Van Wincoop 2001). Wang et al. (2015) measure the level of economic volatility comovement among 187 countries over 1987-2007 and find a strong comovement across countries, especially by a significantly higher spatial influence through bilateral trade linkages. Böhm et al. (2022) use country-specific GDP and industrial gross value-added growths as business cycle indices, and unwrap the substantial heterogeneity of spillover shocks across 10 EU countries over 1996-2017, though a positive spillover becomes more sizeable, boosting BCS across financially linked countries, especially during financial turmoils.

The third group of studies apply a panel data model that accommodates cross-section dependence mainly through accommodating unobserved factors. Kose et al. (2003*a*) employ a Bayesian dynamic latent factor model to decompose the macroeconomic aggregates into world, regional and country-specific factors in a sample of 60 countries. They capture the degree of BCS by the proportion of variance in the primary indicators of business cycle volatility, finding that the global factor can explain a sizable share of economic fluctuations in developed economies while the country-specific and the idiosyncratic factors are more effective at explaining the volatility in developing economies. Kose et al. (2008) estimate common and country-specific components in the macroeconomic aggregates for the G7 countries and find that the degree of BCS has increased over time mainly due to the growing importance of common factors in driving business cycle fluctuations. Beck (2021) analyses the multilevel factors model of the sectoral growth for a sample of 17 sectors in EU countries, where BCS is measured by the share of variance explained by the three (global/country/sector) factors. He finds that bilateral trade, bilateral FDI holdings and monetary policy similarity can amplify BCS whilst the EU business cycle divergence is mainly driven by different sectoral factors. Francis et al. (2017) explore the dynamics of international business cycles across countries through a factor model that decomposes BCS into global and regional/cluster factors, and find that the endogenously clustered BCS influence their economic fluctuations. Chen et al. (2024) (hereafter CSX) address the joint issue of simultaneity and cross-section dependence in an analysis of the fundamental relationship between trade/financial intensities and BCS. Applying a pooled CCE-IV estimation to a simultaneous panel data model with interactive effects, they find a positive effect of trade intensity but a negative effect of financial intensity. The relationship between financial intensity and BCS turns to be positive during financial turmoil periods while it remains negative during tranquil periods. Servén & Abate (2020) apply the QML estimation to a dynamic spatial panel data model of output growths with unobserved factors. Using the trade- and distance-based spatial weights matrices they evaluate the variance decomposition of cyclical comovements, showing that the interdependent aggregate economic growth is driven jointly by latent global shocks and spatial effects from neighbouring countries. They also find that an omission of spatial spillovers and common shocks can result in a pronounced decline in the forecasting performance of the model.

In sum the existing literature examines how BCS changes with trade/financial intensities, while incorporating the simultaneity, the local neighbour spillovers and the global shocks through unobserved factors, separately. They tend to produce the mixed findings due to the differences in various respects such as economic structures, institutional development, market integration level and the nature of shocks. However, most studies impose the parameter homogeneity and present the pooled estimation results that are likely to obscure an important individual-specific information, since the cross-section parameter heterogeneity in the presence of interdependence between different countries is not controlled for. In this regard, the existing studies may lead to an incomplete conclusion.

Finally, we provide a brief review on the related econometric methods for the panel data model with both spatial dependence and common factors. Pesaran & Tosetti (2011) is the first paper that proposes a modified common correlated effects (CCE) estimator by Pesaran (2006). The popular quasi-maximum likelihood (QML) is developed by Bai & Li (2013) and Shi & Lee (2017) while the GMM estimation is proposed by Kuersteiner & Prucha (2020). Yang (2021) proposes the pooled 2SLS and GMM estimators. Furthermore, the spatial simultaneous equation model has been developed. The IV estimation is proposed by Kelejian & Prucha (2004) while the QML estimation by Yang & Lee (2017). Finally, Lu (2022) is the only work addressing both spatial spillover and interactive effects in the simultaneous equation panel data model, though she only proposes the pooled QML and an iterative generalised principal components estimators by imposing the homogeneous parameters.

We aim to investigate the fundamental relationship between trade/finance intensities and the BCS. To this end we develop an integrated panel data model that accommodates all the key elements: simultaneity, spatial spillovers, interactive effects and the parameter heterogeneity. To jointly cover all the four effects, we propose modifying the CCEX-IV estimator advanced by Chen et al. (2022) to consistently estimate the spillover effect and the effects of bilateral trade and finance intensities on BCS for the 136 pairs of the seventeen OECD countries over the period 1995-2019. Next, as a complete package, we conduct the spatial and GCM network analysis advanced by Greenwood-Nimmo et al. (2021) and Shin & Thornton (2021), and analyse the diffusion network impacts of the trade and capital intensities on the BCS across the country-pairs or the selected clusters.

1.3 The Model

Given the simultaneous relationship between business cycle synchronisation and trade/finance intensity, we propose a simultaneous equation panel data model that takes into account (local) spatial and (global) factor dependence as well as country-pair parameter heterogeneity:

$$\begin{aligned}
S_{it} &= \rho_{1i}S^*_{it} + \gamma_{11i}T_{it} + \gamma_{12i}K_{it} + \beta_{1i}sim_{it} + e_{1it}, \quad e_{1it} = \alpha_{1i} + \boldsymbol{\lambda}'_{1i}\mathbf{f}_{1t} + u_{1it}, \\
T_{it} &= \rho_{2i}T^*_{it} + \gamma_{21i}S_{it} + \gamma_{22i}K_{it} + \beta_{2i}exr_{it} + e_{2it}, \quad e_{2it} = \alpha_{2i} + \boldsymbol{\lambda}'_{2i}\mathbf{f}_{2t} + u_{2it}, \\
K_{it} &= \rho_{3i}K^*_{it} + \gamma_{31i}S_{it} + \gamma_{32i}T_{it} + \beta_{3i}inr_{it} + e_{3it}, \quad e_{3it} = \alpha_{3i} + \boldsymbol{\lambda}'_{3i}\mathbf{f}_{3t} + u_{3it},
\end{aligned} \tag{1.3.1}$$

for $i = 1, \dots, N$ and $t = 1, \dots, T$, where $N = n(n-1)/2$ is the total number of (undirectional) country pairs and n is the number of countries included in the dataset. In (1.3.1), S_{it}, T_{it} and K_{it} are three endogenous variables, measuring business cycle synchronisation, bilateral trade intensity and financial intensity, respectively, of the i-th country pair at time t. $S^*_{it} = \Sigma_{j=1}^N w_{ij}S_{jt}, T^*_{it} = \Sigma_{j=1}^N w_{ij}T_{jt}$ and $K^*_{it} = \Sigma_{j=1}^N w_{ij}K_{jt}$ are the spatial lag variables of S_{it}, T_{it} and K_{it} with w_{ij} being the (i,j)th element of the $N \times N$ spatial weights matrix, $\boldsymbol{W}$. We also include exogenous regressors, sim_{it}, exr_{it} and inr_{it}, that measure the size similarity, exchange rate variation and the short-term real interest rate fluctuation of the country pair. See Appendix A.1 for variables construction and expected signs of their impacts. We allow the error component, e_{lit} for $l = 1, 2, 3$ to follow the multi-factor structure with α_{li} being the unobserved individual effect, $\mathbf{f}_{lt}$ and $\boldsymbol{\lambda}_{li}$, being $r_l \times 1$ vectors of unobserved common factors and heterogeneous loadings, and u_{lit} being the idiosyncratic error. Each equation in 1.3.1 is just-identified.[3]

In this paper, we focus on the estimation of parameters in the first equation of (1.3.1), where ρ_{1i}, $i = 1, ..., N$, are the heterogeneous spatial autoregressive coefficients, γ_{11i} and γ_{12i} are heterogeneous parameters of endogenous regressors, T_{it} and K_{it}, respectively, and $\boldsymbol{\beta}_{1i}$ is a vector of heterogeneous parameters on exogenous regressors, sim_{it}. The estimation of parameters in the other equations can be conducted in a similar way. Stacking the first equation in (1.3.1) over t, we have:

$$\begin{aligned}
&\mathbf{S}_i = \rho_{1i}\mathbf{S}^*_i + \gamma_{11i}\mathbf{T}_i + \gamma_{12i}\mathbf{K}_i + \boldsymbol{\beta}_{1i}\mathbf{sim}_i + \mathbf{e}_{1i} = \mathbf{Z}_{1i}\boldsymbol{\delta}_{1i} + \mathbf{e}_{1i}, \\
&\mathbf{e}_{1i} = \mathbf{1}_T\alpha_{1i} + \mathbf{f}_1\boldsymbol{\lambda}_{1i} + \mathbf{u}_{1i}, \ i = 1, ..., N,
\end{aligned} \tag{1.3.2}$$

where $\underset{T\times 1}{\mathbf{S}_i} = (S_{i1}, ..., S_{iT})'$, $\underset{T\times 1}{\mathbf{S}^*_i} = (S^*_{i1}, \dots, S^*_{iT})' = (\boldsymbol{I}_T \otimes \boldsymbol{w}_i)\mathbf{S}$, $\underset{NT\times 1}{\mathbf{S}} = (\mathbf{S}'_1, \dots, \mathbf{S}'_N)'$, $\underset{1\times N}{\boldsymbol{w}_i}$ is the i-th row of $\boldsymbol{W}$, $\underset{T\times 1}{\mathbf{T}_i} = (T_{i1}, ..., T_{iT})'$, $\underset{T\times 1}{\mathbf{K}_i} = (K_{i1}, ..., K_{iT})'$, $\underset{T\times 1}{\mathbf{sim}_i} = (sim_{i1}, ..., sim_{iT})'$. Further, $\underset{T\times 4}{\mathbf{Z}_{1i}} = (\mathbf{S}^*_i, \mathbf{T}_i, \mathbf{K}_i, \mathbf{sim}_i)$, $\underset{4\times 1}{\boldsymbol{\delta}_{1i}} = (\rho_{1i}, \gamma_{11i}, \gamma_{12i}, \boldsymbol{\beta}'_{1i})'$, $\underset{T\times r_1}{\mathbf{f}_1} = (\mathbf{f}_{11}, ...\mathbf{f}_{1T})'$, and $\underset{T\times 1}{\mathbf{u}_{1i}} = (u_{1i1}, ..., u_{1iT})'$.

[3]The order condition for identification of parameters in the l-th equation of (1.3.1) is met if $k - k_l \geq p - 1$, where k_l is the number of exogenous variables in the l-th equation, p the number of equations in the system, and $k = k_1 + \dots + k_p$. The l-th equation is just identified when $k - k_l = p - 1$ and over-identified when $k - k_l > p - 1$. See Yang & Lee (2017).

1.3.1 The CCEX-2SLS estimator

To develop a consistent estimator of the 4×1 parameter vector, $\boldsymbol{\delta}_{1i}$ in (1.3.2), we should address two sources of endogeneity: the correlation between sim_{it} and the unobserved factors $\mathbf{f}_{1t}$ as well as the correlations of the spatial lag term, S^*_{it} and the endogenous regressors, T_{it} and K_{it} with both factors and idiosyncratic error, u_{1it}. Econometric methods have been developed to deal with the spatial effects and factor dependence, separately. The spatial endogeneity can be resolved using QML (Lee 2004) or IV/GMM estimation (Kelejian & Prucha 1998). The common factors can be approximated using the IPC method (Bai 2009) or the CCE method, which is based on the cross-section averages of observable variables (Pesaran 2006). A few studies have recently combined both approaches, e.g., Bai & Li (2014), Bai & Li (2021), Mastromarco et al. (2016), Shi & Lee (2017), Kuersteiner & Prucha (2020), Yang (2021) and Chen et al. (2022).

Here we propose to modify the CCEX-IV approach advanced by Chen et al. (2022), who consider only a single-equation regression instead of a simultaneous equation model. To deal with the endogeneity caused by the correlation between regressors and unobserved factors, they suggest the use of the cross-section averages of only the exogenous variables sim_{it} as proxies for latent factors,[4] since it is sufficient to control for the factors in sim_{it} that are correlated with $\mathbf{f}_{1t}$ in (1.3.2). Then, to deal with the endogeneity of S^*_{it} and T_{it}, K_{it}, we develop a 2SLS procedure by using valid instruments constructed under the maintained assumptions of the model. We call the resulting estimator the CCEX-2SLS estimator.

The CCEX-2SLS estimation algorithm is outlined as follows:

Step 1: Factor proxies and defactorisation. We construct factor proxies by the cross-section average of exogenous regressors given by $\hat{\mathbf{f}}_{1t} = (1, \bar{\mathbf{sim}}_t)'$ with $\bar{\mathbf{sim}}_t = \frac{1}{N}\sum_{i=1}^{N} sim_{it}$.[5] To deal with the correlation between regressors and unobserved factors, we construct the $T \times T$ defactorisation matrix, $\mathbf{M}_{\hat{f}_1} = \boldsymbol{I}_T - \hat{\mathbf{f}}_1(\hat{\mathbf{f}}_1'\hat{\mathbf{f}}_1)^{-1}\hat{\mathbf{f}}_1'$ with $\hat{\mathbf{f}}_1 = (\hat{\mathbf{f}}_{11}, \ldots, \hat{\mathbf{f}}_{1T})'$. Pre-multiplying both sides of (1.3.2) by $\mathbf{M}_{\hat{f}_1}$, we obtain:

$$\tilde{\mathbf{S}}_i = \rho_{1i}\tilde{\mathbf{S}}^*_i + \gamma_{11i}\tilde{\mathbf{T}}_i + \gamma_{12i}\tilde{\mathbf{K}}_i + \boldsymbol{\beta}_{1i}\tilde{\mathbf{sim}}_i + \tilde{\mathbf{e}}_{1i} = \tilde{\mathbf{Z}}_{1i}\boldsymbol{\delta}_{1i} + \tilde{\mathbf{e}}_{1i}, \tag{1.3.3}$$

where $\tilde{\mathbf{S}}_i = \mathbf{M}_{\hat{f}_1}\mathbf{S}_i$, $\tilde{\mathbf{S}}^*_i = \mathbf{M}_{\hat{f}_1}\mathbf{S}^*_i$, $\tilde{\mathbf{T}}_i = \mathbf{M}_{\hat{f}_1}\mathbf{T}_i$, $\tilde{\mathbf{K}}_i = \mathbf{M}_{\hat{f}_1}\mathbf{K}_i$, $\tilde{\mathbf{sim}}_i = \mathbf{M}_{\hat{f}_1}\mathbf{sim}_i$, $\tilde{\mathbf{Z}}_{1i} = \mathbf{M}_{\hat{f}_1}\mathbf{Z}_{1i}$, and

[4] Chen et al. (2022) allow the dependent and independent variables to be influenced by different factors while sharing a subset of common factors. The CCEX approach requires the weaker condition, $T/N^2 \to 0$ whilst the CCE approach, using both $\bar{y}_t$ and $\bar{\boldsymbol{x}}_t$ as proxies for factors, requires the stronger condition, $T/N \to 0$.

[5] For $\bar{\mathbf{sim}}_t$ to be a valid proxy for $\mathbf{f}_{1t}$, we assume that sim_{it} share a subset of the factors in $\mathbf{f}_{1t}$ as in Chen et al. (2022).

$\tilde{\mathbf{e}}_{1i} = \mathbf{M}_{\hat{f}_1}\mathbf{e}_{1i}$.

Step 2: Construction of IVs. To address endogeneity due to the spatial dependence and simultaneity, we construct a set of instruments as

$$\underset{NT\times 4}{\mathbf{H}_1} = (\mathbf{H}_{11}', \ldots, \mathbf{H}_{1T}')'$$

where $\mathbf{H}_{1t} = (\boldsymbol{W}\mathbf{sim}_t, \mathbf{exr}_t, \mathbf{inr}_t, \mathbf{sim}_t)$ is an $N \times 4$ matrix of IVs, $\mathbf{sim}_t = (\mathbf{sim}_{1t}, ..., \mathbf{sim}_{Nt})', \mathbf{exr}_t = (\mathbf{exr}_{1t}, ..., \mathbf{exr}_{Nt})', \mathbf{inr}_t = (\mathbf{inr}_{1t}, ..., \mathbf{inr}_{Nt})'$. We then de-factorise the IVs as

$$\underset{T\times 4}{\tilde{\mathbf{H}}_{1i}} = \mathbf{M}_{\hat{f}_1}(\boldsymbol{I}_T \otimes \mathbf{b}_i')\mathbf{H}_1,$$

which can be written as $\tilde{\mathbf{H}}_{1i} = (\boldsymbol{I}_T \otimes \mathbf{b}_i')(\mathbf{M}_{\hat{f}_1} \otimes \boldsymbol{I}_N)\mathbf{H}_1 = (\mathbf{M}_{\hat{f}_1} \otimes 1)(\boldsymbol{I}_T \otimes \mathbf{b}_i')\mathbf{H}_1 = \mathbf{M}_{\hat{f}_1}(\mathbf{I_T} \otimes \mathbf{b}_i')\mathbf{H}_1$, where $\mathbf{b}_i$ is an $N \times 1$ column vector with the i-th entry being 1 and 0 otherwise.

Step 3: Computation of CCEX-2SLS estimator. The CCEX-2SLS individual estimator is computed as

$$\hat{\boldsymbol{\delta}}_{1i} = (\tilde{\mathbf{Z}}_{1i}'\boldsymbol{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i})^{-1}\tilde{\mathbf{Z}}_{1i}'\boldsymbol{\Pi}_{1i}\tilde{\mathbf{S}}_i, \;\; i = 1, ..., N, \tag{1.3.4}$$

where $\boldsymbol{\Pi}_{1i} = \tilde{\mathbf{H}}_{1i}(\tilde{\mathbf{H}}_{1i}'\tilde{\mathbf{H}}_{1i})^{-1}\tilde{\mathbf{H}}_{1i}'$.

Following Chen et al. (2022) and the simultaneous equations literature, we can establish that under some regularity conditions, as $(N, T) \to \infty$, the CCEX-2SLS individual estimator, $\hat{\boldsymbol{\delta}}_{1i}$ is consistent for $\boldsymbol{\delta}_{1i}$. Furthermore, as $(N, T) \to \infty$ and $T/N^2 \to 0$,

$$\sqrt{T}(\hat{\boldsymbol{\delta}}_{1i} - \boldsymbol{\delta}_{1i}) \xrightarrow{d} N(\mathbf{0}, \boldsymbol{\Omega}_{1i}), \quad i = 1, ..., N, \tag{1.3.5}$$

where $\boldsymbol{\Omega}_{1i} = \boldsymbol{\Xi}_{1i}^{-1}\boldsymbol{\Theta}_{1i}\boldsymbol{\Xi}_{1i}^{-1}$, in which $\boldsymbol{\Xi}_{1i}$ is a symmetric nonsingular matrix such that $\frac{1}{T}\tilde{\mathbf{Z}}_{1i}'\boldsymbol{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i} \xrightarrow{p} \boldsymbol{\Xi}_{1i}$, and $\boldsymbol{\Theta}_{1i}$ is a positive definite matrix such that $Var\left(\frac{1}{\sqrt{T}}\tilde{\mathbf{Z}}_{1i}'\boldsymbol{\Pi}_{1i}\tilde{\mathbf{e}}_{1i}\right) \longrightarrow \boldsymbol{\Theta}_{1i}$.

The asymptotic covariance matrix $\boldsymbol{\Omega}_{1i}$ can be consistently estimated by

$$\hat{\boldsymbol{\Omega}}_{1i} = \left(\frac{\tilde{\mathbf{Z}}_{1i}'\boldsymbol{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i}}{T}\right)^{-1}\left(\frac{\tilde{\mathbf{Z}}_{1i}'\tilde{\mathbf{H}}_{1i}}{T}\right)\left(\frac{\tilde{\mathbf{H}}_{1i}'\tilde{\mathbf{H}}_{1i}}{T}\right)^{-1}\hat{\boldsymbol{\Sigma}}_{1i}\left(\frac{\tilde{\mathbf{H}}_{1i}'\tilde{\mathbf{H}}_{1i}}{T}\right)^{-1}\left(\frac{\tilde{\mathbf{H}}_{1i}'\tilde{\mathbf{Z}}_{1i}}{T}\right)\left(\frac{\tilde{\mathbf{Z}}_{1i}'\boldsymbol{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i}}{T}\right)^{-1}, \tag{1.3.6}$$

in which $\hat{\boldsymbol{\Sigma}}_{1i}$ is a robust estimator (Newey & West 1987) given by

$$\hat{\boldsymbol{\Sigma}}_{1i} = \hat{\boldsymbol{\Sigma}}_{1i,0} + \sum_{h=1}^{p_T}\left(1 - \frac{h}{p_T + 1}\right)(\hat{\boldsymbol{\Sigma}}_{1i,h} + \hat{\boldsymbol{\Sigma}}_{1i,h}')$$

with p_T being the bandwidth of the Bartlett kernel, $\hat{\mathbf{\Sigma}}_{1i,h} = \sum_{t=h+1}^{T} \hat{e}_{1it}\hat{e}_{1i,t-h}\tilde{\mathbf{H}}_{1it}\tilde{\mathbf{H}}'_{1i,t-h}/T$, $h = 0, 1, \ldots, p_T$, $\hat{\mathbf{e}}_{1i} = \mathbf{M}_{\hat{f}_1}(\tilde{\mathbf{y}}_{1i} - \tilde{\mathbf{Z}}_{1i}\hat{\boldsymbol{\delta}}_{1i}) = (\hat{e}_{1i1}, \ldots, \hat{e}_{1iT})'$, and the $\tau_1 \times 1$ vector $\tilde{\mathbf{H}}_{1it}$ being the transpose of the t-th row of $\tilde{\mathbf{H}}_{1i}$.

With the individual estimates, we can construct the CCEX-2SLS mean-group (MG) estimator for $\boldsymbol{\delta}_1 = E(\boldsymbol{\delta}_{1i})$ as

$$\hat{\boldsymbol{\delta}}_{1,MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\boldsymbol{\delta}}_{1i}. \tag{1.3.7}$$

Then, we can show that under the random-coefficient model, $\boldsymbol{\delta}_{1i} = \boldsymbol{\delta}_1 + \boldsymbol{\varepsilon}_{\delta_1,i}$ with $\boldsymbol{\varepsilon}_{\delta_1,i} \sim$ i.i.d.$(\mathbf{0}, \mathbf{\Omega}_{\delta_1})$, and some regularity conditions, as $(N,T) \to \infty$, we have

$$\sqrt{N}\left(\hat{\boldsymbol{\delta}}_{1,MG} - \boldsymbol{\delta}_1\right) \xrightarrow{d} N\left(\mathbf{0}, \mathbf{\Omega}_{\delta_1}\right).$$

The covariance matrix $\mathbf{\Omega}_{\delta_1}$ can be consistently estimated by the nonparametric estimator (Pesaran 2006):

$$\hat{\mathbf{\Omega}}_{MG} = \frac{1}{N-1}\sum_{i=1}^{N}(\hat{\boldsymbol{\delta}}_{1i} - \hat{\boldsymbol{\delta}}_{1,MG})(\hat{\boldsymbol{\delta}}_{1i} - \hat{\boldsymbol{\delta}}_{1,MG})'. \tag{1.3.8}$$

Remark: In Appendix A.5, we conduct Monte Carlo simulation studies, which demonstrate the satisfactory finite sample performance of the CCEX-2SLS individual and mean-group estimators.

1.3.2 The network analysis

Following Shin & Thornton (2021) and Mastromarco et al. (2023), we turn to developing network analysis capable of highlighting the spatial/network interactions captured by the model (1.3.2). Based on a sequence of network connectedness matrices that can be interpreted as output network matrices resulting from the input network matrix, $\boldsymbol{W}$, and the heterogeneous coefficients, we propose a comprehensible method for the presentation of results to analyse the systemic importance of particular nodes within a network. For these practical network-oriented measures, we need only $\sqrt{T}$-consistent estimators of the individual heterogeneous parameters. A pooled or mean group estimator will net out heterogeneous signs and, therefore, fail to reveal the relative importance of individual nodes beyond what is assumed *ex ante* via the spatial weights matrix, $\boldsymbol{W}$.

Stacking first equation in (1.3.1) over $i = 1, ..., N$:

$$\boldsymbol{S}_t = \boldsymbol{P}_1\boldsymbol{W}\boldsymbol{S}_t + \mathbf{\Gamma}_{11}\boldsymbol{T}_t + \mathbf{\Gamma}_{12}\boldsymbol{K}_t + \boldsymbol{B}_1\boldsymbol{sim}_t + \boldsymbol{e}_{1t}, \quad \text{with } \boldsymbol{e}_{1t} = \boldsymbol{\alpha}_1 + \mathbf{\Lambda}_1\boldsymbol{f}_{1t} + \boldsymbol{u}_{1t}, \tag{1.3.9}$$

where $\boldsymbol{S}_t = (S_{1t}, ..., S_{Nt})'$, $\boldsymbol{T}_t = (T_{1t}, ..., T_{Nt})'$, $\boldsymbol{K}_t = (K_{1t}, ..., K_{Nt})'$, $\boldsymbol{sim}_t = (sim_{1t}, ..., sim_{Nt})'$, $\boldsymbol{f}_{1t} = (f_{11t}, ..., f_{1rt})'$, $\boldsymbol{\alpha}_1 = (\alpha_{11}, \ldots, \alpha_{1N})'$, and $\boldsymbol{\Lambda}_1 = (\boldsymbol{\lambda}_{11}, ..., \boldsymbol{\lambda}_{1N})'$, $\boldsymbol{P}_1 = diag(\rho_{11}, ..., \rho_{1N})$, $\boldsymbol{\Gamma}_{11} = diag(\gamma_{111}, ..., \gamma_{11N})$, $\boldsymbol{\Gamma}_{12} = diag(\gamma_{121}, ..., \gamma_{12N})$, and $\boldsymbol{B}_1 = diag(\beta_{11}, ..., \beta_{1N})$ are diagonal matrices consisting of the heterogeneous parameters.

Our main interest is to understand the effects of $\boldsymbol{T}_t$ and $\boldsymbol{K}_t$ on $\boldsymbol{S}_t$. To measure the direct and indirect effects, we consider the following transformation of (1.3.9):

$$\boldsymbol{S}_t = (\boldsymbol{I}_N - \boldsymbol{P}_1\mathbf{W})^{-1}(\boldsymbol{\Gamma}_{11}\boldsymbol{T}_t + \boldsymbol{\Gamma}_{12}\boldsymbol{K}_t + \boldsymbol{B}_1\boldsymbol{sim}_t + \boldsymbol{e}_{1t}), \tag{1.3.10}$$

where $(\boldsymbol{I}_N - \boldsymbol{P}_1\mathbf{W})^{-1}$ is a spatial multiplier that explains the interdependencies among different country pairs. Denote $\boldsymbol{\psi}_1 = (\boldsymbol{I}_N - \boldsymbol{P}_1\boldsymbol{W})^{-1}\boldsymbol{\Gamma}_{11}$ and $\boldsymbol{\psi}_2 = (\boldsymbol{I}_N - \boldsymbol{P}_1\boldsymbol{W})^{-1}\boldsymbol{\Gamma}_{12}$. Then, $\boldsymbol{\psi}_1$ accounts for both the immediate impact of a change in $\boldsymbol{T}_t$ of a given country pair and the impacts of changes in $\boldsymbol{T}_t$ in neighbouring country pairs on the $\boldsymbol{S}_t$ of the country pair, and $\boldsymbol{\psi}_2$ represents the direct and indirect effects of $\boldsymbol{K}_t$ on $\boldsymbol{S}_t$.

We compute the heterogeneous direct, spill-in and spill-out effects of $\boldsymbol{T}_t$ ($\boldsymbol{K}_t$) for the i-th country pair as follows:

- Heterogeneous direct effect (HDE): the direct effect of trade (finance) intensities on BCS is given by the i-th diagonal element of $\boldsymbol{\psi}_1$ ($\boldsymbol{\psi}_2$).

- Heterogeneous spill-in effect (HSI): the sum of the effects of trade (finance) intensities from all the other country-pairs on BCS of the i-th country pair is given by the i-th row-sum minus the i-th diagonal element of $\boldsymbol{\psi}_1$ ($\boldsymbol{\psi}_2$).

- Heterogeneous spill-out effect (HSO): the sum of the effects of trade (finance) intensities from the i-th country pair on BCS of all the other country-pairs is given by the i-th column-sum minus the i-th diagonal element of $\boldsymbol{\psi}_1$ ($\boldsymbol{\psi}_2$).

To avoid the curse of dimensionality or processing constraints, we follow the GCM approach by Greenwood-Nimmo et al. (2021) and consider an intermediate level of aggregation (i.e., by groups). Suppose there are R groups, each with N_k, $1 \leq k \leq R$, number of country pairs, with $N_1 + \ldots + N_R = N$. We analyse the bilateral linkages among these R groups. To this end, we first write $\boldsymbol{\psi}_1$ as the following $N \times N$ connectedness matrix:

$$\underset{(N\times N)}{\boldsymbol{\psi}_1} = \begin{bmatrix} \psi_{1\leftarrow 1} & \cdots & \psi_{1\leftarrow N_1} & \psi_{1\leftarrow N_1+1} & \cdots & \psi_{1\leftarrow N_1+N_2} & \cdots & \psi_{1\leftarrow N} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \psi_{N_1\leftarrow 1} & \cdots & \psi_{N_1\leftarrow N_1} & \psi_{N_1\leftarrow N_1+1} & \cdots & \psi_{N_1\leftarrow N_1+N_2} & \cdots & \psi_{N_1\leftarrow N} \\ \psi_{N_1+1\leftarrow 1} & \cdots & \psi_{N_1+1\leftarrow N_1} & \psi_{N_1+1\leftarrow N_1+1} & \cdots & \psi_{N_1+1\leftarrow N_1+N_2} & \cdots & \psi_{N_1+1\leftarrow N} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \psi_{N_1+N_2\leftarrow 1} & \cdots & \psi_{N_1+N_2\leftarrow N_1} & \psi_{N_1+N_2\leftarrow N_1+1} & \cdots & \psi_{N_1+N_2\leftarrow N_1+N_2} & \cdots & \psi_{N_1+N_2\leftarrow N} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \psi_{N\leftarrow 1} & \cdots & \psi_{N\leftarrow N_1} & \psi_{N\leftarrow N_1+1} & \cdots & \psi_{N\leftarrow N_1+N_2} & \cdots & \psi_{N\leftarrow N} \end{bmatrix}. \tag{1.3.11}$$

Consider the (k, l)-th block, $\mathbf{B}_{k\leftarrow l}$, $k, l = 1, ..., R$, given by

$$\underset{(N_k\times N_l)}{\mathbf{B}_{k\leftarrow l}} = \begin{bmatrix} \psi_{\tilde{N}_k+1\leftarrow \tilde{N}_l+1} & \cdots & \psi_{\tilde{N}_k+1\leftarrow \tilde{N}_l+N_l} \\ \vdots & \ddots & \vdots \\ \psi_{\tilde{N}_k+N_k\leftarrow \tilde{N}_l+1} & \cdots & \psi_{\tilde{N}_k+N_k\leftarrow \tilde{N}_l+N_l}, \end{bmatrix}, \tag{1.3.12}$$

where $\tilde{N}_k = \sum_{j=1}^{k-1} N_j$ for $k = 2, ..., R$, and $\tilde{N}_1 = 0$. We then normalise the sum of the elements of $\mathbf{B}_{k\leftarrow l}$ by the average number of country pairs in the k-th and l-th groups:

$$\phi_{k\leftarrow l} = \frac{1}{0.5(N_k + N_l)} \boldsymbol{\iota}'_{N_k} \mathbf{B}_{k\leftarrow l} \boldsymbol{\iota}_{N_l}, \tag{1.3.13}$$

where $\boldsymbol{\iota}_{N_k}$ is an $N_k \times 1$ column vector of ones. Then, we can construct the following $R \times R$ connectedness matrix at the group level:

$$\underset{(R\times R)}{\mathbf{C}_R} = \begin{bmatrix} \phi_{1\leftarrow 1} & \phi_{1\leftarrow 2} & \cdots & \phi_{1\leftarrow R} \\ \phi_{2\leftarrow 1} & \phi_{2\leftarrow 2} & \cdots & \phi_{2\leftarrow R} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{R\leftarrow 1} & \phi_{R\leftarrow 2} & \cdots & \phi_{R\leftarrow R} \end{bmatrix}. \tag{1.3.14}$$

Using (1.3.14), we construct the direct, spill-in and spill-out effects at the group level as[6]

$$GDE_i = \phi_{i \leftarrow i}; \quad GSI_i = \sum_{j=1, j \neq i}^{R} \phi_{i \leftarrow j}; \quad GSO_i = \sum_{j=1, j \neq i}^{R} \phi_{j \leftarrow i}. \tag{1.3.15}$$

1.4 Empirical Application

1.4.1 The data

We collect the data measuring output growth synchronisation, bilateral trade and financial intensities for 17 OECD countries.[7] In total there are 136 non-overlapping country pairs over the period from 1995Q1 to 2019Q4. For the dependent variable BCS (denoted S), we employ a widely used measurement, which is 100 times the negative of the absolute difference of GDP growth between two countries (Imbs 2004, Kalemli-Ozcan, Papaioannou & Peydro 2013). With this measurement of BCS, the values of S are negative, and an increase in S reflects a higher level of BCS between two economies with $S = 0$ indicating a perfect co-movement. Given that economic activities may respond to global and country-specific shocks differently, we follow Cesa-Bianchi et al. (2019) and construct the systematic component of BCS that are proxied by common factor components (denoted S^F), obtained from $S = S^F + S^\varepsilon$, where S^ε is the idiosyncratic component.[8] Bilateral trade intensity (denoted T) is measured by the product of the total trade between two countries and global GDP relative to the product of the two countries' GDP. Financial integration (denoted K) is similarly measured by the intensity of bilateral banking activities. See Appendix A.1 for detailed variable construction.

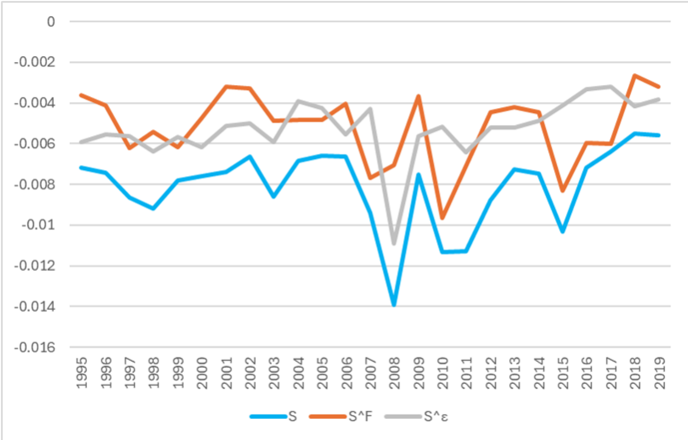
Figure 1.1 displays the evolution of the BCS components over the sampling period, suggesting that growth co-movement in developed countries is more associated with its systematic component than its idiosyncratic component, in line with Cesa-Bianchi et al. (2019).

[6] The R code of CCEX-2SLS estimation and network analysis is accessible via the shared link `https://drive.google.com/drive/folders/1Ooy2WqZ261f-EmCCIOCsSb438OKENrrv?usp=sharing`.

[7] The sample countries consist of Australia, Austria, Canada, Switzerland, Germany, Spain, Finland, France, United Kingdom, Greece, Italy, Ireland, Japan, Netherlands, Portugal, Sweden and the United States. We consider only advanced economies mainly due to data availability.

[8] Cesa-Bianchi et al. (2019) decompose shocks into common and idiosyncratic parts to explain the heterogeneous effects of banking integration on business cycle co-movement. We identify three common factors within the GDP growths of 17 countries by the Bayesian information criterion (BIC) advanced by Bai & Ng (2002), see Appendix A.1 for details. The systematic component, S^F isolates the shared influences, providing a more granular understanding of the underlying mechanisms. The consistency of results between BCS and its systematic component reinforces the robustness of our findings.

Figure 1.1: Business cycle synchronisation components



Notes: This figure displays the respective cross-section averages of aggregate business cycle synchronisation and its systemic and idiosyncratic components, S, S^F and S^ε, between 1995Q1-2019Q4.

Table 1.1: Descriptive statistics of BCS and trade/finance intensities

Variable	Obs	Mean	Std.dev	Min	Max
S	13600	-0.809	0.914	-11.899	-0.0001
S^F	13600	-0.519	0.867	-11.420	-1.3e-05
T	13600	0.422	1.327	-3.569	3.863
K	13600	1.665	1.662	-4.357	6.437

Notes: we report the descriptive statistics of the quarterly data on BCS, trade intensity and financial intensity for the full 136 non-overlapping country pairs over 1995Q1–2019Q4.

Table 1.1 reports the descriptive statistics of the key variables. BCS indicators, S and S^F, have relatively small means, and comparable standard deviations. Based on the time average over 1995Q1-2019Q4, among 136 country pairs, the country-pairs with the strongest and weakest BCS are France-UK ($S = -0.4$) and Greece-Ireland ($S = -2.1$) whilst those with the strongest and weakest systematic BCS are Austria-Switzerland ($S^F = -0.03$) and Greece-Ireland ($S^F = -2.2$). Next, significant variations are observed in the bilateral trade and financial intensities. On average, the Finland-Sweden pair has the highest trade intensity ($T = 3.45$), while the Canada-Greece pair has the least trade intensity ($T = -2.29$). K displays very large fluctuations. On average the maximum financial intensity is observed for the Ireland-Netherlands pair ($K = 4.85$), while the minimum is observed for the Japan-Portugal pair ($K = -2.58$).

1.4.2 The spatial weights matrix

It is not straightforward to construct the spatial weights matrix for the $N = n(n-1)/2$ undirectional country-pairs, unlike the directional traffic flows (including self-flows) considered by LeSage & Pace

(2008), who propose the spatial filtering method given by $(\boldsymbol{I}_{n^2} - \rho_o \boldsymbol{W}_o)(\boldsymbol{I}_{n^2} - \rho_d \boldsymbol{W}_d) = (\boldsymbol{I}_{n^2} - \rho_o(\boldsymbol{W} \otimes \boldsymbol{I}_n))(\boldsymbol{I}_{n^2} - \rho_d(\boldsymbol{I}_n \otimes \boldsymbol{W})) = \boldsymbol{I}_{n^2} - \rho_o \boldsymbol{W}_o - \rho_d \boldsymbol{W}_d + \rho_w \boldsymbol{W}_w$, where $\rho_w = \rho_o \rho_d$, $\boldsymbol{W}_w = \boldsymbol{W} \otimes \boldsymbol{W}$ and $\boldsymbol{W}$ is an $n \times n$ spatial weights matrix for n countries. In the current case we cannot construct the spatial weights matrix by directly applying $\boldsymbol{W}_o$, $\boldsymbol{W}_d$ and $\boldsymbol{W}_w$, see also Cainelli et al. (2021) and Shin et al. (2025).

In Appendix A.3 we follow Shin et al. (2025), and describe a general approach to constructing the $N \times N$ spatial weights matrix among the N undirectional country-pairs, based on the $n \times n$ distance (or spatial) based weights matrix among n countries. To capture network proximity among the N country-pairs in the model (1.3.1), we propose constructing the $N \times N$ spatial weights matrix $\boldsymbol{W}_B$ based on a shared border by

$$\boldsymbol{W}_B = \begin{bmatrix} 0 & w_{B,12} & \cdots & w_{B,1N} \\ w_{B,21} & 0 & \cdots & 0_{B,2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{B,N1} & w_{B,N2} & \cdots & 0 \end{bmatrix}, \tag{1.4.16}$$

where we assign $w_{B,ij} = 1, i \neq j$, if country pair i and country pair j share a common country, meaning that these pairs become neighbours by sharing the common country, and $w_{B,ij} = 0$ otherwise. For instance, the weight corresponding to the (Italy, UK) and (UK, US) pairs is 1 while the weight for (Italy, US) and (UK, Japan) pairs is 0.[9] By applying a row-sum normalisation to $\boldsymbol{W}_B$, we construct the spatial lag term as $S_{it}^* = \sum_{j=1}^N w_{ij} S_{jt}$, where

$$w_{ij} = w_{B,ij} / \sum_{j=1}^N w_{B,ij} = \begin{cases} 1/[2(n-2)], & \text{if } i \neq j \text{ and country pairs } i \text{ and } j \text{ share a common country}, \\ 0, & \text{otherwise.} \end{cases}$$

In Appendix A.3 we show that S_{it}^* is a (sparse) average of S_{jt}'s from country pairs that share a common country with the i-th country pair.

[9]The shared country can transmit economic shocks from one country pair to the other. For example, if the Italy-UK pair experiences a positive economic shock, it can be potentially spilled over to the UK-US pair through the shared country (i.e., UK). Furthermore, we can easily adjust the weights as described in Appendix A.3. For example, if the UK's influence on its partner countries is stronger than other countries, we can assign a higher weight for the two country pairs sharing the UK as the common country.

1.4.3 The CCEX-2SLS estimation results

We investigate the impacts of trade and finance intensities on BCS by applying the CCEX-2SLS approach to the model (1.3.1), where we consider both S and S^F as a dependent variable for the first equation. In what follows, we report the estimation results based on the use of T and K as trade and financial intensities.

As a benchmark, in Table 1.2, we report the pooled estimation results for model (1.3.1) by imposing parameter homogeneity (over i).[10] The full sample results for the aggregate BCS (S) show that the spatial coefficient is positive and significant, implying that a country pair's BCS has a positive spillover from BCSs of its neighbouring country pairs. The impacts of trade intensity and financial intensity on BCS are negative and significant. Tuning to the results for the systematic component of BCS proxied by S^F, we find significant positive spillover effect. Furthermore, trade intensity influences S^F positively while the financial intensity exerts a negative impact on S^F, and both coefficients are larger in magnitude than their counterparts for S. Although the CCEX-2SLS pooled estimation results for S^F are mostly consistent with the existing studies (e.g., Liao & Santacreu (2015)), the negative impact of trade intensity on aggregate BCS is rather surprising. However, the pooled estimation results are likely to obscure important individual-specific information in the presence of parameter heterogeneity.[11] Furthermore, the pooled estimator is likely to be sensitive to outlying individual estimation results as reported in Tables 1.3 and 1.4 below. In this regard, we re-estimate the pooled model for the stable sample that excludes seven outlying country pairs. The results presented in Panel B of Table 1.2 look more reasonable, showing positive impact of trade intensity and negative impact of financial intensity on BCS, which are more or less consistent with existing studies, e.g., Kalemli-Ozcan, Papaioannou & Peydro (2013).

[10] We apply the CD test by Pesaran (2015) to the residuals obtained from the panel data regression without controlling for spatial and factor dependence. The CD statistics are 125.6 for S and 156.9 for S^F, both of which are well above the 5% critical value, providing strong evidence of cross-section dependence.

[11] The pooled estimator is shown to be inconsistent in the presence of spatial parameter heterogeneity (Chen et al. 2022).

Table 1.2: The pooled CCEX-2SLS estimation results

Covariate coefficients \ Dependent variables	S	S^F	S	S^F
	Panel A: full samples		Panel B: stable sample	
$\hat{\rho}_1$	0.091***	0.122***	0.064***	0.069***
	(0.002)	(0.005)	(0.002)	(0.003)
$\hat{\gamma}_{11}$	-0.380***	0.526***	0.199*	0.394***
	(0.027)	(0.068)	(0.118)	(0.112)
$\hat{\gamma}_{12}$	-0.058*	-0.343***	-0.473***	-0.457***
	(0.030)	(0.045)	(0.126)	(0.127)
$\hat{\beta}_1$	0.536***	-0.135***	-0.155	-0.689***
	(0.041)	(0.056)	(0.156)	(0.149)

Notes: In Panel A we report the pooled estimation results for model (1.3.1) using the quarterly data for the full 136 non-overlapping country pairs over 1995Q1–2019Q4. Panel B presents the results for the subsample of country pairs that excludes seven outlying pairs. Standard errors are in parentheses. ***, ** and * indicate the significance of the coefficient at the 1%, 5% and 10% levels, respectively.

To examine the heterogeneous spatial dependence in BCS and the heterogeneous impacts of trade and financial intensities on BCS, we apply the CCEX-2SLS individual estimator to model (1.3.1), and present the individual and mean group (MG) estimation results for the full sample and the stable sample (that excludes seven outlying results via winsorising below) in Panels A and B of Table 1.3, respectively. From the results for S in Panel A, we find that the spatial coefficients ($\hat{\rho}_{1i}$) are mostly positive (75.7%) and significant (83.8%), though its MG estimate is small (0.037) and insignificant. The impacts of trade intensity ($\hat{\gamma}_{11i}$) are mostly significant (80.9%) and positive (55.2%), although its MG estimate is surprisingly negative (-0.53). The financial intensity coefficients ($\hat{\gamma}_{12i}$) are mostly significant (78.4%) and slightly more positive (52.2%), while its MG estimate is slightly positive (0.11) and insignificant. Turning to the results for the systematic component of BCS (S^F), we have more positive coefficients for the spatial spillovers and trade intensities (83.8% and 55.9%), although their MG estimates are small (0.031 and 0.13) and insignificant. The proportion of the financial intensity effects being positive or negative is equal, while its MG coefficient is slightly negative (-0.013) and insignificant.

In Table 1.4 we present the descriptive statistics of the individual spatial spillover, trade- and financial-intensity coefficients. They exhibit substantial heterogeneity across country pairs while the results for S display a higher volatility. From the kernel density estimates displayed in the top panel of Figures 1.2 and 1.3, we observe that there are a small number of extreme values. To mitigate this issue, we apply the winsorising to $\hat{\gamma}_{11i}$ and $\hat{\gamma}_{12i}$ at the 5% level, and identify seven outlying country pairs for the regression equation of S.[12]

[12]The spatial stationarity condition is satisfied for all country pairs. The outlying country pairs identified are Finland-UK ($\hat{\gamma}_{11i} = -28.7$), Finland-Ireland ($\hat{\gamma}_{11i} = -19.4$), France-UK ($\hat{\gamma}_{11i} = -15.8$), Australia-Canada ($\hat{\gamma}_{11i} = -13.3$ and $\hat{\gamma}_{12i} = 9.6$), Australia-Japan ($\hat{\gamma}_{11i} = -11.8$), Switzerland-France ($\hat{\gamma}_{11i} = 10.43$) and Ireland-Italy ($\hat{\gamma}_{12i} = -9.5$). Similarly, there are seven outlying country pairs for the regression of S^F, such as Ireland-Netherlands ($\hat{\gamma}_{11i} =$

By eliminating these outlying pairs, we re-estimate the model for the stable sample with 129 country pairs and report the results in Panel B of Table 1.3. For the stable sample, the spatial coefficients are mostly positive (76.7%) and significant (83.7%) for S while the percentages of positive and significant coefficients are 85.3% and 72.9% for S^F. Similar to their full-sample counterparts, their MG estimates are small (0.037 and 0.032) and insignificant. The descriptive statistics show that spatial effects on S lie between -0.74 and 0.63, while they become less spread-out (between -0.62 and 0.21) for S^F (see in Panel B of Table 1.4). Secondly, the trade-BCS relationship is more compactly distributed than its full-sample counterpart. Panel B of Table 1.3 shows that more than half of the individual trade-BCS coefficients are positive for S (57.4%) and S^F (55.8%) with positive but insignificant MG estimates. The impact of financial intensity has a slight higher proportion of positives for S (52.7%), while it has an equal proportion of positives and negatives for S^F. The corresponding MG estimate is slightly positive (0.088) for S but negative (-0.013) for S^F.

The individual estimation results clearly indicate the importance of explicitly taking heterogeneity into account in the analysis of BCS. Moreover, in many applications, there are no economic theories to indicate that coefficients of a model should share a common sign.[13] We document the evidence that the proportion of positive and negative effects of trade- and financial-intensities on BCS are more or less similar. More importantly, their MG estimates become small and insignificant, although the MG estimates are also profoundly affected by outlying observations.[14] A pooled or mean-group estimator subject to such netting off has the potential to produce a misleading global picture and fail to reveal the relative importance of individual nodes beyond that pre-supposed by the spatial weights matrix, $\boldsymbol{W}$. This could provide some explanations behind the mixed findings reported in the existing studies, indicating that they conceal essential heterogeneous information. Furthermore, in the current model, the coefficients of trade and financial intensities, γ_{11} and γ_{12}, cannot be interpreted as marginal effects owing to the presence of the spatial dependence. In this regard, we will conduct a diffusion network analysis to investigate the direct effects from the trade and financial channels and the indirect effects from neighbouring country pairs' trade and finan-

12.8), UK-Sweden ($\hat{\gamma}_{11i} = 7.5$), Austria-Greece ($\hat{\gamma}_{11i} = 6.5$ and $\hat{\gamma}_{12i} = 7.6$), Finland-Ireland ($\hat{\gamma}_{11i} = -11.7$), Australia-US ($\hat{\gamma}_{11i} = -10.6$), Ireland-Italy ($\hat{\gamma}_{12i} = -6.2$) and Spain-France ($\hat{\gamma}_{12i} = -3.30$).

[13] Masten (2018) considers a random coefficients generalisation of the widely used social interactions models, the linear-in-means model and the linear-in-means network model that incorporates observed network data, and derives sufficient conditions for point identification of the distribution of the endogenous social interaction parameter. Importantly, these models do not require all individuals to be positively or negatively affected by their peers. Furthermore, some individuals may be strongly affected by their peers while others are only moderately affected. By applying a nonparametric kernel-based estimator to analyse peer effects in educational achievements using the Add Health dataset, he documents evidence of significant heterogeneity.

[14] We have already shown that both pooled and MG estimation can produce surprisingly negative results of trade intensity on BCS, mainly due to the large negative outlying effects, e.g., -28.7 for the Finland-UK pair. By eliminating these outliers, both pooled and MG estimates show a positive trade intensity effect on both S and S^F (see Tables 1.2 and 1.3).

cial linkages, respectively. Our approach contrasts with the pooled or mean-group versions of the estimator, which has been routinely proposed in the literature.

Table 1.3: Individual and MG CCEX-2SLS estimation results

Panel A: full sample							
Variables		Sample size	Positive%	Significant%	Significantly positive%	Significantly negative%	MG
S	$\hat{\rho}_{1i}$	136	75.74	83.82	67.65	16.18	0.037 (0.128)
	$\hat{\gamma}_{11i}$	136	55.15	80.88	42.65	38.24	-0.528 (4.310)
	$\hat{\gamma}_{12i}$	136	52.21	78.68	40.44	38.24	0.114 (1.862)
	$\hat{\beta}_{1i}$	136	52.94	82.35	39.71	42.65	-1.421 (41.008)
S^F	$\hat{\rho}_{1i}$	136	83.82	74.26	66.91	7.35	0.031 (0.090)
	$\hat{\gamma}_{11i}$	136	55.88	62.5	36.03	26.47	0.125 (2.142)
	$\hat{\gamma}_{12i}$	136	50	68.38	39.71	28.68	-0.013 (1.108)
	$\hat{\beta}_{1i}$	136	38.97	62.5	24.26	38.24	-1.133 (17.568)
Panel B: stable sample							
Variables		Sample size	Positive%	Significant%	Significantly positive%	Significantly negative%	MG
S	$\hat{\rho}_{1i}$	129	76.74	83.72	68.22	15.50	0.037 (0.119)
	$\hat{\gamma}_{11i}$	129	57.36	79.84	44.19	35.66	0.103 (2.238)
	$\hat{\gamma}_{12i}$	129	52.71	77.52	40.31	37.21	0.088 (1.332)
	$\hat{\beta}_{1i}$	129	53.49	81.40	39.53	41.86	-1.043 (39.676)
S^F	$\hat{\rho}_{1i}$	129	85.27	72.87	67.44	5.43	0.032 (0.072)
	$\hat{\gamma}_{11i}$	129	55.81	60.47	34.88	25.58	0.103 (0.841)
	$\hat{\gamma}_{12i}$	129	50.39	66.67	39.53	27.13	-0.013 (0.506)
	$\hat{\beta}_{1i}$	129	40.31	61.24	24.81	36.43	0.278 (11.498)

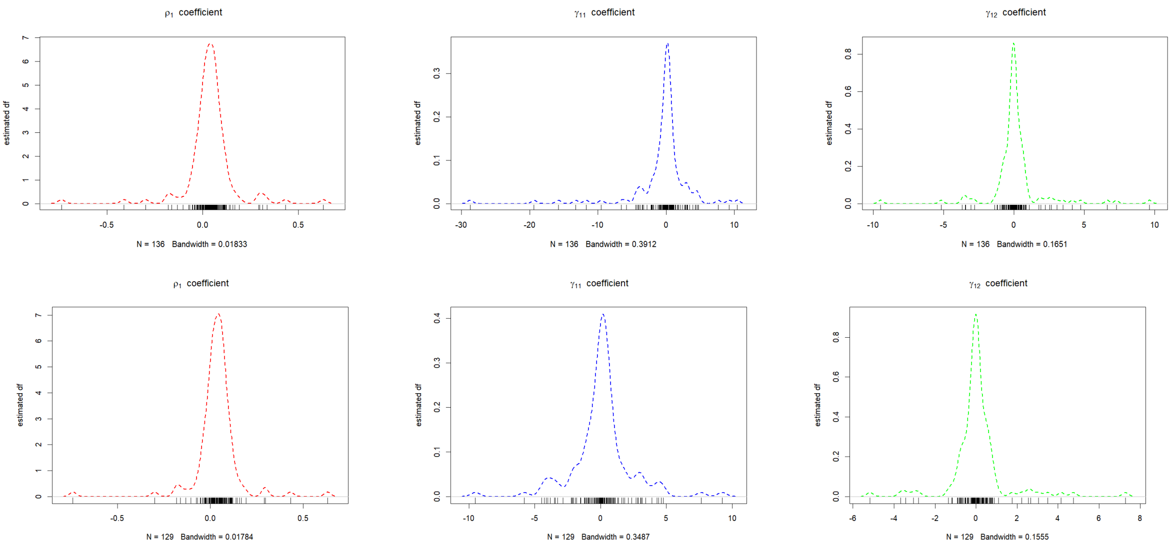
Notes: The column labelled 'Sample Size' shows the number of country pairs used in the estimation. The 'Positive%' column exhibits the percentage of positive coefficients. The 'Significantly%' column reports the percentage of significant coefficients at a 95% confidence level. The columns 'Significantly positive%' and 'Significantly negative%' give the percentages of coefficients that are significantly positive and negative. The 'MG' column shows the mean group estimates with standard errors in parentheses. See also footnotes to Table 1.2.

Table 1.4: Descriptive statistics for individual CCEX-2SLS estimates

	Panel A: full sample			Panel B: stable sample		
S	$\hat{\rho}_{1i}$	$\hat{\gamma}_{11i}$	$\hat{\gamma}_{12i}$	$\hat{\rho}_{1i}$	$\hat{\gamma}_{11i}$	$\hat{\gamma}_{12i}$
Min.	-0.739	-28.748	-9.480	-0.739	-9.519	-5.165
Max.	0.631	10.434	9.632	0.631	9.234	7.281
Median	0.038	0.079	0.024	0.039	0.115	0.027
Mean	0.037	-0.528	0.114	0.037	0.103	0.088
SD	0.128	4.326	1.869	0.120	2.247	1.338
S^F	$\hat{\rho}_{1i}$	$\hat{\gamma}_{11i}$	$\hat{\gamma}_{12i}$	$\hat{\rho}_{1i}$	$\hat{\gamma}_{11i}$	$\hat{\gamma}_{12i}$
Min.	-0.616	-11.719	-6.178	-0.616	-2.301	-2.422
Max.	0.278	12.788	7.597	0.208	3.859	2.347
Median	0.033	0.040	0.006	0.033	0.032	0.012
Mean	0.031	0.125	-0.013	0.032	0.103	-0.013
SD	0.090	2.150	1.112	0.073	0.844	0.508

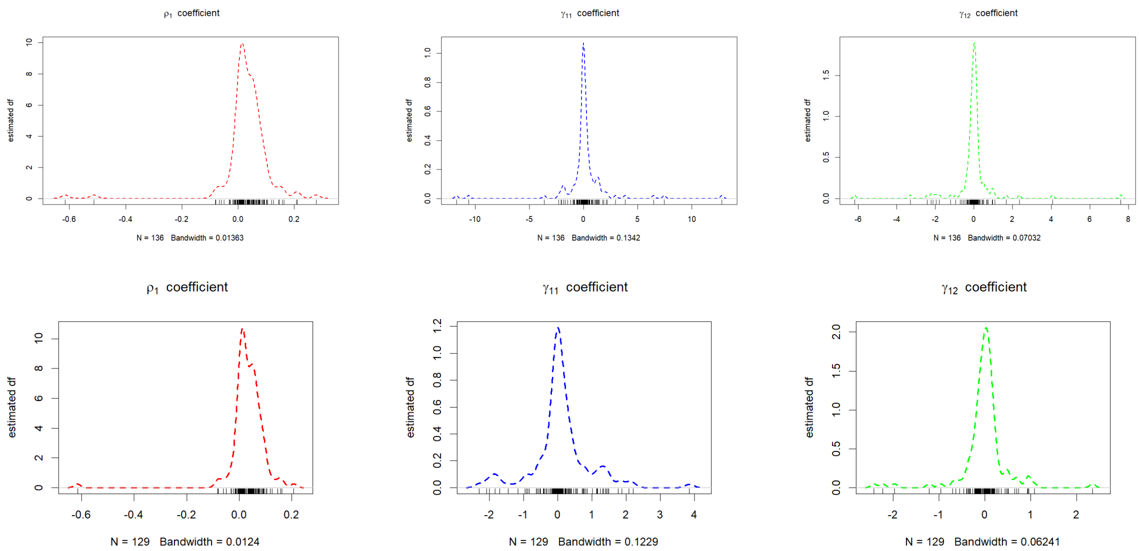
Notes: See also footnotes to Table 1.2.

Figure 1.2: Kernel densities of individual CCEX-2SLS estimates for S



The top (bottom) panel displays the results for the full (stable) sample. See Table 1.2 footnotes.

Figure 1.3: Kernel densities of individual CCEX-2SLS estimates for S^F



The top (bottom) panel displays the results for the full (stable) sample. See Table 1.2 footnotes.

1.4.4 Network multipliers of trade/finance intensities on BCS

We focus on the results for S in the stable sample that excludes 7 outlying country pairs. Table 1.5 displays the descriptive statistics for HDE, HSI and HSO that are derived from the highly heterogeneous CCEX-2SLS estimation results for the model (1.3.1). HDEs of trade intensity are more positive (57.36%), and their average is positive at 0.13, suggesting that increased trade intensity between two countries directly leads to more synchronous business cycles. The average of both HSIs and HSOs of trade intensity is negative (-0.21). HSO exhibits a higher volatility (6.1) than HSI (1.69) (see similar findings in Diebold & Yılmaz (2014)).

Meanwhile, the network multipliers of financial intensity ψ_2 exhibit a slightly more positive direct effect on BCS (51.2% positive with a mean of 0.04), suggesting that financial intensity within a country pair exerts slightly favourable effects on the local business cycle synchronicity. On the contrary, financial intensity in neighbouring countries has an adverse spillover on BCS with means of HSIs and HSOs being -0.06, suggesting that increased financial intensity in neighbouring country pairs may inhibit BCS.

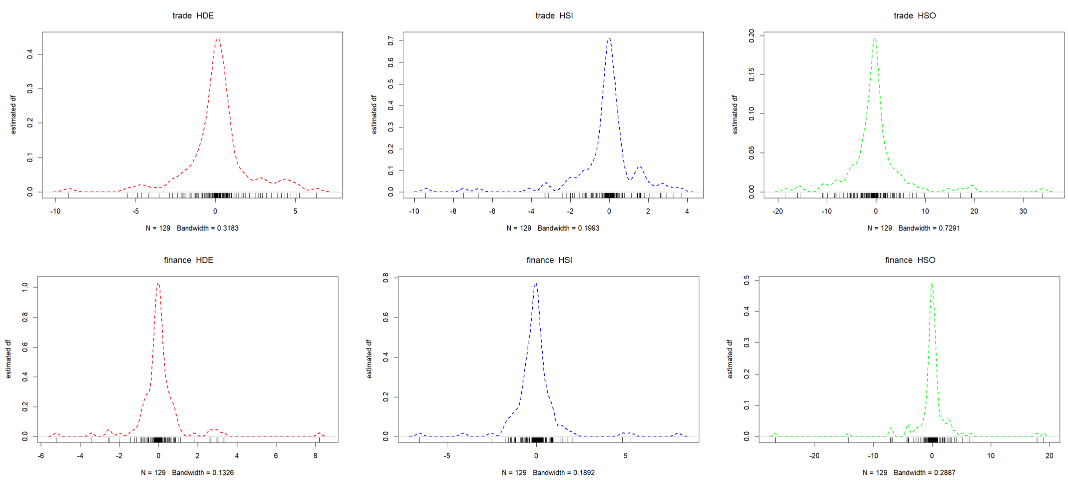
Table 1.5: Descriptive statistics for network multipliers of trade/finance intensities on S

	ψ_1			ψ_2		
	HDE	HSI	HSO	HDE	HSI	HSO
Min.	-9.199	-9.409	-18.411	-5.222	-6.551	-26.764
Max.	6.315	3.660	33.918	8.199	7.910	19.018
Median	0.117	-0.033	-0.241	0.019	-0.072	-0.011
Mean	0.126	-0.210	-0.210	0.042	-0.063	-0.063
SD	2.033	1.689	6.101	1.231	1.358	4.011
$\% > 0$	57.36	45.74	40.31	51.16	43.41	49.61

ψ_1 (ψ_2) represents the network multipliers of trade (finance) intensity on BCS, S while HDE, HSI and HSO refer to heterogeneous direct, spill-in and spill-out effects, respectively, as described in Section 3.2. See also footnotes to Table 1.2.

The kernel density estimates for HDE, HSI and HSO are displayed in Figure 1.4, which shows almost symmetric distributions centred around zero, with heavy tails. This clearly suggests the use of the heterogeneous coefficients models instead of a restrictive homogeneous model.

Figure 1.4: Kernel densities of trade & finance HDE, HSI and HSO on S



The top (bottom) panel displays the results for trade (financial) intensity. See Table 1.2 footnotes.

We turn to addressing the important issue of which country-pairs contribute to boosting or inhibiting BCS through trade/financial intensities, using the two network measures, HDE and HSO, and assigning country pairs to one of the following four categories: (i) they boost BCS directly through HDE and indirectly through HSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly. Figure 1.5 shows the scatter plots of HSO vs. HDE for trade and finance intensities based on the network multipliers for the 129 country-pairs in the stable sample. Following the existing studies which usually report a positive (negative) effect of trade (finance) intensity on BCS based on homogeneous models and pooled estimates, we may expect that more country-pairs belong to category (i) for trade intensity and to category (iv) for finance intensity. However, we observe quite different patterns: 3.9%, 53.5%, 36.4% and 6.2% of the sample belong to categories (i)-(iv) for trade intensity while 5.4%, 45.7%, 44.2% and 4.7% belong to categories (i)-(iv) for finance intensity.

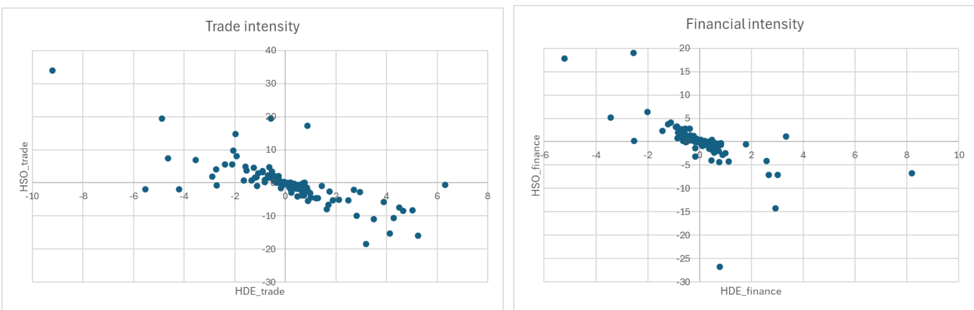
Bilateral trade can amplify structural imbalances when two economies have significantly diversified trade patterns (Gräbner & Hafele 2020). Duval et al. (2014) suggest that both trade intensity and type of trades matter as an essential propagation mechanism. Thus, the direct and indirect effects of trade intensity depend on the nature of trade and the spatial spillovers from the neighbouring country pairs, resulting in positive or negative outcomes on BCS. On one hand, different economies become more interconnected when they engage in intra-industry trade (Fidrmuc 2004), and are likely to experience similar global market scenarios, directly boosting BCS through trade integration. However, the increase in intra-industry trade may shift commerce away from their neighbouring partners. Hence, negative spatial spillovers may be present when more trade between two countries comes at the cost of a decline in trade with the neighbouring countries. On the other hand, when different countries engage in inter-industry trade (still a sizable share in the EU market), the increased specialisation amplifies economic divergence through inefficient shock transmission. Although economies with more asymmetric structures of production tend to directly inhibit BCS (Calderon et al. 2007), neighbouring countries can still benefit from the economic diversification due to trade specialisation and positive spillovers through enhanced trade opportunities and investment/technological improvement (Ponnusamy 2022), boosting BCS indirectly.

For financial intensity, its effects on BCS are ambiguous and mixed in the literature.[15] We find that most country-pairs belong to categories (ii) and (iii) with opposite signs of direct and indirect effects on BCS through the financial channel. According to Davis (2014), enhanced financial

[15]Balance sheet and wealth effects provide two core mechanisms to explain the impact of financial integration on BCS. Financial intensity can generally boost BCS through balance sheet effects whilst its impact through wealth effects are inconclusive. Kalemli-Ozcan et al. (2003) and Imbs (2006) document that financially integrated economies with higher asset price correlations have higher BCS. On the contrary, Davis (2014) suggests that enhanced financial linkages lead to misalignment of business cycles through wealth effects. Furthermore, the literature doesn't clarify how balance sheet and wealth effects work in terms of the direct and indirect effects, respectively.

linkages lead to the alignment of business cycles through balance sheet effects (due to easy access to credit) and risk sharing, whilst they also lead to misalignment of business cycles through wealth effects due to volatile asset prices. Nonetheless, the interaction with neighbouring countries involves indirect spatial spillovers whose nature is determined by the financial stability and policy resilience of neighbouring partners. From the perspective of balance sheet effects, intensive cross-border financial transactions enhance regional financial integration and risk mitigation, boosting BCS (Lane & Milesi-Ferretti 2008).[16] At the same time, negative indirect impacts of financial intensity may spill out to neighbouring country pairs. Capital reallocation is closely related to the level of financial integration, which may cause financial instability and divergence in economic activities (Claessens et al. 2012). With respect to wealth effects, higher financial intensity introduces larger volatilities in asset prices, driving economic activities in different countries out of sync.[17] However, positive indirect effects can occur when financial linkages can reduce risk and enhance financial stability in neighbouring countries, synchronising the business cycles (Dees et al. 2007).

Figure 1.5: Scatter plots of HSO vs. HDE for trade and finance intensities on S



Notes: This figure displays the scatter plots of HSO against HDE for 129 country-pairs in the stable sample. Each country pair is assigned to one of the following four categories: (i) they boost BCS directly through HDE and indirectly through HSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly.

Next, we conduct GCM analysis of the network multipliers of bilateral trade and financial intensities on BCS among country pairs from 3 selected groups, as described in Section 3.2. We divide the 17 countries in the sample into the 3 groups of EU core (EC), EU periphery (EP) and

[16] The integration of EU financial market allows member countries to easily obtain credit and invest in new projects. Even during the European debt crisis, firms in vulnerable states like Spain can receive funding from banks in other members like Germany to mitigate domestic financial constraints, resulting in increased BCS.

[17] The bursting of 2008 housing bubble led to sharp declines in asset prices and shrinkage in consumption in Spain and Ireland, inducing misaligned business cycles with other countries with stable household wealth like Germany.

non-EU (NEU) countries.[18] Based on this country grouping, we allocate the 136 country pairs into 6 clusters: EC-EC, EC-EP, EC-NEU, EP-EP, EP-NEU, and NEU-NEU. This analysis enables us to examine the role of each cluster in the diffusion of trade/capital intensities. Table 1.6 reports the direct, spill-in and spill-out effects of trade/financial intensities on BCS for the six clusters.

For trade intensity, the direct effects are positive for EC-EC, EC-NEU and EP-NEU but negative for EC-EP, EP-EP and NEU-NEU. Summing over the 6 clusters, we find that the aggregate direct effect is positive (0.283), although it is smaller than the aggregate indirect spillover effect (-0.789). Hence, an aggregate total effect is negative (-0.506). Turning to the total effect of the trade intensity on BCS in each cluster, measured by the sum of GDE and GSI, we find that it is negative for EC-EC, EC-NEU, EP-EP and NEU-NEU. For EC-EC and EC-NEU, negative spill-ins (mainly from clusters associated with EP country-pairs) dominate positive direct effects, whereas negative direct effect prevails for the EP-EP and NEU-NEU clusters. Furthermore, substantial positive (negative) spill-outs are observed in EC-EC and NEU-NEU (EC-EP and EP-NEU) clusters. This implies that the advanced country-pairs are influential transmitters of trade intensity for cycle alignment, while clusters associated with less developed country-pairs tend to transmit adverse shocks which inhibit BCS.

For financial intensity, the direct effects are positive for EC-NEU, EP-EP and NEU-NEU, negative for EC-EC, and negligible for EC-EP and EP-NEU. The aggregate direct effect is positive (1.0) and larger than the aggregate indirect spillover effect (-0.465), indicating that the aggregate total effect is positive (0.539). The total effect of the financial intensity on BCS in each cluster is substantially (slightly) negative for EC-NEU and EP-NEU (EC-EC) clusters. For EC-NEU and EP-NEU clusters negative spill-ins (mainly from clusters associated with EU country-pairs) dominate, whereas negative direct effect prevails for the EC-EC cluster. Furthermore, substantial positive (negative) spill-outs are observed in EC-NEU and NEU-NEU (EC-EC and EP-EP) clusters. This implies that advanced country-pairs are likely to spread out positive financial shocks to boost BCS, although financial intensity tends to inhibit BCS for intra-EU clusters.

[18] Austria, Germany, Finland, France, the Netherlands, Sweden and the UK are core EU countries, while Spain, Greece, Ireland, Italy and Portugal are periphery countries. Further support for this classification can be found in Appendix A.2. Australia, Canada, Switzerland, Japan and the US are non-EU countries.

Table 1.6: Group direct, spill-in, spill-out effects across the six clusters for S

Group Connectedness Matrix - Trade Intensity						
	EC-EC	EC-EP	EC-NEU	EP-EP	EP-NEU	NEU-NEU
EC-EC	0.322	-0.262	0.164	-0.499	-0.882	0.849
EC-EP	0.078	-0.159	-0.115	0.474	-0.035	0.210
EC-NEU	0.534	-0.578	0.368	-0.337	-0.521	0.340
EP-EP	0.283	-0.239	0.169	-0.735	-0.230	0.333
EP-NEU	-0.174	-0.035	-0.303	0.313	1.022	-0.376
NEU-NEU	0.044	0.018	0.115	-0.020	-0.106	-0.535
GDE	0.322	-0.159	0.368	-0.735	1.022	-0.535
GSI	-0.632	0.613	-0.562	0.316	-0.576	0.052
GSO	0.765	-1.097	0.030	-0.069	-1.774	1.356
GTE	-0.31	0.454	-0.194	-0.419	0.446	-0.483
GNE	1.397	-1.710	0.592	-0.385	-1.199	1.304
Group Connectedness Matrix - Financial Intensity						
	EC-EC	EC-EP	EC-NEU	EP-EP	EP-NEU	NEU-NEU
EC-EC	-0.197	-0.023	0.144	-0.179	-0.095	0.299
EC-EP	-0.242	-0.001	0.076	0.413	0.154	0.139
EC-NEU	-0.581	-0.039	0.099	-0.208	-0.176	0.146
EP-EP	-0.299	0.007	0.090	0.960	0.062	0.125
EP-NEU	0.109	-0.001	0.085	-0.395	-0.029	-0.214
NEU-NEU	-0.025	0.024	0.001	0.063	0.077	0.172
GDE	-0.197	-0.001	0.099	0.960	-0.029	0.172
GSI	0.145	0.540	-0.859	-0.015	-0.416	0.140
GSO	-1.039	-0.033	0.396	-0.307	0.021	0.496
GTE	-0.052	0.539	-0.76	0.945	-0.445	0.312
GNE	-1.184	-0.573	1.255	-0.292	0.438	0.356

We divide 17 countries into 3 groups of EU core (EC), EU periphery (EP) and non-EU (NEU), and construct 6 clusters, EC-EC, EC-EP, EC-NEU, EP-EP, EP-NEU and NEU-NEU. GDE, GSI and GSO refer to group direct, spill-in and spill-out effects, respectively. GTE is the group total effect, measured by the sum of GDE and GSI. GNE is the group net effect, measured by the difference between GSO and GSI.

We now discuss the GCM analysis of the network GDE and GSO multipliers of trade and finance intensities on BCS across the six clusters displayed in Figure 1.6. The EC-EC cluster stands out as a (direct and indirect) BCS booster through trade intensity, mainly due to strong intra-regional trades and similar economic structures. Due to the adoption of the euro and coordinated trade agreements, EU core countries benefit from elimination of exchange rate risk, trade liberalisation and economic stability. All these help to boost BCS. On the contrary, the EC-EP cluster becomes a (direct and indirect) BCS inhibitor through trade intensity. Core and periphery countries engage more in inter-industry trade, leading to divergent industry composition and asymmetric exposure to trade shocks (Azcona 2022). The early liberalisation policies intended to guarantee competition interrupted the industrialisation processes in periphery countries (Simonazzi et al. 2013). These collectively contribute to a more favourable position for core countries, leading to reduced BCS. In addition, owing to trade diversion, higher trade intensity in neighbouring country-pairs may drive the business cycles out of sync.[19] The EC-NEU cluster becomes a direct BCS booster (with

[19] Core economies tend to exchange goods and services with neighbouring core countries, which strengthens the

almost zero indirect effects). The exchange of comparable but differentiated commodities, and technology and innovation transfers are involved in the intra-industry trade within this cluster. Specialisation further increases trade intensity between countries with similar sectoral structures and consumer preferences (Dées & Zorell 2012), leading to a high level of economic interdependence and efficient shock transmission, enhancing BCS. This is reinforced by free trade agreements between the EU core and non-EU countries, although they are not fully coordinated yet, providing an explanation for why the indirect effect on BCS is negligible. Next, the EP-EP cluster is a direct BCS inhibitor (with almost zero indirect effects) through trade intensity. EU periphery countries have more diverse economies due to deficient infrastructures, less coordinated economic policies, and unbalanced economic structures (Gräbner & Hafele 2020), which collectively inhibit BCS. The EP-NEU cluster stands out as an indirect BCS inhibitor due to less trade integration. Such a negative effect is reinforced by divergences in specialisation, regulatory frameworks, financial market maturity and monetary policies, which limit trade opportunities (Baldwin & Wyplosz 2022). Although these differences introduce exposure to asymmetric shocks, we still observe that this cluster is a direct BCS booster through trade intensity. Finally, the NEU-NEU cluster turns out to be an indirect BCS booster, but a direct BCS inhibitor through trade intensity. The NEU countries share close trading relationships with both regional and global partners, regarded as the major exporters of commodities, technology and services. This enhances output productivity and BCS through technology and innovation spillovers. However, their trade patterns are globally diversified. These economies do not necessarily have common economic priorities or trade patterns to generate systemically consistent responses to shocks (Giovanni & Levchenko 2009). This leads to a lower degree of intra-industry trade while raising specialisation, which further magnifies the divergences in industrial structures and economic activities. All these diversities are likely to contribute to less BCS within this cluster.

We turn to the network multipliers of financial intensity, which are displayed on the right-hand-side panel of Figure 1.6. The EC-EC cluster stands out as a BCS inhibitor both directly and indirectly, implying that high volumes of financial transactions between EC countries can lead to less BCS. Although core EU countries have highly developed financial markets, structural differences and policy constraints can lead to high volumes of financial transactions negatively impacting BCS, as different fiscal policies and economic priorities can result in asymmetric responses to financial shocks. Furthermore, being a part of the EMU can potentially weaken their abilities

interconnected trade linkages within core-core pairs while increasing the disparity with periphery economies. Increasing bilateral trade between periphery EU and non-EU economies amplifies the exposure of periphery economies to cyclical fluctuations outside the EU region, thereby reducing the output correlations in core-periphery pairs.

to mitigate uneven shocks by adopting country-specific monetary policies and regulations (Wyplosz 2006). All these dampen BCS. The EC-EP cluster slightly inhibits BCS indirectly (with almost zero direct effects). An increase in financial intensity in neighbouring country-pairs can induce financial contagion, which is risky, especially for periphery economies (Dées & Zorell 2012).[20] Compared to core EU countries that are equipped with advanced financial markets and expanded fiscal capacity, periphery countries, which have more debt burden, fragile institutions and inflexible capital flows, are more vulnerable to financial shocks. All these exacerbate economic disparities between core and periphery countries, leading to divergent BCS. Meanwhile, the EC-NEU cluster becomes a direct and indirect BCS booster through finance intensity. The advanced financial frameworks, substantial capital flows and resource allocation in these countries collectively lead to more financial integration, enhancing common shock transmission and BCS (Caballero et al. 2018). Next, the EP-EP cluster is a direct BCS booster but indirect BCS inhibitor. Countries can benefit from risk sharing in financial markets (Kalemli-Ozcan, Papaioannou & Peydro 2013), enhancing similar economic activities and BCS. Nevertheless, the potential gains from risk sharing may not be completely achieved in the presence of barriers to financial flows in this cluster. Furthermore, the different degrees of financial integration within this cluster may result in incoherent responses and less BCS. The EP-NEU cluster is a direct BCS inhibitor mainly due to a relatively lower degree of financial integration, different financial systems, and geographical and regulatory barriers (e.g., higher transaction costs and longer supply chains), which can raise financial barriers and limit cross-border capital flows (Nurboja & Košak 2017). Finally, the NEU-NEU cluster stands out as a direct and indirect BCS booster. These economies have advanced financial markets/integration and engage in substantial global financial activities, which results in greater risk sharing and capital flow liberalisation (Evans & Hnatkovska 2014). Their advanced financial systems increase the similarities in their economic structures, leading to more synchronised business cycles (Caballero et al. 2018).

Figure 1.6: GCM analysis of GDE/GSO across the six clusters for S

[20]During the global financial crisis in 2008, Spanish banks faced considerable financial troubles, owing to the heavy dependence on real estate sector, which led to liquidity shortages and bank failures in neighbouring countries like Italy.

Notes: This figure displays the GDE/GSO for the six clusters. Each cluster is assigned to one of the following four categories: (i) they boost BCS directly through GDE and indirectly through GSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly.

1.4.5 Policy implications

From the GCM analysis of the network multipliers of trade and finance intensities on BCS across the six clusters, while GDEs tend to positively influence BCS, we observe the dominance of indirect spillovers and the surprisingly negative aggregate total effect of trade intensity on BSC. Although advanced country-pairs are influential transmitters of trade intensity for cycle alignment (e.g., the EC-EC cluster stands out as a direct and indirect BCS booster), they receive larger adverse spill-in effects, mostly from the clusters associated with EP, that lead to cycle misalignment. Next, spillovers of both trade and financial intensities on BCS are negative, mainly from EU country-pairs due to fundamental imbalances. Furthermore, the EC-EC cluster stands out as a BCS inhibitor through finance intensity both directly and indirectly, implying that high volumes of transactions within this cluster can lead to negative impact of financial intensity on BCS. This may suggest that EU economies are not fully integrated yet for fulfilling the optimal currency area (OCA) criteria, see, e.g., Krugman (2009). More importantly, the current structure of EU integration, instead of integration itself, may contain flaws and generate asymmetries. It has been found in the prior studies that intra-EU supply chains (direct effect) synchronise business cycles, but excessive sectoral specialisation (indirect effect) may create divergence (Baxter & Kouparitsas 2005). Cross-border banking activities (direct effect) harmonise cycles in stable times, but sudden stops or fragmentation (indirect effect) worsen divergence (Kalemli-Ozcan, Papaioannou & Peydro 2013). However, historical evidence still supports better integration improving BCS. For instance, the Eurozone crisis revealed that unbalanced financial integration (e.g., cross-border credit booms without risk-sharing) increased divergence, whereas post-crisis reforms (e.g., Banking Union) helped restore cycle synchronisation (Lane 2012, De Grauwe & Ji 2022). Hence, the EU should encourage diversified, supply-chain-based trade and deepen symmetric financial integration, e.g., capital markets union, to neutralise adverse spillovers. Integration may need complementary policies, e.g., pairing with fiscal buffers (e.g., EU recovery fund) or labour mobility, to exert the positive threshold effects on BCS through trade/financial linkages (Furceri & Zdzienicka 2015).

First, in order to improve the total impacts of trade intensity on BCS for EC-EC and EC-NEU clusters, we should address negative spillovers mainly from country-pairs involving EP. Compared to core countries that are specialised in advanced high-tech industries, EU periphery countries are often skilled in agriculture and low-tech manufacturing. This divergent sectoral specialisation limits the scope for boosting BCS (Wigger 2023). The EU periphery regions support policies (e.g., EU structural funds) that diversify economies through concentrating on value-added but less volatile sectors, such as pharmaceuticals and renewable energy, with higher potential for integration with the core economies (Imbs & Wacziarg 2003). This makes them less vulnerable to sector-specific shocks, leading to more economic stability and BCS with core countries.[21] The EU core countries should team up with the periphery countries in aligning regulatory standards that encourage labour market flexibility and intra-EU trade. A shift towards intra-industry trade helps to reduce asymmetries (Fidrmuc 2004), strengthen economic resilience and boost BCS. Developing the regional value chains in the EU can foster the alignment of production cycles, allowing periphery industries to better integrate into the supply chains of core industries.

To indirectly enhance BCS of the cluster between the EU periphery and non-EU countries through trade intensity, we should address the following additional issues: exchange rate volatility and trade agreements. There is a need for coordinated macroeconomic policies to prevent excessive currency fluctuations by fostering cooperation between the European Central Bank and central banks of non-EU countries (Baimbridge et al. 2017). Moreover, more comprehensive trade agreements (e.g., the EU-Japan Economic Partnership Agreement) can tackle non-tariff barriers, harmonise trade standards, and enhance market access.

Secondly, to improve the total impacts of trade intensity on BCS for EP-EP and NEU-NEU clusters, we need to address their negative direct effects. Here we discuss only for the former cluster, since the latter is beyond the scope of the current paper. To enhance the direct impacts of trade intensity on BCS between the EU periphery countries, they should develop a multifaceted approach to enhance infrastructure quality, address structural imbalances and strengthen regional integration. The periphery countries should invest more in improving infrastructures, such as transportation, digital trade and energy, which can lead to lower trade frictions and stronger interconnection (Herman & Oliver 2023). The key to addressing structural imbalances lies in implementing structural reforms, optimising labour market performance, decreasing public debt, and elevating the key sector's competitiveness (Baldwin & Giavazzi 2015). Concerted efforts in these areas can help boost BCS within this cluster.

Third, to enhance BCS through finance intensity directly and indirectly within the EU core cluster with closer financial linkages, the main priority is to pursue policies related to financial regulatory

[21] The accomplishments in Ireland's technology field play an important role in the synchronisation of their economy with more diversified economies like Germany, which may provide a template for other periphery countries like Greece and Spain.

harmonisation, deeper fiscal coordination, banking union integration and labour market reforms. Since divergent financial regulatory frameworks introduce capital flow constraints (Claessens et al. 2012), harmonisation of financial regulations is recommended to reduce structural differences. The reinforcement of fiscal coordination (e.g., European Stability Mechanism and fiscal oversight by the European Commission) helps to mitigate disparities in business cycles especially in times of stress (Trichet 2013). Labour market reforms can reduce economic disparities and enhance BCS (De Grauwe & Ji 2016). These combined policies can promote financial stability and boost BCS among EU core members.

Finally, to improve the total impacts of financial intensity on BCS for EC-NEU and EP-NEU clusters, we should address negative spillovers mainly from EU country-pairs due to fundamental imbalances and market volatility. Financial openness is a double sword which not only enhances capital integration in the EU but also exacerbates vulnerabilities in peripheral countries. Thus, policies related to financial openness should be coupled with safeguards and regulatory frameworks (e.g., sovereign wealth funds) that protect against capital volatility (Lane & Milesi-Ferretti 2007). Since financial instability in the intra-EU clusters may spread to non-EU countries through cross-border transactions, coordination of regulatory frameworks within the EU is needed to promote synchronisation in financial market development, regulatory practices and economic policies (Lupo Pasini 2013). Deepening intra-EU banking integration and consolidating the EU Banking Union would promote cross-border banking regulation and facilitate financial stability. This may involve the enhanced supervisory roles of the European Central Bank, the European Banking Authority, and the Single Supervisory Mechanism in regulatory monitoring intra-EU banks in overseas financial markets (Avgeri et al. 2021). Less dependence on short-term financing can stabilise the EU financial markets and mitigate negative spillovers to non-EU partners. EU policymakers can also develop long-term investment instruments, e.g., transforming green bonds or infrastructure investments into tradable securities. Moreover, to stabilise the financial environment and diversify financial resources, they should promote EP countries' access to EU capital markets (e.g., pan-European initiatives) (Beck & Levine 2004).

1.5 Concluding Remarks

To investigate the fundamental relationship between trade/finance intensities and the business cycle synchronisation, we develop a simultaneous equation panel data model that jointly controls for spatial spillovers, latent global shocks, simultaneity between business cycle synchronisation (BCS) and trade/financial intensities, and parameter heterogeneity. We follow Chen et al. (2022) and propose the CCEX-2SLS estimator to estimate the spillover effects and the endogenous effects of bilateral trade and finance intensities on BCS. We notice in passing that the BCS is measured by the absolute differential in GDP growth of two countries such that it becomes the symmetric bilateral flow. By selecting non-overlapping $N = n(n-1)/2$ country-pairs, where n is the number of countries, we can analyse the relationship between the 3D BCS and trade/financial intensities using the 2D panel data framework given by (1.3.1). Notice, however, that it is not straightforward to construct the spatial weights matrix to capture network proximity among the undirectional N country-pairs, e.g., Cainelli et al. (2021). We follow a general approach to the construction of bilateral flows advanced by Shin et al. (2025) and construct the $N \times N$ spatial weights matrix based on a shared border, that is shown to be a (sparse) average of the selected pairs sharing a common country.

By applying the CCEX-2SLS estimator to the quarterly data for the 136 pairs of 17 OECD countries over the period 1995Q1-2019Q4, we find that the proportion of positive and negative effects of trade/financial intensities on BCS are similar, whilst their mean-group (MG) estimates are small and insignificant. This clearly demonstrates the importance of explicitly taking heterogeneity into account. It also provides some explanation for the mixed findings reported in the existing studies.

We also conduct the spatial and GCM network analysis advanced by Greenwood-Nimmo et al. (2021) and Shin & Thornton (2021), so as to investigate the direct and indirect network impacts of trade and capital intensities on BCS across the 129 country-pairs or six selected clusters of country-pairs. We observe that 90% of the sample belong to categories where they either boost BCS directly through HDE or inhibit BCS indirectly through HSO, and *vice versa*. More importantly, we observe the surprisingly negative aggregate total effect of trade intensity on BCS and negative spillovers of both trade and financial intensities on BCS. This may suggest that EU countries are not fully integrated yet for fulfilling OCA, and policy recommendations should focus on improving smarter integration (e.g., risk-sharing, diversified trade) rather than just increasing it.

To help policymakers to coordinate across borders and mitigate adverse economic fluctuations, relevant policy implications are provided, such as enhancing trade policies, promoting financial integration, maintaining stability and coordination of macroeconomic policies, improving monitoring and risk management and supporting structural reforms.

Our work opens several avenues for continuing research. On the empirical side, our results motivate similar and robust studies that employ alternative measures of BCS, trade/financial intensities and the spatial weights, as well as including dynamics and more countries in the sample. On the methodological side, there is scope to generalise our approach using the system 3SLS estimation, e.g., Baltagi & Deng (2015).

Chapter 2

Systematic Components in ESG Ratings across Legal Origins

Abstract We aim to identify and analyse systematic components of ESG ratings using the multilevel factor model. Applying the generalised canonical correlation (GCC) approach to the MSCI and Refinitiv datasets across the four legal origins (English, French, German, Scandinavian), we document the presence of one global factor irrespective of ESG rating or its three E/S/G pillars, confirming ESG globalisation while the number of local factors varies across legal origins and subcomponents. We find the dominance of global factors in Refinitiv data but the dominance of local factors in MSCI data in explaining the variance of ESG. Furthermore, we find the mixed evidence on the impacts of legal origin on ESG performance. As the GCC-based approach is data-driven, such different findings point towards the raters' ESG divergence as postulated in the literature. We suggest that the relative importance ratios of the global factor be greatly improved relative to local factors and idiosyncratic components so as to better predict overall ESG performance. Given that the standards of ESG disclosure reporting are currently quite different across civil and common law countries, this goal can be achieved through the enforcement of global mandatory reporting standards.

Keywords: Multilevel Factor Models, Generalised Canonical Correlation Analysis, Systematic Components of ESG Ratings, Legal Origin Theory, Global Mandatory Reporting Standards.

JEL codes: C38, O16, Q01.

2.1 Introduction

Following the United Nation report "Who Cares Wins" in 2004, there has been an increased attention on research involving sustainable finance. Although no clear consensus exists on the definition of sustainable finance and different terms have been toyed with it: environmental, social, and governance (ESG) indicator, socially or sustainably responsible investing, and corporate social responsibility (CSR), a plethora of work exists mainly focusing on ESG issues and financial markets: a) asset pricing model incorporating ESG investors (Kashyap et al. 2021, Broccardo et al. 2022); b) relationship between ESG performance and stock returns where the findings are mixed: higher stock returns for ESG performers (Lins et al. 2017, Albuquerque et al. 2019) as well as lower stock returns; (Chava 2014, Bolton & Marcin 2020); c) literature on ESG rating divergence and uncertainty (Christensen et al. 2022, Avramov et al. 2022, Berg, Koelbel, Pavlova & Rigobon 2022), suggesting that it is difficult to identify the true effect of ESG performance on stock returns in standard regressions. In this paper, using generalised canonical correlation (GCC) approach, we complement the existing literature to explain the systematic global and local factors in ESG and its components across the four legal origins in terms of both macro and firm-specific factors.

Several factors from micro and macro perspectives can determine ESG performance. Financial firm-specific factors, such as size (Drempetic et al. 2020) and financial constraints (Hong et al. 2012), as well as non-financial factors, such as board structure and diversity (Beji et al. 2021, Shy 2024), play a role in explaining ESG performance. Similarly, industry factors, such as competitive intensity of the industry environment (Flammer 2015), diverse regulatory constraints and government enforced sanctions (Aragon-Correa et al. 2019) can impact ESG. ESG covers various dimensions of firm behaviour and includes effort by a firm in addressing different externalities, but all factors determining ESG cannot be under firms' control (Ferrell et al. 2016). Regulations, institutional arrangements and country/regional differences due to differences in government policies and societal preferences would matter in determining firms' ESG (Kitzmueller & Shimshack 2012, Graham 2022). Cai et al. (2016) show that country factors are more strongly associated with corporate social performance compared to firm characteristics.

ESG data can be noisy due to data quality, coverage, metrics, time lag, industry/country regulations and aggregation. Berg, Koelbel & Rigobon (2022) document that the ESG disagreement is fundamentally driven by the divergence in measurement, scope and weighting, stemming from the lack of standardised ESG rating approach, whereas Tsang et al. (2024) emphasise on the monitoring role that the ESG rating agencies can play giving incentives to managers to reduce ESG violations.[1]

[1]For a succinct discussion on green and ethical finance, see Beck et al. (2022) and articles therein.

This is why existing studies fail to reach a consensus on the impact of ESG on financial, social, and environmental performance. We must carefully navigate this noise to make informed decisions, since discrepancies in ratings yield diverging performances (Billio et al. 2021). Furthermore, ESG regulations are multifaceted and can vary by region based on their legal origins (Liang & Renneboog (2017). Navigating all these complexities while aligning with global standards poses challenges and therefore it is imperative to examine the role of legal traditions in shaping ESG/corporate sustainability practices using either the first generation legal origin theory where the main focus is on investor protection and financial development (La Porta et al. 1998) or the second generation theory where the emphasis extends in other areas such as labour regulation, property rights, contract enforcement, and government intervention (Djankov et al. 2003, La Porta et al. 2008).

The legal origin theory postulates that a country's legal origin, as fundamental elements that affect business environments and management philosophies, can exert a significant impact on its economic development, governance and corporate behaviour. The first generation of legal origin theory emphasises solely on direct relationship between legal origins and economic outcomes (Mahoney 2001, La Porta et al. 2002, 2008). They often claim the superiority of the common law system over the civil law system with respect to the dimensions of governance and economic growth, while assuming equality in other dimensions (La Porta et al. 2002, Hansmann & Kraakman 2017). However, these works have been criticised for a lack of consideration in environmental and social outcomes (Collison et al. 2012). Recently, the second generation has paid more attention to environmental and social dimensions (Kock & Min 2016, Liang & Renneboog 2017, Kim et al. 2017). In general, English common law countries follow more flexible and adaptive legal frameworks and their main thrust is profit maximisation of shareholders, thus leading to varied ESG practices across countries. By contrast stakeholder-oriented approach is more prevalent in French, German and Scandinavian civil law origins, emphasising on broader social responsibilities and leading to higher levels of ESG disclosure. Kim et al. (2017) posit that a significantly higher level of corporate environmental responsibility is expected in civil law firms since they emphasise the maximisation of stakeholder values and environmental governance in corporate operations. Kock & Min (2016) show that common law legal origins perform worse than civil law counterparts in terms of CO2 emissions. Liang & Renneboog (2017) document evidence that companies from civil law countries have a higher ESG than those from English common law countries along most ESG pillars. The adoption of ESG initiatives in common law countries is largely determined by corporate discretion, whilst ESG adoption is in the power of laws/regulations or societal demands in civil law countries. Overall, the second generation legal origin theory supports that countries belonging to civil law origins have the higher E/S scores since companies in this group are subject to higher state interventions and regulations.

In this paper we aim to address the aforementioned challenging issues while aligning with the different ESG disclosure reporting standards between common and civil law systems by identifying and analysing systematic and noisy components of ESG ratings. To this end, we apply the generalised canonical correlation (GCC) approach advanced by Choi et al. (2023) and Lin & Shin (2023) to estimate the multilevel factor model and characterise the systematic global and local factors across the four legal origins (English, French, German and Scandinavian), using the MSCI dataset containing monthly observations of IVA rating and its three E/S/G pillars for $3,911$ companies over January 2014–December 2023 as well as Refinitiv/LSEG dataset containing annual observations of ESG rating and its three components for $2,306$ companies over 2002–2023. The respective estimation results share some similarities and differences. First, we find one global factor in both datasets, clearly confirming ESG trend/globalisation. The time-varying patterns of global common components of ESG ratings closely resemble the raw data, with Scandinavian origin as the top performer. On the other hand the number of local factors varies and the time-varying patterns of local common components are significantly heterogeneous across legal origins and sub-components of ESG. This reflects presence of multiple local factors driving the ESG practices across legal origins with different goals due to varying cultures, economies, environments and political systems. Second, although the time-varying patterns of the ESG data and global common components of both raters are qualitatively similar to each other, we observe the dominance of global factors in Refinitiv data but the dominance of local factors in MSCI data, in explaining the variance of ESG. This may suggest that the former prioritises universal ESG standards and international benchmarks while the latter puts more emphasis on local regulations and cultural norms in ESG assessment.

Next, we explore the association of the ESG data and their global and local common components with country-specific macro and firm-specific variables along with Covid pandemic and legal origin dummies, following 'doing well doing good' literature (Martiny et al. 2024). Although the estimation results are qualitatively different between MSCI and Refinitiv datasets (for example, the impacts of GDP growth and inflation are mostly positive for MSCI data, but mostly negative for Refinitiv data), the sign and significance associated with these determinants for the systematic components of ESG match in almost all cases with those of raw data. The impacts of company size and ROE are mostly positive and significant for both datasets while the impacts of leverage ratio are significant and negative only for MSCI data. The impacts of the Covid dummy remain positive and significant for both datasets, suggesting that the COVID crisis can act as a positive catalyst for ESG, aligning with flight-to-quality hypothesis (Urbonavicius & Chirita 2023). Furthermore, systematic global components can be well predicted by these determinants while the raw data and local components are harder to predict. Together with much higher relative importance of idiosyncratic components estimated in MSCI data, we conjecture that the MSCI data is likely to be subject to more noises and uncertainties related to ESG disclosures. Finally, we find the mixed evidence on the impacts of legal origin on the ESG performance. The MSCI results are generally inconsistent with the existing studies (Kock & Min 2016, Liang & Renneboog 2017, Kim et al. 2017) whereas the Refinitiv results provide some support for the second generation legal origin theory.

As the GCC-based approach is data-driven, such different findings point towards the raters' ESG divergence as postulated in the literature (Avramov et al. 2022, Christensen et al. 2022, Berg, Koelbel, Pavlova & Rigobon 2022). Hence, it is still complex to uncover the fundamental relationship between ESG factors and firm characteristics/macro variables/legal origins. We suggest that the relative importance ratios of the global factor be greatly improved relative to local factors and idiosyncratic components so as to better predict overall ESG performance. Given that the standards of ESG disclosure reporting are currently quite different across civil and common law countries, this goal can be achieved through enforcement of global mandatory reporting standards. Following the growing trend towards global harmonisation of sustainability reporting (Threlfall et al. 2020), policymakers in all countries are encouraged to adopt global standards (e.g., International Sustainability Standards Board) as a benchmark. It is also beneficial to actively implement international ESG training programs (e.g., United Nations Principles for Responsible Investment Academy and International Finance Corporation ESG Training Program) to facilitate collaborations and synchronise ESG disclosures.

While our study focuses on legal origins as a foundational institutional framework (La Porta et al. 1998), we acknowledge that ESG ratings are also shaped by broader contextual factors, such as political systems, cultural norms, industry composition, etc. Regulatory enforcement of ESG standards often varies with political systems and governance structures.[2] Societal values (e.g., individualism vs. collectivism) also shape corporate priorities in E/S/G components (Liang & Renneboog 2017). Regarding the industry composition, resource-dependent economies (e.g., Australia) face stricter environmental scrutiny, whereas service-dominated economies (e.g., Switzerland) emphasise governance and data privacy (Khan et al. 2016, Christensen et al. 2022). While these factors are analytically relevant, our multilevel factor model focuses on systematic components shared across firms within legal origins, as these frameworks provide the foundational institutional "filter" through which other contextual factors (e.g., politics, culture) operate. See Liang & Renneboog (2017) and Kurbus & Rant (2025) for legal origins as ESG moderators.

[2]For instance, countries with stronger state intervention (e.g., China) prioritise governance factors tied to political objectives (Marquis & Qian 2014), while liberal markets (e.g., U.S.) emphasise investor-driven ESG metrics (Khan et al. 2016).

The paper is organised as follows: Section 2.2 describes the model and empirical methodology. Section 2.3 present the main empirical results using the MSCI dataset. Section 2.4 provides a robustness check using the Refinitiv/LSEG ESG dataset. Section 2.5 offers concluding remarks. The data descriptions and GCC estimation algorithms are relegated to the Appendix.

2.2 The Model and Methodology

Consider the following three-dimensional panel data with the multilevel factors for ESG activities:

$$ESG_{ijt} = \boldsymbol{\gamma}_{ij}'\boldsymbol{G}_t + \boldsymbol{\lambda}_{ij}'\boldsymbol{F}_{it} + u_{ijt},\ i = 1, ..., R,\ j = 1, ..., N_i,\ t = 1, ..., T, \tag{2.2.1}$$

where ESG_{ijt} represents the ESG ratings by firm j in group i at time t, $\boldsymbol{G}_t = [G_t^1, ..., G_t^{r_0}]'$ is the $r_0 \times 1$ vector of latent global factors which influence all firms' ESG activities (e.g., climate change and global regulations/standards), $\boldsymbol{F}_{it} = [F_{it}^1, ..., F_{it}^{r_i}]'$ is the $r_i \times 1$ vector of latent local factors in the group i, that affects ESG performance of firms in the group i only, capturing the common trend within the group (e.g., cultural norms, local stakeholder pressure and regional economic conditions). $\boldsymbol{\gamma}_{ij}$ and $\boldsymbol{\lambda}_{ij}$ are the corresponding heterogeneous factor loadings measuring the sensitivity of individual firms to the global and local factors, respectively. u_{ijt} is the idiosyncratic error.

Following the seminal paper by Kose et al. (2003*b*), there has been a growing literature on the multilevel factor models. To deal with the primary issue of identifying the global and local factors separately, a number of alternative methods have been developed. The principal component (PC) estimation, a popular method in the single-level factor model, fails to separately identify the global and local factors. Breitung & Eickmeier (2023) and Choi et al. (2018) propose the use of the canonical correlation analysis (CCA) for consistent estimation. Andreou et al. (2019) develop a CCA-based asymptotic theory for the estimated factors and loadings, though their approach can be applied to the case with the two groups only. Choi et al. (2023) develop consistent selection criteria for the number of global and local factors based on the average canonical correlations among all group pairs. Recently, Lin & Shin (2024) propose the generalised canonical correlation analysis (GCC) by conducting the simultaneous analysis of the factor spaces of all groups along with a GCC-based selection criteria for identifying the number of the global/local factors.

2.3 The Empirical Application

2.3.1 The data

Our dataset contains monthly observation of 3,911 companies for 54 countries over the period January 2014 to December 2023, collected from the MSCI database. We use the intangible value assessment (IVA) as the aggregate rating, and the three components constituting the IVA: the environmental, social and the governance scores[3] (see Appendix B.1 for data details). Referring to the classification established by La Porta et al. (1997) and La Porta et al. (1998), we group the firms according to legal origins and construct the four clusters: English common law origin and French/German/Scandinavian civil law origins.[4] Similar to Liang & Renneboog (2017), the firm's legal origin is in accordance with the company law or commercial code of the country where the firm is headquartered. This is consistent with the seminal works of La Porta et al. (1998) and La Porta et al. (2008), which tie legal origin to the jurisdiction where a firm is legally domiciled. In what follows we apply the GCC approach to studying the global and local ESG activities using the multilevel factor model, (2.2.1), see Appendix B.2 for detailed estimation algorithms.

The descriptive statistics for MSCI based on legal origin grouping are presented in Table 2.1, showing that countries in the Scandinavian origin top the list in IVA as well as in individual E/S/G pillars. However, the ranking among English, French and German legal origins is not monotonic. For IVA and E/S pillars, French legal origin has a higher score than German and English counterparts. On the other hand English legal origin presents a higher score than German and French counterparts for the G pillar. The variability is relatively higher for the E pillar while Scandinavian legal origin displays the smallest variations except social score.[5]

[3]We select the companies that satisfy the two conditions: (i) balanced monthly data covering the whole sample period and (ii) the data with variance larger than zero to apply the GCC regression.

[4]Socialist legal tradition began in the Soviet Union and spread to Eastern Europe and China, reverting to pre-revolutionary French or German civil law systems after the Berlin Wall fell. In this regard, Socialist legal origin has been mostly ignored in the literature. Even if we recategorise three countries (Macau, Panama and Poland) from French to German legal origins following Bradford et al. (2021), our results remain qualitatively the same.

[5]Using a paired t-test involving means of the different indicators we find a significant difference between English, French, German and Scandinavian legal origins for IVA as well as E/S/G ratings. For the E pillar such differences exist between English vs Scandinavian, for the S pillar between English vs Scandinavian, English vs French, French vs Scandinavian and for the G pillar English vs Scandinavian, English vs French, French vs Scandinavian and German vs Scandinavian. Overall, 11 out of 24 correlations turn out to be significant at the 10% level. These results are available upon request.

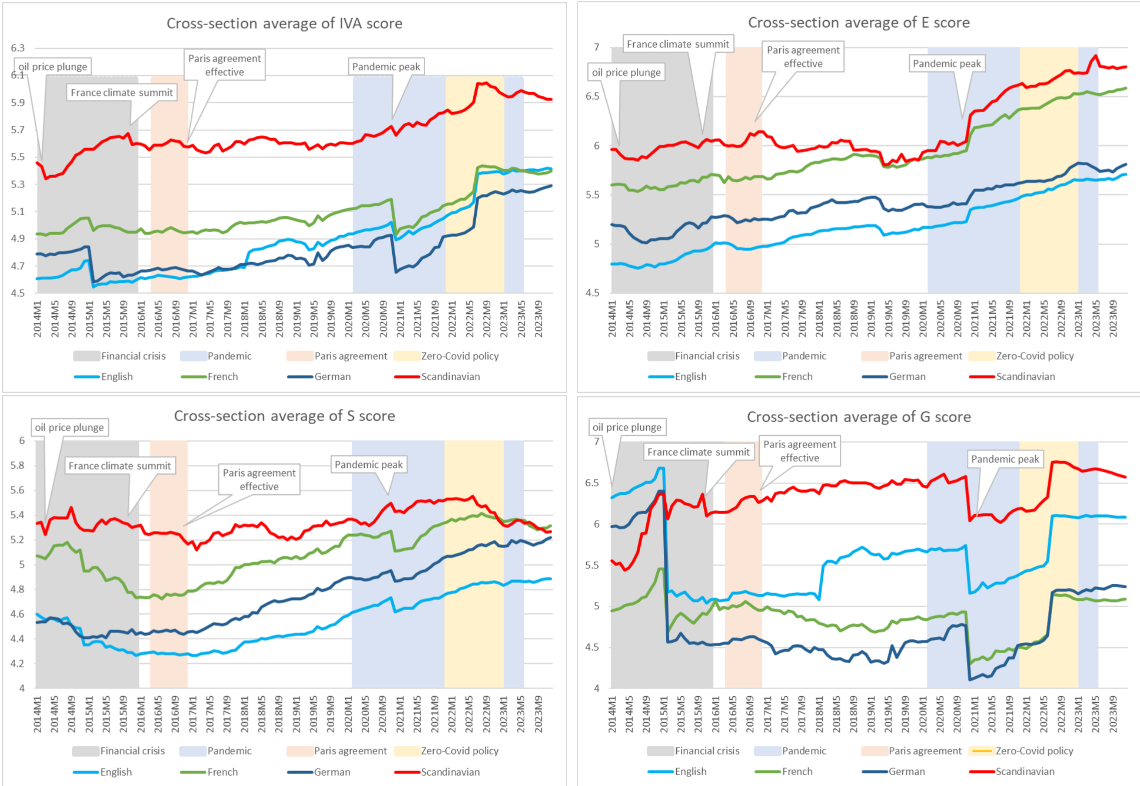
Table 2.1: Main empirical results for 4 legal origins

Variable	Legal origin	N_c	N_i	Mean	Std	$\hat{r}_0$	$\hat{r}_i$	RI_G	RI_F	RI_E
IVA rating	English	16	2718	4.883	1.053	1	1	0.187	0.337	0.475
	French	25	445	5.086	1.177	1	1	0.193	0.349	0.458
	German	9	643	4.828	1.030	1	2	0.204	0.454	0.342
	Scandinavian	4	105	5.674	0.873	1	1	0.258	0.353	0.389
	Sum/Average	54	3911	4.919	1.070	1		0.211	0.373	0.416
Environmental score	English	16	2718	5.184	2.328	1	2	0.110	0.515	0.375
	French	25	445	5.949	2.382	1	1	0.207	0.341	0.452
	German	9	643	5.409	2.054	1	2	0.124	0.489	0.387
	Scandinavian	4	105	6.183	1.902	1	1	0.128	0.357	0.515
	Sum/Average	54	3911	5.335	2.298	1		0.142	0.426	0.432
Social score	English	16	2718	4.538	1.608	1	2	0.069	0.496	0.435
	French	25	445	5.09	1.596	1	2	0.091	0.484	0.424
	German	9	643	4.755	1.580	1	2	0.090	0.483	0.427
	Scandinavian	4	105	5.341	1.621	1	2	0.097	0.498	0.405
	Sum/Average	54	3911	4.658	1.617	1		0.087	0.490	0.423
Governance score	English	16	2718	5.599	1.773	1	2	0.059	0.546	0.395
	French	25	445	4.864	1.831	1	2	0.046	0.523	0.431
	German	9	643	4.774	1.806	1	2	0.046	0.576	0.378
	Scandinavian	4	105	6.332	1.564	1	1	0.090	0.390	0.519
	Sum/Average	54	3911	5.400	1.821	1		0.060	0.509	0.431

We report the GCC estimation results for (2.2.1) using the monthly data for 3,911 companies over Jan. 2014–Dec. 2023. N_c and N_i are the number of countries and firms in each legal origin. Mean and Std represent the mean and standard deviation of ESG scores. $\hat{r}_0$ is the number of global factor estimated from the model (2.2.1) by the GCC criterion, while $\hat{r}_i$ is the number of local factors estimated by the ER criteria after projecting out one global factor. RI_G, RI_F and RI_u are the relative importance ratios of global, local and idiosyncratic components measuring the contribution of each component to the explained variance of ESG metrics (see also footnote 2).

Figure 2.1 displays the time-varying patterns of the raw ESG data, measured as the cross-section averages within each of legal origins. IVAs show a smooth increase pattern for all legal origins. Scandinavian legal origin tops the list, followed by French legal origin. Initially, English legal origin lagged behind but outperformed German legal origin from 2018. Since 2023, English legal origin began to slightly outperform French legal origin. Scandinavian legal origin exhibits a relatively stable pattern but sustains a decline after the mid 2022. Three other legal origins experience two major declines in IVA during the Russian crisis (2014M12-2015M1) and during the COVID pandemic peak (2020M12-2021M1). The first decline is mainly attributed to the sharp fall in the G pillar while the second is attributed to the drop in both S and G pillars. E scores continue to gradually increase across legal origins (with the ranking of Scandinavian, French, German and English legal origins), reflecting the impacts of various factors such as the UN Sustainable Development Goals, more emphasis on ESG considerations in investment decisions by institutional investors and stakeholders and rise in consumers' awareness of the environmental and social impacts of products and services. Despite two main declines during the Russian crisis and the Pandemic peak, S scores continue to rise, though Scandinavian legal origin recently sustained a sharp decline and lost its leading position,

Figure 2.1: Cross-section averages of IVA, E, S and G scores across 4 legal origins



surpassed by French legal origin.[6] Post-pandemic growth follows mainly due to the strong recovery in E and S pillars. G pillar shows higher volatilities than other pillars. Initially, English legal origin dominated. Following the Russian crisis, only Scandinavian legal origin did not suffer from a significant decline though the other three legal origins were faced with a sharp fall. This shifts the ranking to Scandinavian, English, French and German legal origins.

In sum, countries belonging to civil law origin have the higher ESG activities *ex ante* since companies in this group are subject to higher state interventions and regulations, which is in line with the existing literature (e.g., Liang & Renneboog (2017), although the performance gap between the legal origins of English and French/German becomes negligible for IVA.

2.3.2 Global and local common components of ESG ratings across legal origins

We apply the GCC criterion developed by Lin & Shin (2024) to the multilevel ESG model, (2.2.1), estimate the number of global factors, and use the ER criterion by Ahn & Horenstein (2013) to the de-factored data in each legal origin $i = 1, ..., 4$ to estimate the number of local factors. We also report the relative importance ratios of the factors for each legal origin, measuring the strength of

[6]This may be due to the French Duty of Vigilance Law in 2017, which mandates that French multinational companies publish annual reports on their social and environmental impacts, including labour conditions and human rights risks.

both global and local factors relative to idiosyncratic components in explaining ESG variance.[7]

Table 2.1 shows presence of one global factor irrespective of IVA ratings or its three components. The number of local factors is 2 for social scores and ranges between 1 and 2 for IVA and environmental/governance scores, respectively.

Given the global concerns regarding the climate change, human rights, corruption and the interconnectedness of the global economy, we would expect that these issues require synchronised action across countries irrespective of their legal origins, thereby resulting in single global factor in overall ESG as well as in its three components. ESG ratings influenced by one global factor reflects worldwide ESG convergence due to regulatory harmonisation, investor preferences and supply chain pressures. Global frameworks (e.g., UN PRI, TCFD, EU Taxonomy) incentivise firms worldwide to adopt standardised ESG practices (Eccles & Serafeim 2013). The rise of cross-border ESG funds driven by global initiatives (e.g., Net Zero Asset Managers Alliance) creates demand for comparable ratings across markets and sustainable assets, as institutional investors integrate sustainability into portfolio selection to mitigate long-term risks (e.g., climate transition liabilities) and align with stakeholder preferences (Dyck et al. 2019). Multinational firms (e.g., Apple, Unilever) impose uniform ESG requirements on suppliers globally, propagating common standards. Common ESG data providers (e.g., MSCI, Sustainalytics) whose methodologies often apply universal criteria (Berg, Koelbel & Rigobon 2022). In this regard, the global factor may capture ESG globalisation trend.

Local factors, however, are subject to different goals and challenges due to varying cultures, economies, environments, and political systems. Here, 'one size fits all' would not apply and hence companies including the multinationals need to tailor their ESG strategies keeping in mind the diverse needs of countries irrespective of their legal origins. ESG ratings influenced by local factors may arise from jurisdictional differences, such as (i) legal origins, for example, civil law countries may emphasise stakeholder-centric laws, stricter environmental and labour rules, elevating E and S factors (e.g., climate change, labour rights, board worker representation), while common law countries prioritise shareholder rights (G) (La Porta et al. 1998); (ii) cultural norms, for example, Nordic firms often lead in environmental performance due to societal sustainability values (Gjølberg 2009); (iii) local policies, for instance, China's ESG ratings incorporate state-owned enterprise governance structures (Wei & Zhou 2024). The legal origin theory postulates that a country's legal origin, as fundamental elements that affect business environments and management philosophies,

[7]The relative importance ratios are evaluated using the variance decomposition based on the estimated ESG regression given by $ESG_{ijt} = \hat{\boldsymbol{\gamma}}_{ij}'\hat{\boldsymbol{G}}_t + \hat{\boldsymbol{\lambda}}_{ij}'\hat{\boldsymbol{F}}_{it} + \hat{u}_{ijt}$, where $\hat{\boldsymbol{G}}_t$ and $\hat{\boldsymbol{\gamma}}_{ij}$ ($\hat{\boldsymbol{F}}_{it}$ and $\hat{\boldsymbol{\lambda}}_{ij}$) are the GCC estimates of global (local) factors and loadings from the multilevel ESG factor model, (2.2.1), and $\hat{u}_{ijt}$ are the residuals. Then, we obtain: $RI_G = Var(\hat{\boldsymbol{\gamma}}_{ij}'\hat{\boldsymbol{G}}_t)/Var(ESG_{ijt})$, $RI_F = Var(\hat{\boldsymbol{\lambda}}_{ij}'\hat{\boldsymbol{F}}_{it})/Var(ESG_{ijt})$ and $RI_u = Var(\hat{u}_{ijt})/Var(ESG_{ijt})$. By construction, $RI_G + RI_F + RI_u = 1$.

can exert a significant impact on its economic development, governance and corporate behaviour. Referring to Liang & Renneboog (2017), legal origin is more strongly associated with corporate social performance compared to country factors and firm characteristics. Local factors vary across legal origins and ESG components. In terms of the E pillar, local climate policies (e.g., EU carbon taxes vs. US state-level regulations) create divergent pressures. Regarding the S pillar, cultural norms (e.g., gender diversity in Scandinavia vs. emerging markets) drive regional variations. With respect to the G pillar, common law highlights shareholder primacy, leading to G factors dominating local ESG weights.

We find the dominance of local factors in explaining the variance of ESG, and this dominance is more pronounced in E/S/G pillars. Scandinavian origin has a higher relative importance (RI) ratio of global factor (25.8%), reflecting its stronger sensitivity to the global shock, though the influence of the global factor remains non-negligible for the other legal origins (18.7%–20.4%). Regarding the RI ratios of local factors in IVA, German legal origin (45.4%) is ranked at the top. Moreover, idiosyncratic components are more important in explaining the IVA variations in English and French legal origins, reflecting substantial uncertainties related to their ESG disclosure.

Turning to the three E/S/G components, local factors exhibit substantially higher RI ratios than the global factor for all the legal origins. Such dominance is prominent especially for S and G pillars, where average RIs of global and local common components are 8.7% and 49% for S pillar and 6% and 50.9% for G pillar, respectively. This suggests that local factors provide a more comprehensive explanation behind ESG transitions. Notice that RIs of global factor are significantly smaller in S and G pillars than in E pillar as well as in IVA. This is mainly because environmental issues, such as climate change, pollution and biodiversity loss, have received more attention and indicators included in the E pillar are more tangible than those measured in S and G pillars. This finding is in line with studies that highlight the increasing emphasis on environmental issues in the overall ESG score due to global climate change concerns (Environment 2020), overshadowing S and G pillars. The primary focus of MSCI is financial materiality, evaluating the long-term resilience of companies that could impact their financial performance (LLC 2024). Research by MSCI highlights the different impacts of ESG components on financial performance, with environmental factors often having a more pronounced effect (Ankit & Bentley 2020).

Finally, the RI ratios of the idiosyncratic components range between 41.6% and 43.2% while they are more prominent for IVA and S scores of English legal origin and for E and G scores of Scandinavian legal origin. We also note that the nature of ESG disclosure reporting is quite different between common and civil law systems without the standardised mandatory reporting. This combined with the specific local factors in which companies function would exert more immediate impact on ESG compared to the global factors.[8] Overall, these results confirm the substantial noises and uncertainties related to ESG disclosures.

The common component in our multilevel factor model captures systematic ESG shocks that are shared across firms, as opposed to idiosyncratic firm-level practices. Its importance lies in (i) affecting investors' decision-making since the common component reveals whether ESG ratings are driven by universal standards which are useful for global portfolios, or localised risks that are critical for regional allocations; (ii) providing policy implications so that regulators can target global vs. local drivers, e.g., harmonising carbon disclosure vs. adapting labour norms (Kotsantonis & Serafeim 2019); (iii) inspiring firm strategy since firms operating globally must balance adherence to global norms (e.g., GHG reporting) with local expectations (e.g., community engagement in emerging markets).

Figure 2.2 displays the time-varying patterns of (average) global common components ($\bar{\hat{\boldsymbol{\gamma}}}\hat{\boldsymbol{G}}_t = \frac{1}{4}\sum_{i=1}^{4}[N_i^{-1}\sum_{j=1}^{N_i}\hat{\boldsymbol{\gamma}}_{ij}'\hat{\boldsymbol{G}}_t]$) of IVA rating as well as the three components along with global events for the four legal origins on average, where $\hat{\boldsymbol{G}}_t$ and $\hat{\boldsymbol{\gamma}}_{ij}$ are the GCC estimates of global factor and loadings. The global common components of IVA exhibits an upward trend across legal origins, closely resembling the raw data shown in Figure 2.1. Initially, following a noticeable awareness and adoption of ESG principles among firms and investors,[9] there was a gradual increase in the global common component. The sudden drop in 2015 has been mainly due to the Russian crisis, that led to a reevaluation of environmental risks associated with energy production and supply chains[10], as well as challenges to effective corporate governance. The upward trend continues especially following the Paris agreement on the Climate Summit in 2016, also reflecting the lagged impact of sustainable investing policy on ESG metrics. During the Covid pandemic, sharp falls in global common components of IVA as well as S and G pillars are observed though those of E pillar continue to rise. This may suggest that S and G scores are more tangible metrics of firm resilience in times of crisis, because they reflect a combination of a leaner production process and good governance. Although the S component started showing upward trend immediately after the pandemic, firms may still struggle to increase the G scores given the resource constraints due to the pandemic.[11]

[8] Some examples of local contexts could include factors like supply chain disruptions, labour rights violations, political instability and corruption.

[9] Governments and regulatory bodies increasingly focused on sustainability and responsible business practices. International agreements (e.g., the UN Sustainable Development Goals), encouraged firms to enhance their performance. As consumers are becoming more conscious of the environmental and social impacts of products and services, companies responding to consumer preferences for sustainable and socially responsible options can enhance their ESG performance.

[10] This crisis caused severe global supply chains disruption, including labour practices and product responsibility. Companies with less-than-average management performance on ESG issues, such as carbon emission and climate change, see their scores largely driven down. Baid & Jayaraman (2022) highlight the importance of social responsibility in supply chain finance and management in promoting the S pillar in ESG investing.

[11] Despite the substantial declines in G scores, the aggregate ESG score tends to follow the growth of E and S

Figure 2.2: Global common components of ESG, E, S and G scores

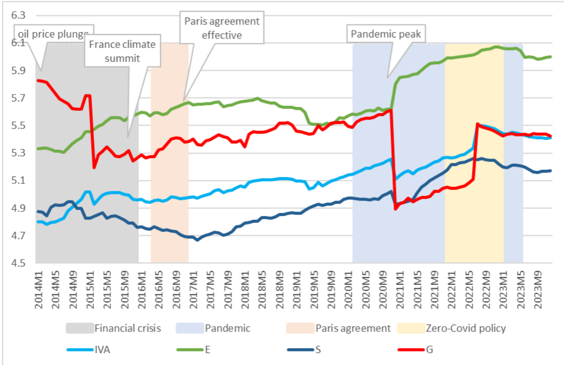


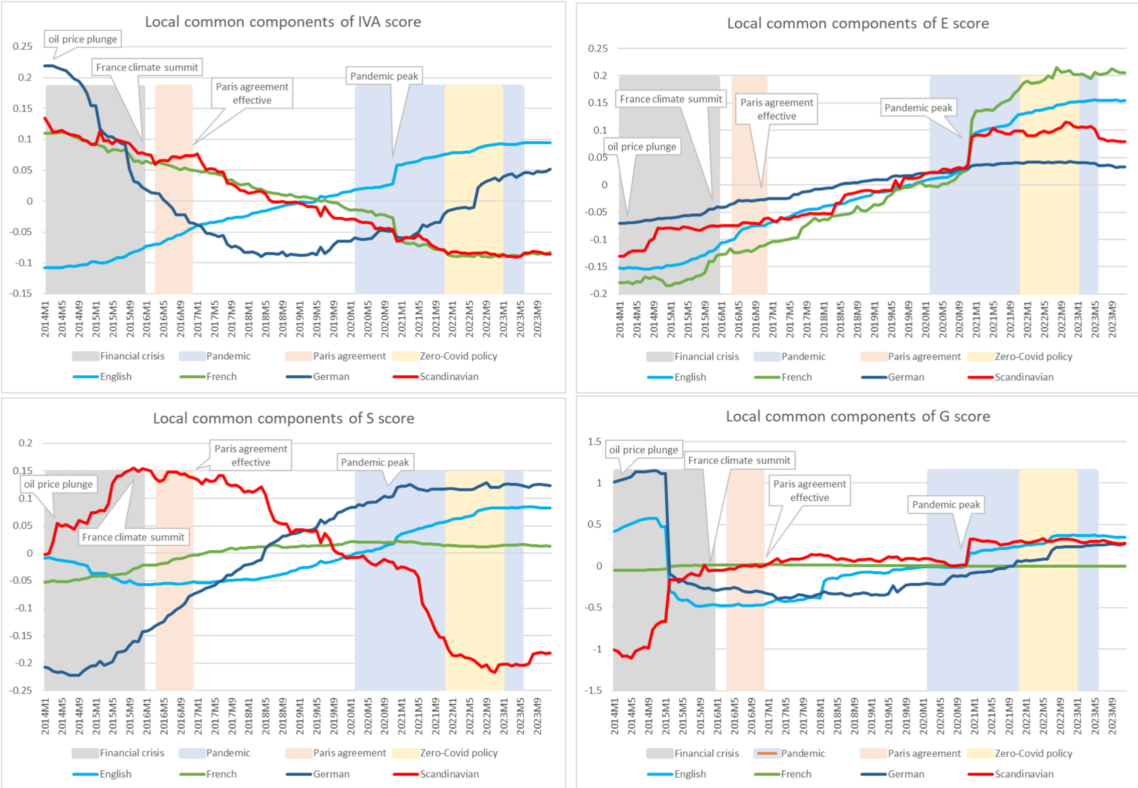
Figure 2.3 portrays the time-varying patterns of (average) local common components ($\hat{\boldsymbol{\lambda}}_i'\hat{\boldsymbol{F}}_{it} = N_i^{-1}\sum_{j=1}^{N_i}\hat{\boldsymbol{\lambda}}_{ij}'\hat{\boldsymbol{F}}_{it}$) for each legal origin $i = 1, ..., 4$, where $\hat{\boldsymbol{F}}_{it}$ and $\hat{\boldsymbol{\lambda}}_{ij}$ are the GCC estimates of local factors and loadings. Several observations can be made: significant heterogeneity gets reflected across legal origins, irrespective of aggregate or the three components. Time-varying patterns of local common components of IVA consist of three groups. First, local common components of IVA for English legal origin show an increasing trend (even more during the pandemic). Next, German legal origin exhibits almost an U-shape whilst companies in Scandinavian and French legal origins sustained significant falls in IVA ratings.

The local common components of the E pillar continue to grow and even jump during the pandemic, showing sustained commitments to environmental policies and climate change mitigation. Interestingly, the local E performance of French legal origin eventually tops the list though its initial position started from the bottom. The post-pandemic changes in the local common components of the S pillar of French legal origin are contrasted by those of German and Scandinavian legal origins. The pandemic disrupted global supply chains, trade and business operations. In response, many large businesses and enterprises in the former group stepped up their CSR initiatives to support local economies, displaying an upward trend.[12] The pandemic also highlighted the importance of building genuine relationships with community members, rather than relying on green-washing or advertising slogans as in the Forbes report (Payson 2021). The local common components of the G pillar plunged after the early oil price shock and stayed at the lower level, though some increases

pillars due to lockdown. The pandemic not only posed challenges in social responsibility fulfilment but also built up their resilience and adaptability to shocks by accelerating ESG integration into supply chains. During the period of zero-COVID policy, more rigorous lockdown policies were adopted and companies with robust supply chains were better positioned to respond effectively to the crisis. Thus, the increasing scores in E and S pillars contribute to the improvement in IVA.

[12]Although English and German legal systems in general offer more flexibility and adaptability in response to economic shocks, France adopted a more targeted government support measures to adapt the existing rules for active workers, the unemployed and those suffering from Covid-19, which got reflected in sustained S scores during and beyond the pandemic.

Figure 2.3: Local common components of IVA, E, S and G scores across 4 legal origins



are observed after the pandemic except for French legal origin.

2.3.3 Determinants of ESG ratings and systematic components

Given the heterogeneous time varying patterns of global and local common components of ESG activities, we examine their associations with individual firm characteristics, country-specific macro-variables, the global event and the legal origin dummies, using the following panel data regression model with fixed effects (FE):

$$y_{ijt} = \boldsymbol{\beta}_c' \boldsymbol{x}_{ct-1} + \boldsymbol{\beta}_f' \boldsymbol{x}_{ij,t-1} + \beta_d d_t + \boldsymbol{\beta}_\ell' \boldsymbol{\ell}_i + e_{ijt}, \; i = 1, ..., R, \; j = 1, ..., N_i, \; t = 1, ..., T, \qquad (2.3.2)$$

where $\boldsymbol{x}_{ct}$ is a $k_c \times 1$ vector of country-specific macroeconomic regressors for $c = 1, ..., C$, $\boldsymbol{x}_{ijt}$ is a $k_f \times 1$ vector of firm-specific regressors, d_t is a dummy regressor for the Covid pandemic, $\boldsymbol{\ell}_i$ is a $k_\ell \times 1$ vector dummy regressors for legal origins and $e_{ijt} = \alpha_i + u_{ijt}$ is the one-way error component. We employ ESG_{ijt}, $\widehat{ESG}_{ijt}^G = \hat{\gamma}_{ij}' \hat{G}_t$, $\widehat{ESG}_{ijt}^F = \hat{\lambda}_{ij}' \hat{F}_{it}$ as a respective dependent variable, y_{ijt}, and consider covariates given by $\boldsymbol{x}_{c,t-1} = (g_{c,t-1}, \pi_{c,t-1})$ and $\boldsymbol{x}_{ij,t-1} = (size_{ij,t-1}, ROE_{ij,t-1}, leverage_{ij,t-1})$, where g is the seasonally adjusted quarterly real GDP growth rate (measured in the US dollar), π is the CPI inflation rate (with the base year 2015) collected from IMF, $size$ is the company size measured by the logarithm of total assets, ROE is the return on equity measured by the ratio of net income to shareholder equity, and *leverage* is the ratio of long-term debt to shareholder equity, collected from Compustat. We construct the COVID pandemic dummy, d_t, taking the unity during 2019Q4–2023Q2 and zero otherwise, and legal origin dummies $\boldsymbol{\ell}_i = (French, German, Scandinavian)$. We then apply the FE estimator to (2.3.2) using the dataset containing quarterly observations of 3,892 companies over 2014Q1–2023Q4.[13]

Table 2.2 reports the regression results. First, we observe that the sign and significance associated with the coefficients of GDP growth and inflation for the systematic global and local common components of ESG match in almost all cases with those of raw data except for local common components in the E pillar and global common components in the G pillar. Both GDP growth and inflation enhance ESG activities for IVA and the E/S/G pillars, suggesting that GDP growth enables investments in sustainable practices, green technologies and in regulatory compliance while inflation enhances the profitability of firms and hence motivates firms for improvement in innovation & infrastructure and employment of renewable energy resources, thus explaining the positive association between inflation and ESG or its global components. However, the impact of GDP growth on local common components is negative and insignificant in the E pillar whereas both growth and inflation exert negative impacts on local common components in the G pillar.

Second, the impacts of company size are mostly positive and significant for the raw data and global/local common components except for the G pillar, in line with the stakeholder theory that higher ESG performance is expected in larger firms because of their richer resources and strategy to cope with higher pressure from the public and regulatory bodies (Drempetic et al. 2020). ROE and leverage ratio exert positive and negative impacts on ESG scores and global common components, respectively, whilst their impacts become insignificant for local common components. The positive effect of profitability (ROE) on ESG supports the legitimacy and stakeholder theories documenting that profitable companies, monitored by diverse stakeholders, tend to improve ESG practices as a contribution to the value and well-being of stakeholders and the society (Muttakin & Khan 2014). The negative effect of financial leverage aligns with existing studies showing that highly leveraged companies have limited resources to invest in ESG activities (Lourenço & Branco 2013).

Third, the impacts of the Covid dummy remain positive and significant for the IVA and E/S pillars. As awareness of sustainability risk is likely to increase in the long run, the COVID crisis can act as a positive catalyst for ESG, aligning with flight-to-quality hypothesis (Urbonavicius

[13] The quarterly data is employed to match data frequency of macro covariates. As GDP are unavailable for 2 countries (Bermuda in English legal origin and Panama in French legal origin), we remove 19 out of 3,911 companies. To avoid any contemporaneous endogeneity, we use the lagged values of firm and macro covariates. The coefficients on legal origin dummies are estimated by the 2-step procedure: we first construct the residuals from (2.3.2) by $\hat{e}_{ijt} = y_{ijt} - \hat{\boldsymbol{\beta}}_c' \boldsymbol{x}_{ct-1} - \hat{\boldsymbol{\beta}}_f' \boldsymbol{x}_{ij,t-1} - \hat{\beta}_d d_t$, where $\hat{\boldsymbol{\beta}}_c, \hat{\boldsymbol{\beta}}_f and \hat{\beta}_d$ are the FE estimates. Next, we run the between regression of $\hat{e}_{ijt} = a_i + \boldsymbol{\beta}_\ell' \boldsymbol{\ell}_i + error_{ijt}$ to estimate $\hat{\boldsymbol{\beta}}_\ell$.

& Chirita 2023). Given the widespread lockdowns and less industrial activities caused by the pandemic, the external environment with less pollution and emission contributes to higher E scores for companies (Al Amosh & Khatib 2023). Moreover, the pandemic underscored the important engagement with diverse stakeholders through initiatives such as safety and health measures and remote work, improving S scores (Obrenovic et al. 2020). But, we have mixed results for the G pillar. Although some companies exhibit higher resilience with strong ESG ratings, this unprecedented crisis led to challenges in corporate governance, such as risk management, effective oversight and decision-making.

Fourth, taking the English common legal origin as a benchmark, the positive (negative) dummy coefficients imply that the civil legal origin can produce a higher (lower) ESG performance than the English counterpart. For the raw ESG data Scandinavian legal origin is the only one that dominates English legal origin except the G pillar, though the difference is significant only for IVA. However, the coefficients on the French and German legal origin dummies become significantly negative except the E pillar, implying that the English common law counties can achieve higher performance than French and German counterparts in S and G pillars. Our results are not in line with Liang & Renneboog (2017), who document the positive coefficients on all three civil legal origins across the E/S/G pillars. This difference may be due to the use of different samples and time periods. Notice that our data covers more recent period including both voluntary and mandatory reporting periods. Furthermore, the civil legal origin dummy coefficients are mostly negative for both global and local common components of IVA and E/S/G pillars, indicating that the systematic ESG activities are weaker for civil law system than for common law system. Taken together, these results do not provide support for the second generation of legal origin theory (Kock & Min 2016, Liang & Renneboog 2017, Kim et al. 2017), showing hat ESG performance is always stronger in civil law countries than in common law countries.

Finally, the adjusted R^2s for global common components are substantially higher than those for the raw data and local common components in all cases. In particular, R^2s for the raw data, global and local common components in IVA are 7.4%, 50.6% and 1.1%, respectively. This implies that systematic global common components can be well predicted by company and macro determinants while the raw data and local common components are harder to predict.

In sum, our findings show the presence of single global factor across legal origins in overall ESG as well as in three of its components, thereby reflecting the ESG trend/globalisation. The single global factor signals for integration of ESG in investment strategies where ESG principles can turn out to be another dimension of risk-return diversification. High R^2 in explaining global factors using macroeconomic and firm-specific variables along with global event and legal origins

Table 2.2: Determinants of ESG and systematic components

X \ Y	IVA	IVA_G	IVA_F	E	E_G	E_F
GDP growth	2.128*** (0.745)	0.704** (0.354)	0.058 (0.459)	1.292* (0.778)	1.915*** (0.400)	-0.262 (0.698)
Inflation	12.29*** (3.712)	9.013*** (2.295)	1.920 (1.241)	10.027*** (2.175)	11.28*** (2.889)	5.003** (2.124)
Company size	0.253*** (0.035)	0.193*** (0.019)	0.061*** (0.023)	0.318*** (0.059)	0.170*** (0.017)	0.107*** (0.042)
ROE	0.003*** (0.001)	0.001* (0.001)	-0.001 (0.001)	-0.005* (0.003)	0.001** (0.001)	-0.002 (0.003)
Leverage ratio	-1.78E-04*** (6.62E-05)	-6.11E-05* (3.17E-05)	6.17E-05 (7.07E-05)	1.58E-04 (1.27E-04)	-5.22E-05* (3.03E-05)	1.03E-04 (1.81E-04)
COVID	0.257*** (0.012)	0.205*** (0.005)	0.060*** (0.010)	0.202*** (0.018)	0.162*** (0.006)	0.122*** (0.018)
French law	-0.097** (0.039)	-1.116*** (0.094)	-1.357*** (0.124)	0.013 (0.09)	-1.160*** (0.099)	-1.273*** (0.113)
German law	-0.322*** (0.033)	-1.726*** (0.081)	-2.282*** (0.106)	-0.756*** (0.077)	-1.822*** (0.085)	-2.085*** (0.097)
Scandinavian law	0.398*** (0.075)	-0.045 (0.183)	-0.226 (0.241)	0.251 (0.174)	-0.075 (0.193)	-0.162 (0.220)
First-stage R^2 Second-stage R^2 Observations	7.38% 3.24% 92561	50.57% 11.98% 92561	1.11% 11.68% 92561	2.52% 2.53% 92561	36.99% 11.95% 92561	0.99% 11.82% 92561

X \ Y	S	S_G	S_F	G	G_G	G_F
GDP growth	2.079*** (0.767)	0.391 (0.413)	0.976* (0.513)	0.216 (1.372)	-2.731*** (0.261)	1.704* (0.968)
Inflation	7.526*** (2.667)	9.655*** (2.591)	2.002 (1.387)	14.16*** (4.502)	-4.419*** (1.040)	13.21*** (4.638)
Company size	0.135*** (0.049)	0.111*** (0.011)	0.056 (0.039)	-0.062 (0.052)	-0.031*** (0.004)	0.133*** (0.042)
ROE	0.004** (0.002)	0.001* (3.53E-04)	0.003 (0.002)	0.004** (0.002)	-0.001* (3.06E-04)	-0.001 (0.004)
Leverage ratio	-1.67E-04* (9.27E-05)	-4.09E-05** (1.85E-05)	-1.10E-04 (1.24E-04)	-3.42E-04*** (1.10E-04)	3.74E-06 (1.69E-05)	1.01E-04 (2.14E-04)
COVID	0.327*** (0.018)	0.209*** (0.005)	0.069*** (0.016)	0.003 (0.019)	-0.139*** (0.002)	0.249*** (0.019)
French law	-0.350*** (0.089)	-1.259*** (0.112)	-1.366*** (0.125)	-1.573*** (0.152)	-1.535*** (0.147)	-1.217*** (0.106)
German law	-1.374*** (0.077)	-2.050*** (0.096)	-2.302*** (0.107)	-2.757*** (0.130)	-2.690*** (0.126)	-1.952*** (0.091)
Scandinavian law	0.039 (0.174)	-0.149 (0.217)	-0.232 (0.243)	-0.376 (0.295)	-0.360 (0.286)	-0.116 (0.206)
First-stage R^2 Second-stage R^2 Observations	1.37% 7.66% 92561	55.21% 11.81% 92561	0.35% 11.66% 92561	0.29% 11.27% 92561	12.92% 11.4% 92561	0.38% 11.86% 92561

Note: We report the FE estimation results for (2.3.2) using the quarterly data for 3,892 companies over 2014Q1–2023Q4. IVA, IVA_G and IVA_F refer to the aggregate ESG score, the global common component and the local common components, respectively. Similarly for E, S and G pillars. First-stage R^2s refer to the variances of ESG scores explained by the macro and firm-specific variables and COVID dummy. Second-stage R^2s refer to the variances of ESG scores explained by legal origin dummies. Robust standard errors are included in parentheses. ***, ** and * indicate the significance of the coefficient at the 1%, 5% and 10% level, respectively.

dummies imply 'doing well doing good' works well here, in contrast to raw data and local factors. The presence of multiple local factors portrays volatile components of ESG due to region-specific environmental, social, and governance factors that are formed by local culture, laws, development and institutional norms, thereby demanding for region specific strategies and resolutions. The higher relative importance ratios of local factors and idiosyncratic components combined with low R^2s in regression analysis reflects noises and uncertainties of the ESG disclosure and data.

Using extended data covering both voluntary and mandatory reporting periods, our findings are generally inconsistent with the earlier studies, e.g., Liang & Renneboog (2017). This finding may suggest that an extended legal origin theory perhaps work better, along with a call for political and adaptability mechanism as postulated by Graff (2008). If firms belonging to a certain legal origin country already attains a certain level of corporate sustainability, its importance appears to decrease. Investing in corporate sustainability in less sustainable countries turns out to be advantageous, though this relationship may not be valid in more sustainable countries since firms have already exploited many of the existing opportunities, thus leading to over-investment in corporate sustainability.[14] Adaptations in local legal and cultural factors could lead to diverse approaches to ESG implementation, potentially undermining a universal approach. This suggests that the global mandate reporting standards would be a more important determinant of ESG performance and focus on global factor can improve (future) ESG disclosure.

2.4 Robustness Analysis using the Refinitiv ESG Data

To investigate the robustness of the above results, we consider the alternative dataset containing annual observation of 2,306 companies from 60 countries over the period 2002 to 2023, collected from the Refinitiv database. We use the ESG aggregate rating and the three components constituting the ESG: the environmental, social and the governance scores (see Appendix B.1 for data details).[15]

The descriptive statistics for Refinitiv ESG data reported in Table 2.3, show that the Scandinavian legal origin ranks the first in ESG and individual E/S pillars while the ranking among English, French and German legal origins is not monotonic. For ESG and S pillar, French legal origin has a higher score than German and English counterparts. For E pillar, German legal origin shows a higher score than French and English counterparts. On the other hand, English legal origin records

[14] Common law system is shown to exhibit the stronger positive reaction of environmental performance in response to international agreements, e.g., Kyoto protocol (Eberlein & Matten 2009, Kock & Min 2016). This reflects that civil law countries have already incorporated stakeholders' environmental demands into their institutional logic, with limited scope for changing the policy.

[15] Refinitiv dataset is of annual frequency and covers longer time periods while MSCI data is of monthly frequency subject to more short-term fluctuations and covers shorter periods. Both datasets cover different firms sample.

a top score for the G pillar, followed by French, Scandinavian and German legal origins. Overall, the civil legal origins tend to outperform the common legal origin in terms of ESG and E/S scores whilst the reverse holds for the G pillar. These results are qualitatively similar to those obtained for the MSCI dataset.

Table 2.3 shows presence of one global factor irrespective of ESG ratings or its three components. The number of local factors is 1 for ESG and 2 for E scores, and mostly ranges between 1 and 2 for S and G scores, respectively. We now notice the dominance of global factors in explaining the ESG variances. For example, RI ratios of global common components in aggregate ESG are well over 55.5%. Turning to the E/S pillars, global common components still exhibit higher RI ratios than the local counterparts for all legal origins, except for S pillar in German legal origin. This suggests that global common components provide a more comprehensive explanation behind ESG transitions. The G pillar displays an opposite pattern, showing higher RI ratios for local components than global ones across legal origins. Finally, we observe that the average RI ratios of idiosyncratic components range between 16.6% and 33.8% in three individual pillars while RI ratios in aggregate ESG are smaller than 14% across legal origins. Overall, the current results are quite different from those obtained for MSCI data. Combining significantly higher RIs of the global common components and relatively negligible RIs of idiosyncratic components, we conjecture that the Refinitiv ESG data is likely to be subject to less noises and uncertainties related to ESG disclosures than MSCI data.

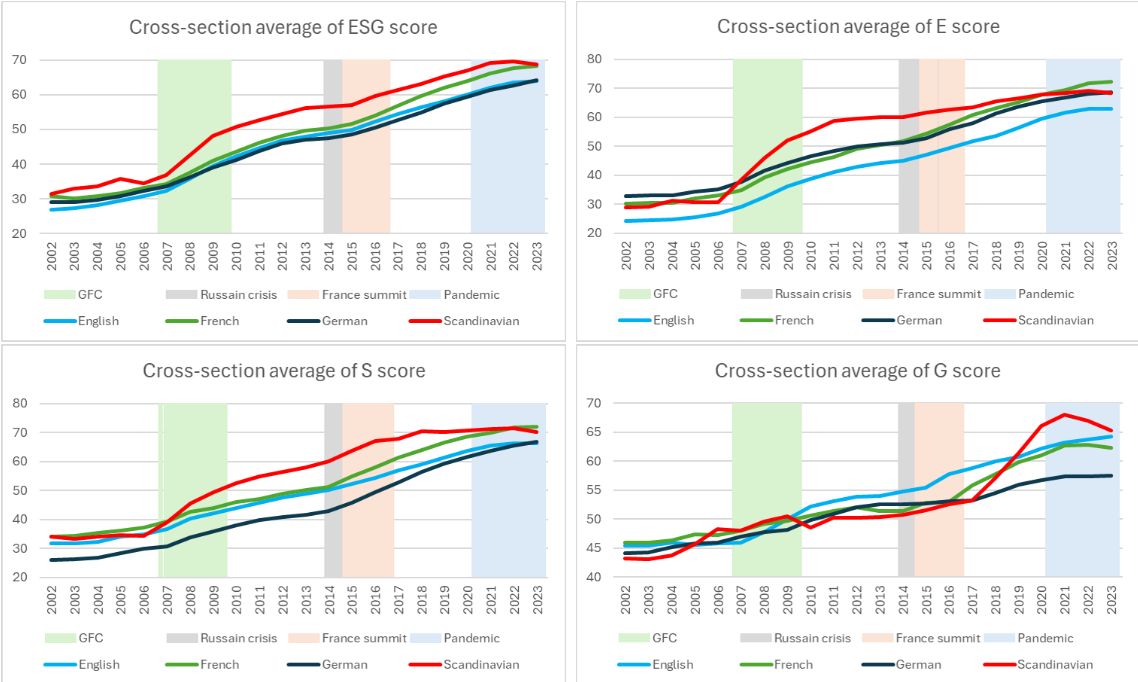
Table 2.3: Main empirical results for 4 legal origins using Refinitiv/LSEG ESG scores

Variable	Legal origin	N_c	N_i	Mean	Std	$\hat{r}_0$	$\hat{r}_i$	RI_G	RI_F	RI_E
ESG score	English	18	1210	45.496	21.870	1	1	0.559	0.325	0.116
	French	31	420	48.035	23.507	1	1	0.555	0.329	0.116
	German	7	576	45.301	22.934	1	1	0.567	0.292	0.142
	Scandinavian	4	100	52.152	21.190	1	1	0.641	0.233	0.126
	Sum/Average	60	2306	46.199	22.473	1		0.580	0.295	0.125
Environmental score	English	18	1210	42.786	26.501	1	2	0.411	0.408	0.181
	French	31	420	49.871	27.770	1	2	0.474	0.370	0.156
	German	7	576	49.965	26.789	1	2	0.464	0.379	0.157
	Scandinavian	4	100	53.386	26.944	1	2	0.460	0.370	0.170
	Sum/Average	60	2306	46.329	27.092	1		0.452	0.382	0.166
Social score	English	18	1210	48.428	22.916	1	2	0.485	0.384	0.131
	French	31	420	51.477	26.344	1	1	0.487	0.266	0.247
	German	7	576	43.706	26.057	1	2	0.416	0.419	0.166
	Scandinavian	4	100	54.924	24.185	1	2	0.506	0.309	0.184
	Sum/Average	60	2306	48.086	24.614	1		0.473	0.345	0.182
Governance score	English	18	1210	53.894	22.111	1	2	0.272	0.401	0.328
	French	31	420	52.930	21.860	1	1	0.312	0.320	0.369
	German	7	576	51.098	22.961	1	1	0.269	0.336	0.395
	Scandinavian	4	100	52.921	22.431	1	3	0.290	0.450	0.260
	Sum/Average	60	2306	52.978	22.324	1		0.286	0.377	0.338

We report the GCC estimation results for (2.2.1) using the annual data for 2,306 companies over 2002–2023 from the Refinitiv/LSEG Database. N_c and N_i are the number of countries and firms in each legal origin. Mean and Std represent the mean and standard deviation of ESG scores. $\hat{r}_0$ is the number of global factor estimated from the model (2.2.1) by the GCC criterion, while $\hat{r}_i$ is the number of local factors estimated by the ER criteria after projecting out one global factor. RI_G, RI_F and RI_u are the relative importance ratios of global, local and idiosyncratic components measuring the contribution of each component to the explained variance of ESG metrics (see also footnote 2).

Figure 2.4 displays the time-varying patterns of the raw ESG data, displaying a smooth upward trend for all legal origins. Scandinavian legal origin tops the list, followed by French legal origin. English legal origin began to outperform German legal origin since 2009. After the Covid pandemic, Scandinavian legal origin sustains a mild decline, but three other legal origins stay relatively stable. E scores continue to gradually increase across legal origins, with English legal origin at the bottom. Prior to the global financial crisis (GFC), German and French legal origins outperformed. Then, Scandinavian legal origin gained an edge until 2020, after which it is overtaken by French legal origin. The time varying patterns of S scores look similar to those of E scores with the main difference that German legal origin remains at the bottom. Again, Scandinavian origin began to outperform during GFC, but lost its leading position, surpassed by French legal origin after the pandemic. G pillar shows substantially higher volatilities especially for Scandinavian legal origin. Since GFC, English legal origin remained on top, but Scandinavian legal origin experienced a rapid rise from mid 2017 and became the top performer since 2019. We note two stylised findings: first, Scandinavian legal origin maintains the best performance. Next, civil law countries outperform common law countries in ESG and E/S pillars, while English common legal origin achieves higher scores than French and German counterparts for the G pillar. Overall, these results are qualitatively

Figure 2.4: Cross-section averages of Refinitiv ESG, E, S and G scores across 4 legal origins

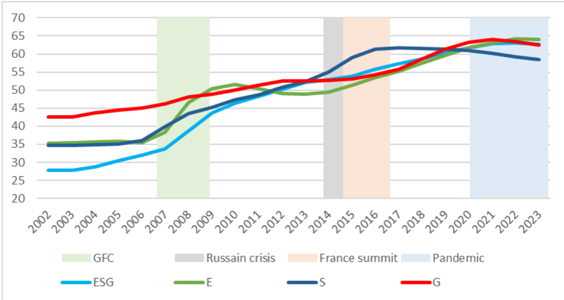


similar to those obtained for the MSCI dataset.

Figure 2.5 displays the time-varying patterns of (average) global common components. The global common components of ESG exhibits a smooth upward trend, closely resembling the raw data in Figure 2.4. Initially, there was a gradual increase in the global common component, followed by a significant increase during GFC. Although this crisis destroyed public trust in the financial industry, it still underscored the importance of integrating non-financial factors into investment decisions to implement stricter corporate regulations and oversight. The upward trend continues, especially following the Paris Climate Summit in 2016. During the Covid pandemic, global common components of S and G pillars started to decline while those of E pillar continued to rise. As a result, global common components of the aggregate ESG remained unchanged. In particular, slow-downs of global common components have recently been observed in both datasets, implying that ESG measurement and framework tend to be standardised, following recent mandatory reporting initiatives. This can improve the quality and coherence of ESG datasets between raters (Ioannou & Serafeim 2019).

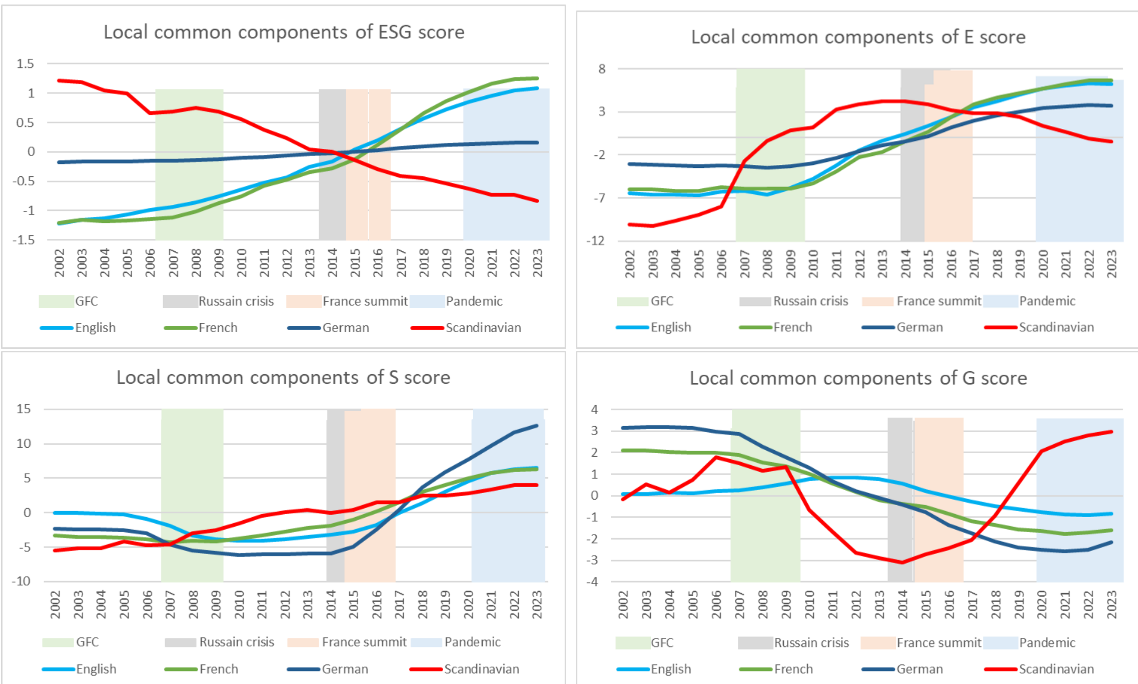
Figure 2.6 portrays the time-varying patterns of (average) local common components. Significant heterogeneities are observed across legal origins. Time-varying patterns of local common components of ESG consist of three groups. The local common components of ESG for English and French legal origins display an increasing trend while German legal origin stays relatively stable. Scandinavian legal origin exhibits a declining trend mainly caused by G pillar and to some extent by E pillar after

Figure 2.5: Global common components of Refinitiv/LSEG ESG, E, S and G scores



the pandemic. Following the pandemic shocks, companies in Scandinavian origin sustained a further fall in ESG and E ratings. The local common components of the E pillar continue to grow gradually for the three legal origins, except Scandinavian legal origin that exhibits an inverse U-shape, with an initial upward trend (even a jump during GFC) and a downward trend starting from the Russian crisis. Interestingly, the local E performance of English and French legal origins eventually tops the list. During the GFC period the local common components of the S pillar in Scandinavian legal origin continued to rise while those of the other legal origins sustained falls. German legal origin experienced a rapid rise from 2015 and began to outperform the other three legal origins since 2018. The local common components of the G pillar plunged during GFC, except English legal origin. They continued to decline though only Scandinavian legal origin started to bounce back and grow. Overall, time-varying patterns of local common components become significantly different between Refinitiv and MSCI datasets, indicating that there are substantial heterogeneities in local factors.

Figure 2.6: Local common components of Refinitiv/LSEG ESG, E, S and G across 4 legal origins



Next, we examine the associations of Refinitiv ESG datasets and their global and local common components with macro factors, firm-specific characteristics, the COVID dummy and the legal origin dummies containing annual observations of $2,211$ companies during 2002 and 2023.[16] Table 2.4 reports the regression results. First, we also observe that the sign and significance of the coefficients of GDP growth and inflation for the systematic global and local common components of ESG match in almost all cases with those of raw data except for local common components in ESG and G pillar. Unlike in MSCI data, however, the impacts of both GDP growth and inflation are mostly negative for ESG and E/S/G pillars.

Second, the impacts of firm characteristics share some similarities and differences to those from MSCI data. The impacts of company size and ROE are mostly positive and significant for the raw data and global/local common components. On the contrary, the impacts of leverage ratio become mostly insignificant.

Third, the COVID pandemic exerts a significantly positive effect on ESG data and their global/local common components. This is in line with the previous results for MSCI dataset.

Fourth, turning to the legal origin dummies, we find that Scandinavian and French legal origins significantly outperform English legal origin for ESG scores and global common components except G pillar whilst the German legal origin is outperformed by English legal origin except E pillar. These results provide some support for existing studies (e.g., Liang & Renneboog (2017)), documenting that ESG performance tends to be stronger in civil law countries. Next, unlike in MSCI dataset, the dummy coefficients are mostly positive for both global and local common components in the civil law system except G pillar, implying that their systematic ESG activities can be stronger than those in common law system.

Finally, R^2s for global common components are significantly higher than those for the raw data and local common components in all cases. For instance, R^2s for the raw data, global and local common components in ESG are 23.2%, 32.1% and 0.1%, respectively, also confirming that systematic global common components can be better predicted by company and macro determinants.

2.4.1 Discussions

In sum, our analysis using Refinitiv ESG data reveals presence of a single global factor across legal origins, also reflecting ESG trend/globalisation. Although the time-varying patterns of the ESG data

[16] All the variables are measured in annual frequency. As GDP and CPI data are unavailable for 5 countries (Bermuda, Jersey and Cayman Island in English legal origin, Puerto Rico in French legal origin, and Taiwan in German legal origin), we remove 95 out of $2,306$ companies.

Table 2.4: Determinants of Refinitiv/LSEG ESG and systematic components

X \ Y	ESG	ESG_G	ESG_F	E	E_G	E_F
GDP growth	-74.19***	-89.72***	4.37***	-85.89***	-58.48***	-27.81***
	(1.902)	(1.456)	(1.173)	(2.372)	(1.104)	(1.725)
Inflation	-111.6***	-130.8***	9.84**	-125.5***	-59.87***	-68.13**
	(8.048)	(6.162)	(4.963)	(10.04)	(4.671)	(7.298)
Company size	0.701***	0.731***	0.219***	0.149	0.284***	-0.195
	(0.102)	(0.078)	(0.063)	(0.127)	(0.059)	(0.093)
ROE	0.085*	0.133***	-0.040	0.035	0.100***	0.016
	(0.046)	(0.035)	(0.028)	(0.057)	(0.027)	(0.042)
Leverage ratio	0.001	0.009	-0.006	0.007	0.006	-0.004
	(0.007)	(0.006)	(0.004)	(0.009)	(0.004)	(0.007)
COVID	18.57***	16.31***	-0.042	20.37***	14.87***	5.628***
	(0.176)	(0.135)	(0.109)	(0.219)	(0.102)	(0.160)
French law	3.014***	3.234***	-0.422***	8.663***	8.211***	0.446
	(0.277)	(0.242)	(0.110)	(0.343)	(0.274)	(0.159)
German law	-3.937***	-4.619***	-0.365***	5.669***	5.297***	0.578
	(0.249)	(0.218)	(0.099)	(0.309)	(0.247)	(0.144)
Scandinavian law	6.060***	5.649***	0.241	10.395***	10.145***	0.264
	(0.477)	(0.418)	(0.190)	(0.592)	(0.472)	(0.275)
First-stage R^2	23.16%	32.13%	0.09%	18.43%	38.57%	4.38%
Second-stage R^2	1.72%	2.65%	0.06%	2.28%	3.21%	0.04%
Observations	39799	39799	39799	39799	39799	39799

X \ Y	S	S_G	S_F	G	G_G	G_F
GDP growth	-77.04***	-85.12***	-1.302	-28.21***	-31.79***	7.474***
	(2.130)	(1.308)	(1.389)	(2.242)	(0.723)	(1.508)
Inflation	-126.6***	-174.2***	-23.47***	-56.52***	-63.33***	1.025
	(9.015)	(5.534)	(5.878)	(9.488)	(3.060)	(6.383)
Company size	0.533***	0.659***	0.056	0.416***	0.257***	0.176**
	(0.114)	(0.070)	(0.075)	(0.120)	(0.039)	(0.081)
ROE	0.046	0.115***	-0.047	0.134**	0.051***	0.056
	(0.051)	(0.031)	(0.033)	(0.054)	(0.017)	(0.036)
Leverage ratio	0.002	0.005	-0.007	-0.005	0.008***	-0.010*
	(0.008)	(0.005)	(0.005)	(0.009)	(0.003)	(0.006)
COVID	20.01***	10.40***	7.881***	10.09***	12.60***	-1.900***
	(0.197)	(0.121)	(0.129)	(0.207)	(0.067)	(0.140)
French law	4.143***	4.442***	-0.270***	-1.347***	-1.014***	-0.306**
	(0.308)	(0.261)	(0.128)	(0.297)	(0.222)	(0.139)
German law	-8.406***	-9.062***	-0.573**	-5.240***	-4.885***	-0.479***
	(0.278)	(0.235)	(0.115)	(0.268)	(0.200)	(0.125)
Scandinavian law	6.075***	6.048***	-0.156	-1.570***	-1.338***	-0.298
	(0.532)	(0.450)	(0.221)	(0.513)	(0.383)	(0.240)
First-stage R^2	21.31%	22.16%	4.15%	1.40%	49.35%	0.68%
Second-stage R^2	3.97%	6.19%	0.06%	0.95%	1.49%	0.03%
Observations	39799	39799	39799	39799	39799	39799

Note: We report the FE estimation results for ESG scores on legal origin dummies using the annual data for 2,211 companies over 2002–2023 from the Refinitiv/LSEG Database. ESG, ESG_G and ESG_F refer to the aggregate ESG score, the global common component and the local common components, respectively. Similarly for E, S and G pillars. First-stage R^2s refer to the variances of ESG scores explained by the macro and firm-specific variables and COVID dummy. Second-stage R^2s refer to the variances of ESG scores explained by legal origin dummies. Robust standard errors are included in parentheses. ***, ** and * indicate the significance of the coefficient at the 1%, 5% and 10% level, respectively.

and global common components are qualitatively similar to those obtained for the MSCI dataset,[17] we now observe the dominance of global factors in explaining the ESG variances, compared to local factors. The higher importance of the local common component presented in MSCI data may suggest that they put more emphasis on local regulations and cultural norms in ESG assessment, whereas a greater importance of the global common component observed in Refinitiv data reflects that they prioritise universal ESG standards and international benchmarks.[18] This finding highlights significant discrepancies in ESG factor structures across legal origins, particularly in the MSCI dataset, where local factors dominate due to inconsistent reporting practices. Prior literature (Berg, Koelbel & Rigobon 2022, Christensen et al. 2022) demonstrate that jurisdictional differences in ESG disclosure requirements lead to incomparable and noisy data. Mandatory global standards, such as those proposed by the International Sustainability Standards Board (ISSB) under IFRS S1 (general requirements for disclosure of sustainability-related financial information) and S2 (climate-related disclosures), aim to harmonise disclosures, reducing measurement divergences (see IFRS Foundation annual report in 2023). Furthermore, combining Refinitiv's much smaller relative importance of idiosyncratic components compared to MSCI data and higher R^2 in explaining global factors using macroeconomic and firm-specific variables, we argue that the Refinitiv ESG data is likely to be more standardised and subject to less noises and uncertainties related to ESG disclosures than MSCI ESG data. A mandatory reporting regime like the EU's Corporate Sustainability Reporting Directive (CSRD) has been shown to improve data comparability by enforcing double-materiality assessments and third-party assurance. See the Proposal for a directive of the European Parliament and of the Council amending Directive by European Commission (2021). Similarly, the climate disclosure rules proposed by the U.S. Securities and Exchange Commission in 2022 emphasise granular, audited ESG data, which would enhance the signal-to-noise ratio in ratings (Securities et al. 2022). In addition, the results obtained for Refinitiv ESG data provide some support for the second generation of the legal origin theory (e.g., Kock & Min (2016), Liang & Renneboog (2017) and Kim et al. (2017)).

In terms of data collection/classification and construction of indices, there exists substantial differences between the two raters. On one hand, MSCI follows a dual approach of "exposure" and "management" to evaluate ESG risks and opportunities by using Global Industry Classification

[17] We compute the correlation coefficients for the cross-sectional average of overall rating as well as ratings for different pillars across two datasets over 2014-2023 in Table B.3 (see Appendix B.1). The correlations between MSCI and Refinitiv data in overall ESG ratings and E/S pillars are high (except for S pillar in Scandinavian legal origin), while it is low in English legal origin or even negative in French and German legal origins for G pillar. Although the existing studies (Billio et al. 2021, Berg, Koelbel & Rigobon 2022) find that the average pairwise correlation between ESG raters is around 0.5, correlation coefficients being higher than 0.5 in our datasets may be due to the aggregation from the cross-section averages.

[18] "The universe of companies for which ESG data is maintained and ESG scores are calculated consists of 12,000 public and private companies globally" (Refinitiv 2022). ESG scores are updated every week.

Standard (GICS) to classify companies. Also, the G pillar score is treated separately due to its foundational importance in managing risks and opportunities. On the other hand Refinitiv includes broader range of ESG metrics using its own industry classification. MSCI adjusts scores based on relevance and timing of industry-specific factors, though the MSCI's scoring methodology is not always unveiled. MSCI tends to be forward-looking as it evaluates factors such as corporate policies, controversies, and the company's position for future ESG risks and opportunities, whilst Refinitiv relies on publicly reported data, including self-reported information from companies. Past research provides an explanation behind the raters divergence. Chatterji et al. (2016*a*) raise the issue of whether it is measured consistently (called "theorisation" and "commensurability"). Berg, Koelbel & Rigobon (2022) extend this analysis by providing three sources of divergence across the raters: scope, measurement and weight, and show that scope and measurement play a pivotal role. We conclude that it is still complex and multifaceted to uncover the relationships between ESG factors and firm characteristics/macro variables/legal origins, supporting the literature on ESG rating divergence and uncertainty (Avramov et al. 2022, Christensen et al. 2022, Berg, Koelbel, Pavlova & Rigobon 2022). A unified framework not only can strengthen the global factor's dominance by aligning reporting metrics, but also suppress local biases arising from legal origin-specific interpretations. Therefore, we advocate for global adoption of ESG standards, as voluntary frameworks (e.g., SASB, GRI) have proven insufficient in curbing divergence (Christensen et al. 2021). Cross-country regulatory coordination, as seen in the G20's endorsement of ISSB, is critical to ensuring consistency for investors (Financial Stability Board, 2023). In this regard, mandatory global standards are expected to directly address the root causes of ESG data inconsistencies, enhancing the reliability of systematic component of ESG ratings.

2.5 Concluding Remarks

ESG is a framework that considers non-financial factors impacting a company's long-term success. ESG has evolved beyond just environmental issues and now extends to social and governance aspects. However, existing literature fails to reach a consensus on the ESG performance, mainly because ESG data can be noisy and uncertain due to data quality, metrics/aggregation and industry/country regulations. It is challenging to navigate all these complexities while aligning with the different ESG disclosure reporting standards between common and civil law systems. We have addressed this important issue by identifying and analysing systematic and noisy components of ESG activities through employing the multilevel factor model and applying the data-driven GCC approach.

We first conduct the GCC analysis using the MSCI dataset containing $3,911$ companies monthly observations of IVA ratings and its three E/S/G components over January 2014–December 2023, and find one systematic global factors across the four legal origins (English, French, German and Scandinavian) for IVA ratings and its three components, reflecting ESG trend/globalisation. The number of local factors varies across legal origins and sub-components of ESG. We find the dominance of local factors and the large relative importance ratios of the idiosyncratic components in explaining the ESG variance. Next, we use Refinitiv/LSEG dataset containing annual observations of ESG rating and its three components for $2,306$ companies over 2002–2023. We also find a single global factor, but the different number of local factors across legal origins. We now notice the dominance of global factors and negligible RIs of idiosyncratic components in explaining the ESG variances. If all countries belonging to different legal origins be subject to the global mandatory reporting system, then we expect that the RIs of global factors can be stronger than RIs of local factors and idiosyncratic components. In this regard, we conjecture that the MSCI ESG data is likely to be subject to more noises and uncertainties associated with ESG disclosures than the Refinitiv ESG data.

Next, we explore the association between the ESG data and their global and local common components with country-specific macro and firm-specific variables along with Covid pandemic and legal origin dummies. Although the estimation results are different between MSCI and Refinitiv datasets, the sign and significance associated with these determinants for the systematic components of ESG still match in almost all cases with those of raw data. Furthermore, systematic global components can be well predicted by these determinants while the raw data and local components are harder to predict. More importantly, we find the mixed evidence on the impacts of legal origin on the ESG performance. The MSCI results are generally inconsistent with the existing studies, documenting that ESG performance is always stronger in civil law countries than in common law countries (Kock & Min 2016, Liang & Renneboog 2017, Kim et al. 2017). On the other hand the Refinitiv data provide some support for the second generation of the legal origin theory. As the GCC-based approach is data-driven, such different findings using two datasets point towards the raters' ESG divergence and uncertainty as postulated in the recent literature (Avramov et al. 2022, Christensen et al. 2022, Berg, Koelbel, Pavlova & Rigobon 2022).

We conclude that it is still complex and multifaceted to uncover the relationships between ESG factors and firm characteristics/macro variables/legal origins. We suggest that the relative importance ratios of the global factor be greatly improved relative to local factors and idiosyncratic components so as to better predict overall ESG performance. Given that the standards of ESG disclosure reporting are currently quite different between civil and common law countries, this goal can be achieved through enforcement of global mandatory reporting standards,[19] because the use

[19] While various standards were developed for different reporting purposes, ESG disclosure mandates are expanding.

of global standards and frameworks has a key role to play in making more consistent, comparable and reliable information available to investors.[20] Christensen et al. (2021) conduct a comprehensive literature review to examine the implications of mandatory CSR and sustainability reporting, and suggest that the effectiveness of mandatory reporting depends on the quality and consistency of reporting standards. Furthermore, due to the market-driven mechanism, policymakers in common law countries could enhance market-based incentives for companies with high ESG scores to develop more standardised ESG metrics. On the other hand, the governmental implementation of standardised ESG reporting framework may be more efficient in the rule-based civil law system.

Our work opens several avenues for continuing research. On the methodological side, there is scope to generalise our approach to jointly accommodate the spatial/network dependence in ESG performance. On the empirical side, our results motivate similar studies in other areas of the literature, such as in the commonality analysis of ESG scores across different rating agencies and the network analysis of ESG and sustainable development goal (SDG) across legal origins.

The EU's Corporate Sustainability Reporting Directive went into force in January 2023, requiring estimated 50,000 companies to file annual reports on business risks and opportunities related to social and environmental issues. Moreover, the Corporate Sustainability Due Diligence Directive, starting in 2027, will require qualifying companies to act on adverse human rights and environmental impacts in their own operations as well as their supply chains, see Craig (2024).

[20]Between 2000 and 2019 there was a 92% increase in mandatory and voluntary ESG disclosure frameworks. We are still some way from a global consensus on reporting standards. See six steps to improve your ESG performance by Mark Carney, Former Governor of The Bank of England, via the link https://simplysustainable.com/insights/six-steps-to-improve-your-esg-performance.

Chapter 3

Network Analysis of ESG and SDG across Legal Origins

Abstract We explore the relationship between ESG and SDG across legal origins (English, French, German, Scandinavian) using an integrated panel data model with local spillovers, global shocks and parameter heterogeneity. Applying the CCEX-IV approach and GCM network analysis, we find that civil legal origins show higher direct effects of ESG on SDG within each legal origin while common legal origin exhibits stronger spill-in effects, supporting the first- and second-generation legal origin theory. But, network analysis of aggregate ESG and its pillars indicates that English legal origin has the highest direct effects. Furthermore, heterogeneity is observed within civil legal origins, with German legal origin being the most influential shock transmitter, challenging the monolithic view of civil law countries and thereby raising the importance of accommodating sub-categorisation in legal origin theory.

Keywords: ESG, SDG, Heterogeneous Spatial Panel Data Models with Global Factors, Network Multipliers, Legal Origins, GCM analysis.

JEL codes: C33, O16, Q01.

3.1 Introduction

The United Nations (UN) in 2015 set seventeen interconnected global goals, known as Sustainable Development Goals (SDGs) aiming to address these goals by 2030. For example, the SDGs include poverty, hunger, health, education, gender equality, clean water, and climate action. Although the national governments are primarily responsible for achieving targets of SDGs, the businesses play the pivotal role in realising SDGs. The synchronisation of business activities and sustainable development therefore requires corporate actions with sustainability imperatives, giving rise to a framework known as environmental, social, and governance (ESG). According to Zhao et al. (2021), ESG criteria is closely interconnected with the United Nations' 2030 agenda for sustainable development. Firms following regulations for minimisation of negative environmental impacts could contribute significantly to achieve the SDG goals. Similarly, firm's involvement in protecting the rights of workers as well as maintaining strong and ethical relationships with stakeholders, and enhancing social equity, can not only make a progress towards achievement of the SDGs but also be a step towards resilient and inclusive society.

While ESG mainly emphasises on risks and opportunities related to environmental impact, social responsibility, and corporate governance by businesses, SDG on the other hand is a comprehensive blueprint for addressing global challenges. The adoption of ESG principles by businesses and investors can directly contribute to the achievement of the SDGs and therefore understanding the interplay between these two metrics is important for developing effective practices and strategies from three dimensions: (i) corporates' contributions in achieving the SDGs; (ii) increasing expectations from investors and stakeholders regarding alignment of ESG efforts towards SDGs and (iii) linking corporate ESG disclosures to national SDG commitments by the regulators. It is therefore important to examine the interconnectedness between SDG and ESG as mapping ESG scores against SDGs can guide companies to comply and track their sustainability strategies with sustainable growth, demonstrating the business actions and investment priority for investors and stakeholders. Research investigating the relationship between SDG and ESG is relatively scanty although there are some exceptions. For example, Plastun et al. (2020) document that better ESG performance does not always translate into significantly improved national SDG outcomes, but different impacts are observed in developed and emerging countries. Gidage & Bhide (2024) document significantly positive ESG impact on SDG accomplishment. Gosling & Walkate (2024) document limited contributions of sovereign ESG in achieving SDGs. See also Betti et al. (2018) and Khaled et al. (2021). But these studies suffer from (i) limited scope (focus on specific industries or regions), (ii) ignoring potential trade-offs (e.g., potential conflict between economic growth and environmental sustainability) along with role of corporate governance practices in attaining SDGs, and (iii) neglecting the role of cultural and institutional differences arising from different nature of legal origins in shaping the relationship between SDG and ESG.

Existing literature has almost paid no attention in understanding the spatial dynamics that underlie ESG/SDG outcomes and the interconnections between their relationship due to geographical variability or legal origin. For example, if neighbouring countries adopt stringent ESG regulations, it may prompt others to follow suit, creating a regional push towards sustainability and foster collaboration among firms, industries, and governments, leading to collective actions that enhance not only ESG outcomes but also can be a step towards achieving SDG goals across regions. Investors are increasingly looking at the ESG performance of firms as part of their decision-making processes and therefore understanding spatial dynamics can help investors assessing risks and opportunities more effectively, especially in regions where ESG practices are influenced by local networks or conditions. In practice, firms do not operate in isolation; they are often influenced by their peers and competitors, which can lead to a clustering of ESG practices and may help countries to reach their SDG targets. Given the variations in ESG/SDG strategies due to cultural, economic, and regulatory differences subject to the country's legal origin (Kock & Min 2016, Liang & Renneboog 2017), it is imperative to conduct a spatial analysis to capture these nuances based on legal origin, leading to a more accurate representation of what drives the performance of the overall ESG-SDG nexus. Although the analysis done by Kock & Min (2016) and Liang & Renneboog (2017) focus on legal origins as one of the determinants of ESG (CSR) activities, they remain silent regarding exploring the spatial dynamics that legal origins could play in shaping ESG activities around the world especially in terms of direct and indirect (spillover) effects. We believe that our paper is the first attempt in the existing literature exploiting the spatial dynamics across the legal origins not only in terms of ESG-SDG activities but also in terms of overall ESG ratings and three of its pillars: environment, social and governance.

Past literature remains silent regarding cross-sectional dependence while modelling the relationship between ESG and SDG. Countries and their legal systems are interconnected through trade, financial markets, and international regulations and hence policies and regulations initiated in one country can influence others due to global supply chains, multinational corporations, or international agreements (e.g., the Paris Agreement on climate change). Therefore, the legal origins of countries (civil law versus common law) play a pivotal role regarding the way through which ESG and SDG factors are incorporated into national frameworks. Common law systems often emphasise on greater shareholder protections and hence be more into the integration of ESG practices into corporate governance than the civil law systems as the latter mainly focus on stakeholder rights. On one hand, countries with different legal origins may share common trends in SDG or ESG performance influenced by similar legal or economic forces; on the other hand, countries may differ depending on economic development, regulatory framework and/or institutional quality even belonging to the same legal origin. Hence, allowing for cross-sectional dependence in examining the relationship between SDG and ESG is crucial.

We believe that we have made several contributions in the existing literature. Our first contribution stems from allowance for cross-sectional dependence while unravelling whether certain regions or legal systems share common trends or shocks that drive ESG or SDG outcomes, which has been completely ignored. Second, we contribute in the existing literature by incorporating spatial- and factor-dependence into modelling ESG/SDG scores, which can enhance the understanding of ESG/SDG performance and its determinants. Our estimation methodology also allows global factor dependence and heterogeneity of coefficients. Global factor dependence can mitigate the influences of unobserved external forces that could affect multiple companies/industries/countries and thereby reduce the risk of omitted variable bias whereas allowance for heterogeneity of parameters captures local variations reflecting the complexities of real-world phenomena, thus leading to more robust insights and better-informed decision-making. Third, we use trade weights as the spatial matrix with heterogeneous coefficients capturing economic factors at the country level. Fourth, we construct the network connected matrix at the legal origin level and measure group direct effects (GDE), group spill-in effects (GSI) and group spill-out effects (GSO), where GDE captures the direct impact within each legal origin, while GSI and GSO measure the impacts from other legal origins and the influence to other legal origins, respectively. We move a step further by constructing a two-dimensional analysis between the systematic influence (SI) and external motivation (EM) indices, where SI reveals relationship within the spatial system and EM refers to external factors often influenced by social, economic, political or global elements. Finally, we also uncover the network relationship between ESG and the three pillars.

Using an integrated panel data model that simultaneously accommodates local spillovers, global shocks and the parameter heterogeneity, we apply the CCEX-IV estimator by Chen et al. (2022) to consistently estimate all heterogeneous parameters. Next, we conduct the GCM analysis by Greenwood-Nimmo et al. (2021) and Shin & Thornton (2021), and analyse the network multipliers of SDG with respect to ESG by distinguishing the direct and indirect spillover effects across legal origins.

Using annual SDG Index collected from the SDG Transformation Center and IVA from MSCI Database for 41 countries over 2007-2023, we investigate the network causal relationship from ESG to SDG. By investigating the relative role of each legal origin in terms of respective direct and indirect effects within the system, we find that direct effect of ESG on SDG in civil legal origin is significantly higher than in common legal origin while spill-in effect is stronger in common legal origin. These results provide support to both the first and second generations of legal origin theory. The pronounced heterogeneous spillover patterns are observed across civil legal origins. In particular, spill-out effects from German legal origin dominate while its spill-ins are almost negligible, that renders it to be the most influential ESG shock transmitter in the system. On the other hand, French legal origin takes an opposite pattern while Scandinavian legal origin takes an intermediate position. Finally, the four legal origins lay along a line from north-west to south-east in the (EM, SI) coordinate that provides a vivid representation of their relative position in the ESG-SDG network, and shows that English and French legal origins are the main beneficiaries of ESG shocks, mainly from German legal origin.

As a robustness check, we uncover the determinants of aggregate IVA using the individual E/S/G pillars across legal origins by employing the extended monthly data from MSCI Database for 54 countries over the period January 2014-December 2023. We find that English legal origin obtains the highest GDE of E/S/G pillars on IVA, whereas the GDE ranking of civil legal origins varies across the individual pillar. As group direct effect within civil legal origin is lower than that within common legal origin, this does not support to the second generation of legal origin theory. Group spill-in to common legal origin is still higher than that to civil legal origin. Taken together, English legal origin gets the highest total effects of all E/S/G pillars on IVA. The spillover patterns are still heterogeneous across civil law origins while German legal origin is shown to be systemically most influential.

These findings challenge the presumption of the binary classification within legal origin theory that one legal origin holds universal superiority over another, which may oversimplify the complex interplay between law systems and socio-economic relationships (Acemoglu & Johnson 2005). The prominent spill-outs from German civil legal origin unveil its essential role as an influential contributor and exporter of superior ESG practices in the system whereas the pronounced spill-ins to common legal origin reveal that they tend to import global ESG standards owing to the flexible and market-driven governance and global supply chain integration. Moreover, both applications provide additional evidence of the nuanced divergences in how different civil legal origins process E/S/G integration and propagate shocks from ESG to SDG. Such heterogeneity within civil legal origins can challenge the monolithic view of civil law countries, thereby raising the importance of accommodating sub-categorisation in legal origin theory.

The paper is organised as follows: Section 3.2 presents a critical review of the existing literature. Section 3.3 describes our methodology, the dataset and the development of the main hypotheses, and presents the main empirical results for the ESG-SDG nexus. Section 3.4 conducts the robustness analysis through the network analysis of IVA performance and individual E/S/G pillars. Section 3.5 concludes. The data construction and the estimation algorithms are relegated to the Online Appendix.

3.2 Related Literature

Both sustainable Development Goals (SDG) and Environmental, Social, and Governance (ESG) frameworks aim to foster sustainable development at the firm or the country level. The SDG is a universal framework consisting of 17 interconnected goals addressing a wide range of challenges, including poverty eradication, quality education, gender equality, climate action, and peace, among others, thus emphasising on equitable, inclusive, and sustainable world. The ESG does not directly include financial profit as a component, but consists of a set of non-financial criteria within the corporates regarding environmental impact, social responsibility, and governance practices aiming at their positive contribution to sustainability and societal well-being. By integrating ESG criteria into their operations, businesses can therefore play a pivotal role in advancing the SDGs through ESG acting as a catalyst.

According to the SDG report (2019), although some progress has been made towards health and education, challenges remain in areas like biodiversity & climate change, and reduction of inequality; where the first constitutes an integral part of the E component and the second relates with the S pillar of ESG. Sachs et al. (2024) document that the progress towards achieving the SDG goals by 2030 has been halted or reversed due to several global events, such as COVID-19, the growing conflicts amongst countries, climate shocks and economic turmoil across the world. Wettstein et al. (2019) note that SDGs comprise of a wide range of concerns covering environmental degradation, social disparities and governance hurdles. These issues are also essential parts of ESG activities; therefore ESG can provide a framework for corporations to promote responsible practices, while SDGs create a global blueprint to address issues related to three key elements: economic growth, social progress and environmental sustainability. In this framework ESG can be seen as a sustainable input mechanism designed for promoting SDG outputs. For example, climate action (SDG 13) is interlinked with the E pillar of ESG whereas gender equality (SDG 5) aligns with the S component of ESG. Although the SDGs are primarily framed as targets for national governments, their realisation highlights the critical role businesses play as key stakeholders in this global effort through their ESG activities (Montiel et al. 2021).

Past literature mainly emphasises on the financial implications of ESG practices exploring the link between ESG issues and financial markets from the perspective of both “doing good - doing well” (Friedman 1970) and “doing well - doing good” (Porter & Kramer 2011). Despite the attractiveness of "doing good - doing well" narrative, the findings regarding the relationship between ESG and financial performance remains mixed: some studies find positive relationships, while others document neutral or negative associations, due to the challenges of measurement, data quality, and contextual differences across countries/regions. For example, Lins et al. (2017) and Broccardo et al. (2022) discover the positive effect of better ESG performance on stock returns. Dimson et al. (2015) portray lower volatility in stock prices for firms with better ESG ratings and ESG-focused firms tend to attract socially responsible investors and benefit from cheaper capital due to their reduced risk profile. Zhou et al. (2022) find that the improved ESG performance of listed companies can increase the firm market value through operational capacity. However, López et al. (2007) and Pastor et al. (2022) document the opposite finding that lower returns are expected for higher ESG performers. These contradictory conclusions further encourage the literature on ESG rating divergence and uncertainty, claiming two consequences: ESG rating divergence may reduce the true effect of ESG performance on stock returns (Berg, Koelbel, Pavlova & Rigobon 2022),[1] whereas uncertainty of ESG performance leads to a higher risk premium (Avramov et al. 2022).[2] Most of the studies in these domains even fail to differentiate between reverse causality (where successful companies engage in ESG initiatives) and the intended causal effect (where ESG initiatives drive financial success) with the exception of Auer (2016).

There is a growing interest in the literature regarding the relationship between SDG and ESG especially in context of corporate social responsibility (CSR) and sustainable investment practices. Kotsantonis et al. (2016) document that both ESG and SDG practices aim for long-term sustainability by focusing on the importance of environmental protection, social well-being, and strong governance. Same has been echoed by Zhao et al. (2021) and Khaled et al. (2021). Businesses and organisations play a crucial role in protecting the environment, improving social well-being, and enhancing corporate performance. By adhering to regulations and actively mitigating environmental harm, businesses can contribute to goals such as clean sanitation, clean water, climate protection, good health, and the conservation of natural resources. Additionally, fostering healthy relationships with stakeholders and ensuring social responsibility are integral to advancing the SDGs. Firms that engage in practices that protect stakeholder rights and promote mutual benefits help drive long-term societal progress (Consolandi et al. 2020).

Mapping ESG scores against SDGs can guide companies to comply and track their sustainability strategies with sustainable growth, demonstrating the business actions and investment priority for

[1] Gyönyörová et al. (2023) note that absence of regulatory obligation for companies to unveil non-financial information or apply certain measurements lead to significant noises in the publicly accessed ESG data.

[2] Grewal et al. (2020) cite that data transparency and discrepancies in ESG measurements as one of the main reasons impacting the validity of ESG-related research. In this context, also see Chatterji et al. (2016*b*).

investors and stakeholders. This linkage is based on the "doing good doing well" approach (Lins et al. 2017, Starks 2023). Several studies conduct direct investigation into the firm-level ESG effects on SDG. Plastun et al. (2020) document that better ESG performance does not always translate into improved national SDG outcomes, while different impacts are observed in developed and emerging countries. Developed countries tend to have a higher level of compliance to ESG principles and sustainability strategies relative to developing countries, contributing to higher SDG index ranking. Gidage & Bhide (2024) document significant positive impacts of ESG and economic growth on SDG accomplishment in developing countries. While examining the impacts of the company individual E/S/G pillars on country-specific SDG for three developing countries (India, China and Brazil), Soni (2023) discovers evidence of contributions from the E pillar only. Few studies attempt to map ESG scores against the specific SDG goals (Betti et al. 2018). Khaled et al. (2021) consider an extensive framework to map all the SDG goals with Refinitiv ESG scores in the emerging markets, but find that ESG measures cannot link to all SDGs, covering only 40 out of 169 targets. However, most of existing studies suffer either from analysis only focusing on selected set of countries or from linking company-level ESG performance to SDG scores. The latter poses more problems due to (i) the absence of a standardised mapping framework[3] that creates inconsistencies in the way companies and investors report their contributions to the SDGs (Van der Waal & Thijssens 2020), and (ii) self-reported data on ESG subject to greenwashing and lack of verification (Adams & Abhayawansa 2022).

On the other hand, the SDGs provide a comprehensive and globally accepted framework including a set of standardised indicators for measuring sustainable growth at the country level allowing for cross-country comparisons and benchmarking. In contrast to the "aggregate confusion" observed in corporate ESG scores, due to significant variations in the scopes, metrics and weights adopted by different rating agencies (Berg, Koelbel & Rigobon 2022), sovereign ESG scores exhibit a high correlation across data providers. However, the inherent flaws of sovereign ESG methodologies still remain, e.g., ingrained income bias which lead to underestimation of sustainability efforts and outcomes in lower income countries, lack of standardised evaluation on the environmental dimension, and the conflation of risk and sustainability goals that blurs investor understanding and priorities (Gratcheva et al. 2021).[4]

[3] The existing studies often link sustainability in business to company-level financial performance by defining it as "equilibrating financially sustainable growth" (Bellandi 2023). For instance, Todd et al. (2014) and Pham et al. (2021) construct the sustainable growth rate of the corporation by the product of the company's ROE and the retention ratio, to evaluate the highest growth rate that the company can achieve without relying on external financial leverage. As these indicators are mainly designed to focus on corporate economic and governance dimensions, they are not relevant to the concept of long-term sustainable growth.

[4] Gratcheva & Gurhy (2024) still demonstrate the advantages of using country-level ESG data for a more accurate and comprehensive assessment of sustainability.

It has been shown in the past literature that country's legal origins can be a stronger predictor in company's ESG rating than company and country characteristics (Liang & Renneboog 2017). Allen et al. (2000) demonstrate that the institutional, legal, and cultural environment have enormous impacts on societal expectations of the company's ESG practices. Two generations of legal origin theory are present: the first generation of the legal origin theory mainly focuses on economic development and governance, whereas the second generation extend its attention to environmental and social dimensions. We start with two main legal origins: common law and civil law and then further differentiate the civil law amongst French, German and Scandinavian.[5]

Shareholder theory related to common law system prioritises profit maximisation (Friedman 1975) while stakeholder theory associated with civil law system incorporates broader ethical and social responsibilities (Freeman 2010). La Porta et al. (2008) emphasise higher economic growth in countries with common law systems achieved through better investor protections, greater security of property and contract rights. Shareholder-oriented strategy and a diversified ownership structure are considered as important factors for increasing firm values in common law countries. Superiority of common law systems over civil law systems with respect to governance dimensions, while assuming equality in other dimensions, is also being observed (La Porta et al. 2002, Klapper & Love 2004). However, these works have been criticised for a lack of consideration in environmental and social outcomes (Collison et al. 2012). Civil law systems characterised by presence of stronger labour unions and consumer protections in coordinated markets, often lead to more static job market and stricter regulations according to the demand from the stakeholders (Djankov et al. 2008). Civil legal origin, with a broader stakeholder-centric logic, would thus pay relatively more attention to the environmental and social responsibility, perhaps at the cost of economic development and corporate governance. Kock & Min (2016) show that common law legal origins perform worse than civil law counterparts in terms of CO2 emissions. In similar vein, Kim et al. (2017) document that a significantly higher level of corporate environmental responsibility (CER) in civil law firms, whereas Liang & Renneboog (2017) find that civil legal origin has higher ESG ratings, although civil legal origin with extensive government ownership and regulation may trigger adverse outcomes such as heightened corruption, unregulated market, and higher unemployment. Overall, the second generation legal origin theory supports that countries belonging to civil law origins have the higher ESG scores, especially environmental and social aspects.

Even within the civil law countries, distinction exists. Liang & Renneboog (2017) argue that

[5]Most studies identify the five legal traditions: English common law, French civil law, German civil law, Scandinavian civil law and Socialist legal origin (Spamann 2010, Djankov et al. 2008). Socialist legal origin began in the Soviet Union and reverted to pre-revolutionary French or German civil law systems after the Berlin Wall fell. Hence, we do not consider Socialist legal origin as normally ignored in the literature.

although German and French systems exhibit many procedural similarities, e.g., relying on written codes and statutes, German legal origin allows for more judicial discretion. It implies more flexibilities and dynamics in the German system regarding law interpretation and application, which leads to greater adaptability and more rapid adoption to new ESG standards to keep up with evolving regulations and public expectations. Germany's outsized influence stems from its institutional and economic leverage rather than raw ESG scores. Its hard-law ESG frameworks, e.g., the Supply Chain Due Diligence Act, are adopted by other German legal origin countries, such as Austria and Chile, due to shared legal traditions that favour codification (La Porta et al. 2008). The EU's Corporate Sustainability Reporting Directive also reflects German regulatory priorities, amplifying transmission to other legal origins (Anh 2025). Börzel (2002) and Jänicke (2005) document that North-West European countries like Germany and Denmark tend to be leaders in environmental policy, while most of Mediterannean and East European countries are usually regarded as laggards. In terms of the economic channels, German multinationals (e.g., Volkswagen and Bayer) enforce ESG standards globally through supply chains, while development banks (e.g., KfW) tie financing to SDG-aligned projects in recipient countries (see KfW 2022 Sustainability Report). Germany hosts transnational ESG initiatives, e.g., G7 Sustainable Finance Working Group, creating normative diffusion.[6] In contrast, the French system's rigorous compliance to codified laws may ensure the stability in legal outcomes, at the cost of a lag in responding ESG shocks. On the other hand, Scandinavian legal origin tends to have more incentives for ESG disclosure due to a relative lower level of stakeholder protection and higher institutional ownership (Liang & Renneboog 2017). Scandinavian countries achieve higher domestic ESG scores but lack German regulatory scalability (due to smaller economies) and legal institutionalisation (since their policies rely on informal consensus), resulting in relatively lower exportability (Huang et al. 2025).[7]

The existing literature remains silent regarding the causal relationship from ESG input metrics to SDG output metrics across legal origins. More importantly, issues involving explicit local neighbour spillovers, global shocks and the parameter heterogeneity has not been addressed. Given the alignment of interest among the countries regarding the sustainable globalisation trend, we claim that the international network can transmit regulatory impacts to neighbouring entities through

[6] See German Sustainable Finance Strategy (2021) by the Federal Government of Germany.

[7] Domestic ESG leadership in Scandinavian and common law countries tends to be context-specific and less transferable, stemming from institutional and market structures. Scandinavian law countries often apply inward-focused policies. For instance, Sweden's ESG innovations (e.g., gender equality under SDG 5) are difficult to implement in larger, more diverse economies with complex social structures and cultural norms (Sattari et al. 2022). Common law countries (e.g., UK, US) prioritise shareholder-centric ESG, creating variability that dilutes global standardisation and introduce market-led fragmentation (Armour et al. 2022). Moreover, some countries' (e.g., U.S., Norway) falling rankings reflect governance shifts and decentralisation rather than weaker environmental efforts, while Germany's centralised system kept its policies consistently visible (Pehle 1998).

cross-border trade and FDI. The rise of sustainable investing may incentivise multinational corporations to apply standardised ethical practices across borders to align their strategies with SDG outcomes (Pillai et al. 2024). Environmental issues such as air pollution and climate change do not respect the borders between nations; the social dimension focusing on strong labour practices increase the competitiveness of a country would push neighbours to raise their standards of social responsibility whereas the governance frameworks through "policy transfer" can transmit their impacts across countries.[8] High domestic ESG performance (domestic leadership) where Scandinavian (E and S pillars) and common (G pillar) law countries excel does not necessarily translate into large cross-border spillovers (global impact). Hence, unfolding the spatial dynamics to understand the neighbourhood effect explicitly in a model can effectively assess risks and opportunities across countries in the world. On the other hand, presence of crises, geopolitical conflicts or pandemics could affect multiple companies/countries irrespective of their geographical locations and therefore we need to accommodate global factor dependence even in the spatial context. Finally, in accordance with 'one size may not fit all' we allow for heterogeneity of parameters in our model to capture local variations reflecting the complexities of country-specific information and real-world phenomena.

To fill this gap, we aim to uncover the network causal effect of ESG on SDG across legal origins. To this end we develop an integrated panel data model that simultaneously accommodates all key elements: spatial spillovers, global shocks and the parameter heterogeneity. We propose the use of the CCEX-IV estimator advanced by Chen et al. (2022) to consistently estimate all heterogeneous parameters using the country-level data. Next, we conduct the GCM network analysis advanced by Greenwood-Nimmo et al. (2021) and Shin & Thornton (2021), and analyse the network multipliers of SDG with respect to ESG across legal origins. In doing so, we can distinguish the direct and indirect (spillover) effects where direct effects mostly capture *ex ante* effect, while indirect spillover effects capture network feedback and economic interactions. By investigating the relative role/position of each legal origin in terms of respective direct and indirect effects within the system, the current approach can shed lights on the complex interconnected network across different legal origins. We also develop and test the validity of hypotheses on the predictions of legal origin theories (see Section 3.3.2). As a robustness check, we investigate the determinants of aggregate ESG using the individual E/S/G pillars across legal origins.

[8] Bosáková et al. (2019) suggest that globalisation significantly affects the convergence of corporate governance practices as countries with a robust governance regime may be seen as a benchmark for neighbouring counterparts, therefore introducing similar frameworks in their own corporate governance.

3.3 Application to Network Analysis of SDG and ESG

To investigate the network causal relationship from aggregate ESG metrics to Sustainable Development Goals (SDG) across countries, we consider the panel data model with both (local) spatial and (strong) factor dependence as well as heterogeneous parameters:

$$SDG_{it} = \rho_i SDG^*_{it} + \beta_i ESG_{it} + \boldsymbol{\gamma}_i'\mathbf{f}_t + u_{it},\ i = 1, ..., N,\ t = 1, ..., T \tag{3.3.1}$$

where SDG_{it} and ESG_{it} are the SDG index and ESG score of country i at time t, respectively. $SDG^*_{it} = \Sigma_{j=1}^N w_{ij} SDG_{jt}$ represents the spatial lagged variable (e.g., the weighted average of SDGs of neighbouring trading partner of country i) with w_{ij} being the (i, j)th unit of the $N \times N$ spatial weights matrix, $\mathbf{W}$ where we construct the spatial weights matrix based on the average bilateral trade weights over 2017-2019, and the trade weight is given by

$$w_{ij} = \frac{EXP_{ij} + IMP_{ij}}{\sum_{k=1}^N (EXP_{ik} + IMP_{ik})},\ i, j = 1, ..., N,\ i \neq j, \tag{3.3.2}$$

where EXP_{ij} is the real export from country i to j, IMP_{ij} is the real import of country i from j, and $\sum_{k=1}^N (EXP_{ik} + IMP_{ik})$ denotes the sum of total exports and imports of country i. The heterogeneous parameter, ρ_i captures the spatial spillover. The regressors, ESG_{it} is assumed to be exogenous with β_i being heterogeneous parameters. We allow the error components to follow the m ulti-factor structure, where $\mathbf{f}_t$ and $\boldsymbol{\gamma}_i$, are $r \times 1$ vectors of unobserved common factors and heterogeneous loadings, and u_{it} is the idiosyncratic error. Through $\boldsymbol{\gamma}_i'\mathbf{f}_t$ we can control the effects of unobserved external/global shocks that affect all countries, while reducing the risk of omitted variables bias.

To develop a consistent estimator of all the heterogeneous parameters, ρ_i and β_i for $i = 1, ..., N$ in (3.3.1), we should address two sources of endogeneity: the correlation between the regressors, ESG_{it} and the unobserved factors $\mathbf{f}_t$ as well as the correlations of the spatial lagged term, SDG^*_{it} with both factors and idiosyncratic error, u_{it}. Econometric methods have been developed to deal with the spatial effects and factor dependence, separately. The spatial endogeneity can be resolved using QML (Lee 2004) or IV/GMM estimation (Kelejian & Prucha 1998). The common factors can be approximated using the IPC method (Bai 2009) or the CCE method based on the cross-section averages of observable variables (Pesaran 2006). Recently, a few studies have combined both approaches and developed a spatial panel data model with common shocks, e.g., Kuersteiner & Prucha (2020) and Bai & Li (2021), though they derive the pooled estimators by imposing the homogeneity of the parameters.

To capture local variations that reflect the complex relationship in the real world, we explicitly allow the heterogeneous parameters in (3.4.4) and apply the CCEX-IV estimator advanced by Chen et al. (2022) to consistently estimate ρ_i and β_i for $i = 1, ..., N$. To deal with the endogeneity caused by the correlation between regressors and unobserved factors, we use the cross-section averages of the exogenous regressors only as proxies for latent factors. Next, to deal with the endogeneity of SDG^*_{it}, we develop a 2SLS procedure by using valid internal instruments constructed under the maintained assumptions of the model.[9] We call the resulting estimator the CCEX-2SLS estimator. Instead of reporting the summary measure based on the mean group (MG) estimator only, we follow Shin & Thornton (2021) and Greenwood-Nimmo et al. (2021), and conduct the GCM analysis using the network multipliers of SDG with respect to ESG. Using the spatial weight matrix (e.g., trade weights) and heterogeneous coefficients, we can construct the $N \times N$ connectedness matrix at the country level and then the $R \times R$ connectedness matrix at the group level based on legal origins, from which we can construct GDE (group direct effect), GSI (group spill-in effect) and GSO (group spill-out effect), respectively. Finally, we follow Shin & Thornton (2021) and provide a succinct description of the relative position of network nodes in the 2-dimensional figure with external motivation (EM) and systematic influence (SI) indices.[10] See Appendix C.2 for detailed step-by-step estimation algorithms. Taken together, this approach can shed light on the interconnected network across legal origins.

3.3.1 The data

We employ the dataset that contains annual observations for 41 countries over the period 2007 and 2023.[11] The SDG Index collected from the SDG Transformation Center is the widely-used measure for tracking countries' progress towards the United Nations' Sustainable Development Goals (SDGs). It compiles data from the UN, World Bank, and national statistical offices, to measure progress towards 17 goals. This index has been used in official reports by the United

[9]We employ the IV set $(\boldsymbol{ESG}^*, \boldsymbol{ESG}^{2*})$ to address spatial dependence, where $\boldsymbol{ESG}^{r*} = (\boldsymbol{ESG}_1^{r*}\prime, ..., \boldsymbol{ESG}_N^{r*}\prime)\prime$, $\boldsymbol{ESG}_i^{r*} = (ESG_{i1}^{r*}, ..., ESG_{iT}^{r*})\prime$, and $ESG_{it}^{r*} = \Sigma_{j=1}^N w_{ij}^r ESG_{jt}$ for $r = 0, 1, 2$. This follows seminal work by Hong & Kostovetsky (2012) and Eccles et al. (2014), who argue that the impact of ESG on broader societal metrics (e.g., SDGs) can plausibly be modelled as exogenous when the primary concern is omitted variable bias, instead of reverse causality. SDG achievement is a macro-level outcome unlikely to instantaneously affect firm-level ESG ratings. SDGs aggregate country/industry-level effects, while ESG reflects firm-specific practices (Khaled et al. 2021), supporting to treat ESG as exogenous in SDG-linked analyses while incorporating spatial spillovers. Both spatial lags are constructed using exogenous trade-based spatial weight matrices, further supporting their validity as instruments (Anselin 1988).

[10]We plot the network position along the line from North-West (most influential and least dependent) to South-East (least influential and most dependent). Suppose that the German legal origin is located in North-West while German legal origin in South-East, implying that the former is most influential while the latter is most receptive, in systemically diffusing the spillover impacts of ESG on SDG.

[11]We also use the trade weight matrix over 2014-2021 and 2019–2021, and the data for 40 countries over 2006–2023, and generate qualitatively similar results.

Nations and the European Commission and cited in academic research (e.g., Xu et al. (2020)). Next, we employ the MSCI ESG Ratings as our primary resource for evaluating the sustainability. They are measured using the Intangible Value Assessment (IVA) score, which examines over 35 key ESG issues tailored to the unique characteristics of environmental concerns, social aspects and governance practices. Since MSCI ESG ratings are unavailable at the country-level, we construct them by averaging ESG scores of individual firms within each country.[12] See Appendix C.1 for details.

Table 3.1 reports the descriptive statistics for SDG and ESG across legal origins.[13] See also Tables C.1 and C.2 in Appendix C.1 for details at the country level. We observe that both SDG and IVA averages are higher in civil legal origins than common counterpart with Scandinavian origin at the top followed by German legal origin. This result is mainly consistent with existing studies, e.g., Liang & Renneboog (2017), Khaled et al. (2021) and Gidage & Bhide (2024).

Table 3.1: Descriptive statistics of SDG and ESG data based on the legal origin grouping

Variable	Legal origin	Country	Min	Max	Median	Mean	Std.dev
SDG	English	12	53.80	82.20	72.80	71.43	6.670
	French	17	59.90	82.90	75.00	73.30	5.739
	German	8	62.40	83.80	78.70	77.73	4.732
	Scandinavian	4	78.80	86.40	84.50	83.61	2.013
	Total	41	53.80	86.40	76.30	74.62	6.697
IVA	English	12	31.64	62.23	48.70	48.56	4.906
	French	17	17.00	64.05	48.21	47.96	7.485
	German	8	27.95	61.94	50.56	48.93	7.453
	Scandinavian	4	50.89	64.08	56.19	56.35	3.568
	Total	41	17.00	64.08	49.73	49.14	6.926

This table contains the summary statistics for the annual SDG and ESG scores across legal origins during 2007 and 2023, collected from the SDG Transformation Center and MSCI databases, respectively. To match with the scale of the SDG data (0-100), we multiple the IVA data by 10.

Following Liang & Renneboog (2017), we consider the following dummy regression specification:

$$y_{it} = \alpha + \boldsymbol{\beta}_i' \boldsymbol{Legal}_i + \varepsilon_{it},\ i = 1, ..., N,\ t = 1, ..., T \tag{3.3.3}$$

where the dependent variable, y_{it} is either the overall IVA rating or SDG at the country level, and $\boldsymbol{Legal}_i$ is a 3×1 vector of dummies for French, German and Scandinavian civil legal origins with $\boldsymbol{\beta}_i$ being the dummy coefficients, taking the English legal origin as the benchmark. We apply the pooled OLS estimation to the model (3.3.3) and present the results in Table 3.2. The positive

[12] Due to limited data availability in earlier years, we collect ESG data for 43 countries over 2007-2023. Then we remove Bermuda and Hong Kong from English legal origin due to the lack of SDG indices.

[13] The legal origin is based on the company law/commercial code of the country where the firm is headquartered (Liang & Renneboog 2017).

dummy coefficients imply that the civil law countries achieve higher ESG and SDG scores than the common law countries. We find that the coefficients on three civil legal origins are all positive and significant for SDG with Scandinavian origin ranking the first. Turning to the estimation results for ESG, we obtain the mixed results; only Scandinavian civil law origin maintains positive and significant impacts on ESG whilst the dummy coefficients on French and German legal origins become insignificant or negative, implying that English law counties achieve higher ESG scores than French law countries. Taken together, these results provide a partial support for the existing evidence that ESG are higher in civil law countries than in common law countries (Liang & Renneboog 2017).

This approach tends to make an oversimplified conclusion that the legal origin is a significant determinant of ESG performance. However, this may be simply reflecting that the raw ESG scores of civil law countries are *ex ante* higher than those in the common law countries.

Table 3.2: OLS regression of ESG and SDG scores on legal origin dummies

Covariates \ Dependent variables	SDG	IVA
French	1.870*** (0.513)	-0.605 (0.595)
German	6.306*** (0.621)	0.369 (0.721)
Scandinavian	12.18*** (0.786)	7.792*** (0.912)
intercept	71.43*** (0.393)	48.56*** (0.456)
Adjusted R^2	29.81%	11.65%

Notes: The OLS regressions of SDG and IVA on the legal origin dummies are applied to annual data for 41 countries over 2007-2023. The English law is used as a benchmark and therefore excluded in the estimation result. Standard errors are in parentheses. ***, ** and * indicate the significance of the coefficient at the 1%, 5% and 10% level, respectively.

3.3.2 Hypotheses development

Given the variations in ESG/SDG practices due to cultural, economic, and regulatory differences subject to the country's legal origin, it is important to accommodate the spatial dynamics to capture these nuances based on legal origin, drawing a more accurate representation of the causal relationship from ESG to SDG. We now address the important issues about the direct and indirect role/contribution of IVA to improving SDG across legal origins, which has been completely unexplored in the literature. Stacking the individual regressions, (3.3.1) over $i = 1, ..., N$, we obtain the spatial representation of the system given by (1.3.9), from which we derive the network multipliers in (1.3.11) in Appendix C.2. These network multipliers measure causal effects from ESG to SDG, which can be decomposed into direct and indirect effects across four legal origins. Applying the GCM analysis and using an $R \times R$ connectedness matrix in (1.3.14) with $R = 4$, we construct the group-wise heterogeneous direct, spill-in and spill-out effects of ESG on SDG in (19), denoted GDE, GSI and GSO respectively, for each legal origin. GDE measures the direct effect of ESG on SDG within each legal origin while GSI captures the sum of the spillover effects of ESG on SDG from all the other legal origins and GSO captures the sum of the spillover effects of ESG on SDG to all the other legal origins, respectively. We also construct the group total effects (GTE) by summing GDE and GSI. As direct effects mostly capture the within-group effect, they tend to closely match the data characteristics (e.g., civil legal origin has higher ESG and SDG), in line with the second generation of legal origin theory. On the other hand, indirect spillover effects capture network feedback and economic interactions (e.g., through the global supply chain), more consistent with the first generation of legal origin theory. Using these network measures we now develop the three main hypotheses.

SDGs provide a comprehensive framework for sustainable growth, while ESG metrics serve as a driver for businesses to achieve these goals. Civil law countries tend to be rule-oriented under the strict regulatory framework that stimulates companies to adopt stringent environmental policies to reduce CO2 emissions, contributing to climate action (SDG 13) (Kock & Min 2016), and invests more in renewable energy projects aligning with the clean energy goal (SDG 7). Moreover, they emphasise the maximisation of stakeholder values and long-term sustainability in corporate operations (Kim et al. 2017). ESG-focused investors have higher motivations to adopt sustainable practices.[14] Company's involvement in protecting the rights of workers, fostering social equity as well as maintaining strong and ethical relationships with stakeholders, can make a progress towards not only achievement of the SDGs (SDG 3 and 10) but also a more resilient and inclusive society (Drebee et al. 2020). For example, German-origin countries emphasise on codified laws, strong regulatory backgrounds and stakeholder-oriented governance, thereby leading to strong domestic ESG practices based on environmental protection, social equity, and corporate accountability, resulting in higher direct effects of ESG on SDG. Scherer et al. (2018) also document evidence that companies that follow regulations to minimize negative environmental impacts could contribute significantly to the achievement of the SDG goal.

On the contrary, common law countries rely upon market mechanisms, resulting in selective contributions from ESG practices to SDG achievement. Common law countries mainly focus on shareholder value and emphasise profit maximisation over social and environmental concerns. As a result, domestic ESG activities tend to have limited local impacts on SDGs, as ESG is often driven by voluntary corporate initiatives rather than stringent legal requirements. It also raises

[14]For example, the L'Oréall Group in French legal origin has been committed to Diversity, Equity & Inclusion for more than 20 years and has achieved gender equity in the management crews in 2023 (Groupe 2023).

the conflict between ESG priorities and SDG targets as companies may shift focus to financially material factors but ignore other essential long-term sustainability goals, thereby leading to scant improvement for SDGs requiring systemic changes such as peace, justice, and strong institutions in SDG 16 (Adams 2017). Moreover, some companies in these profit-driven economies employ greenwashing as a marketing purposes, damaging the credibility of ESG practices in promoting SDG (Lyon & Montgomery 2015).

Table 3.1 shows the higher scores of both ESG and SDG observed in civil legal origins, that pays more attention to environmental and social dimensions (Liang & Renneboog 2017). Furthermore, Eccles et al. (2014) find that the integration of ESG consideration into corporate strategies contributes to better sustainability outcomes. In sum, civil legal origin puts more emphasis on sustainability development in the long run, whereas common legal origin has a narrower focus on short-term profits. Hence, we expect that the direct effects of ESG metrics on SDG targets will be stronger within civil legal origin, due to the more closed alignment of regulatory framework and ESG principles with the broader sustainability goals.

Hypothesis 1: GDE is higher in civil legal origin than in common legal origin, aligning with the second generation of legal origin theory.

Common law system is characterised by its economic flexibility and global interconnectedness, facilitating the adaptability to international sustainability regulations across borders through market-oriented approach, global supply chains and the multinational corporations. Eberlein & Matten (2009) and Kock & Min (2016) provide empirical evidence that the common law system exhibits the stronger reaction of environmental performance in response to international agreements, e.g., Kyoto protocol. Moreover, Kolk (2016) documents the particularly important role of global supply chains in disseminating sustainability practices within market-driven economies. The multinational corporations mostly headquartered in common law countries increase economic interconnectedness and exposure to diverse regulatory environments and ESG standards through global supply chains, which makes the process of receiving ESG spillover from international peers and cross-border collaboration more pronounced, in turn promoting SDG achievement.[15] Cross-border innovation and competition are also encouraged in common legal origin, thus creating sustainable consumption and production patterns (Eccles & Serafeim 2013).

On the other hand, the industrial sectors in civil law countries are equipped with well-established environmental regulations (Diana-Mihaela 2023), and have already incorporated stakeholders' environmental demands. This renders them to be more self-sufficient and less dependent upon external

[15]For example, Apple and Microsoft apply standardised ESG practices across regions and adapt to local regulations, setting global standards for sustainable supply chain.

shocks (especially German legal origin). Such a self-support regime can also benefit from stable regulatory compliance for sustained planning and financial commitment, indicating that there is limited scope for sustainable improvement even following the new global standards.

These discussions are mostly related to the first generation of legal origin theory (La Porta et al. 2008, Magill et al. 2015). With the market-driven and flexible system, common law countries are more adaptive to global sustainability trend and spillover shocks. By contrast the stakeholder-centric approach and self-reliant system in civil law countries can slow down the adoption of external ESG standards since the companies attempt to balance competing interests of diverse stakeholders (Aguilera & Jackson 2003). In this regard, we predict that more significant spill-ins of ESG metrics on SDG outcomes are expected in common legal origin than in civil legal origin.

Hypothesis 2: GSI is higher in common legal origin than in civil legal origin, mostly aligning with the first generation of legal origin theory.

The German system is more flexible and dynamic regarding law interpretation and application, which leads to greater adaptability and more rapid adoption to new ESG standards to keep up with evolving regulations and public expectations. The strong and self-sufficient domestic practices also reduce the need for external ESG spillovers. Although French civil law countries have some similarities with German counterparts (e.g., relying heavily on written codes and statutes), they are more centralised and less responsive to local needs at the cost of a lag in adapting to ESG shocks, thus limiting the effectiveness of domestic ESG policies in shaping SDG.[16] Moreover, the higher level of government intervention may also open opportunities for delays, corruption and distortion (La Porta et al. 1999). Based on stakeholder-oriented principle, Scandinavian legal system takes an intermediate position between heavily rule-based and discretion-oriented regimes (Liang & Renneboog 2017), while their ownership structure is more concentrated, compared to German law companies. Thus, Scandinavian countries can also be adaptable to the better global practices.

Due to the powerful market impacts from larger manufacturing and exporting countries, such as Germany, China, Japan and Korea, the ESG investment in German legal origin can play a more significant role in achieving SDGs of external markets through international trade and financial activities (Drempetic et al. 2020, Bissoondoyal-Bheenick et al. 2023). Diaye et al. (2022) document that German law system is already equipped with well-integrated ESG strategies that promotes the propagation of sustainability through multinational business activities. Furthermore, since the adoption of the Supply Chain Due Diligence Act in 2021, the new German law further regulates ESG risks along global supply chains of major companies (Jones 2021, Samardžić & Velić 2024).

[16] Crifo et al. (2019) even find the evidence of negative relationship between corporate sustainability and the activist engagement of investors in France.

In this regard, German legal origin is expected to exert larger direct and spill-out effects than other civil legal origins. Moreover, French legal origin consists of a large number of developing countries with open economy, which is likely to experience relatively large spill-ins from the global market.

Hypothesis 3: There are heterogenous patterns of GDE, GSI and GSO among civil legal origins. GDE within German legal origin is stronger than in French and Scandinavian legal origins while the opposite holds for GSI. Furthermore, GSO from German legal origin dominates.

Combining Hypotheses 1 and 2, whether GTE is stronger in civil or common legal origins remains uncertain. It is empirically determined, depending on the relative strengths of GDE and GSI across legal origins. The GTE analysis can be regarded as a combination of the first and second generations of legal origin theory. Next, *a priori*, we are unclear whether GSO is stronger in civil or common legal origins. But, empirically, GSO from German legal origin is shown to be substantially stronger than GSO from other legal origins, which renders GSO of civil legal origin being stronger than GSO of common legal origin. Hypothesis 3 underscores the importance of refining subcategories within civil law systems by explicitly addressing the heterogeneity patterns among civil legal origins.

3.3.3 Main estimation results

Given the substantial heterogeneity among the individual CCEX-IV estimators, we report the group-wise mean group (MG) estimation results across English, French, German and Scandinavian legal origins in Table 3.3. We find that the spatial spillovers from SDG^* are all significant and positive/persistent for all legal origins. The impacts of ESG on SDG are positive but insignificant with those in civil legal origin larger than in common legal origin. Notice however that the coefficients on ESG performance cannot be interpreted as marginal effects on SDG due to the spatial feedback in the model (3.3.1). Thus, we will examine the direct and indirect effects of ESG on SDG through a diffusion network analysis.

Table 3.3: CCEX-2SLS MG estimation results of SDG on SDG^* and ESG

	English	French	German	Scandinavian
SDG^*	0.969***	0.956***	0.940***	0.933***
	(0.094)	(0.077)	(0.116)	(0.070)
ESG	0.012	0.026	0.149	0.182
	(0.134)	(0.066)	(0.164)	(0.122)

Notes: We report the mean group estimation results across legal origins for the model (3.3.1) using the annual IVA data from MSCI and SDG data from SDG Transformation Center for 41 countries over 2007-2023. Standard errors are in parentheses. ***, ** and * indicate the significance of the coefficient at the 1%, 5% and 10% level, respectively.

The results for the GCM analysis of network multipliers of SDG with respect to ESG across legal origins are presented in Table 3.4. German legal origin achieves the highest GDE followed by Scandinavian legal origin while English and French legal origins display much smaller GDE. On average, GDE within civil legal origin is significantly higher than GDE within common legal origin, in line with Hypothesis 1. This evidence confirms that German legal origin with codified laws, strong regulatory background and stakeholder-oriented governance, can achieve a higher GDE of ESG on SDG whereas English legal origin with its main focus on financially material factors can scantly improve SDG through ESG. Furthermore, German legal origin, regarded as collectivistic society (Hofstede 2001), emphasises the balance among free-market capitalism, social welfare and environmental sustainability. Such collective efforts can create a cultural predisposition towards long-term sustainability and amplify the impact of ESG on SDG. On the contrary, English legal origin, regarded as individualistic society, tends to prioritise economic growth and individual freedoms, leading to a slow integration of ESG principles and thereby weakening the ESG effect on SDG achievement.

Next, GSI to common legal origin is higher than GSI to civil legal origin on average (1.64 vs 0.96), though GSI of French legal origin is slightly higher than English counterpart (1.77 vs 1.64), both of which mainly come from German legal origin. This provides support for Hypothesis 2. These results are closely related to the first generation of legal origin theory (La Porta et al. 2008). Due to the market-driven and flexible system, common law countries are more adaptive to external spillover shocks mainly through global supply chains. The multinational corporations mostly headquartered in common law countries are more likely to be susceptible to ESG spillover from civil law jurisdictions and thus foster progress towards sustainable goals. For instance, being influenced by global framework such as the Task Force on Climate-related Financial Disclosures established by Switzerland in German legal origin, the London Stock Exchange's ESG Reporting Guidance in 2023 mandates listed companies to comply with ESG reporting standards and ethical conducts. On the contrary, German law countries' resistance to external ESG policies can be attributed to resilient domestic regulations and the emphasis on governance traditions tailored to local needs, e.g., Germany's energy transition strategy (Energiewende). However, as the member of supranational organisations, such as the Organisation for the Harmonisation of Business Law in Africa, many French law countries strongly improve their responses to supranational governance, sustainable growth and harmonisation of global ESG standards (Hofmann et al. 2011). In this regard, the external ESG practices can encourage them to increase transparency and accountability in corporate ESG reporting (SDG 12).

Taken together, French legal origin achieves the highest GTE followed by English legal origin mainly because spillovers are stronger than direct effects across legal origins except German legal origin. Indeed, the aggregate spillover effects (the sum of GSIs) dominate the aggregate direct effects (the sum of GDE) (4.52 vs 1.8). This observation indicates that English and French law countries are significant beneficiaries of positive ESG influence mainly from German law countries on SDG, though their domestic ESG activities have relatively limited local impacts.

German legal origin is shown to be systemically most influential as its GSO dominates and the bilateral spillovers from German law countries are well above the direct effects in English, French and Scandinavian legal origins. Notice also that GSI to German legal origin is relatively negligible. As a result, GNE becomes positive only in German legal origin whereas the other legal origins suffer from negative GNE, especially for English legal origin whose GSO to the system is the lowest. Hence, we find that GSO of civil legal origin is stronger than GSO of common legal origin. The proactive regulatory approach and leadership role in shaping ESG regulations collectively extend the ESG impact beyond German legal origin, facilitating the diffusion of ESG practices to other legal origins as a key node in the global network. Such forward-looking strategy can produce innovative ESG practices that set a benchmark for other legal origins. By contrast, English common law countries play a peripheral role in the ESG network as they tend to oppose the Precautionary Principle but instead wait for evidence of actual harm before regulating (e.g., Richter (2000)), leading to weaker influence on other legal origins.

Finally, we notice the pronounced heterogeneous spillover patterns across civil law origins. In particular, the spillover for German legal origins takes the opposite pattern to French legal origin: GSI to German legal origin is much smaller than to French origin (0.31 vs 1.77). By contrast GSO from German legal origin dominates GSO from French origin (3.54 vs 0.28). Scandinavian legal origin takes an intermediate position. Together with German legal origin achieving the highest GDE, these results tend to support Hypothesis 3. Although French civil law countries share some similarities with German counterparts, they are more centralised and static (Beck et al. 2003). Due to the historical legacy subject to colonial influence, the ESG standards in French legal origin creates a path dependency (Acemoglu et al. 2001). This makes the spill-outs to other legal origins limited. Scandinavian law countries adopt a hybrid system that combine both common and civil law traditions, and have the deep-rooted cultural commitment to sustainability, social welfare and equality. All these contribute to a systematic balance.

Table 3.4: GCM analysis of network multipliers of SDG with respect to ESG across legal origins

	English	French	German	Scandinavian
English	0.098	0.124	1.346	0.166
French	0.096	0.180	1.492	0.185
German	0.064	0.095	1.242	0.149
Scandinavian	0.039	0.057	0.704	0.333
GDE	0.098	0.180	1.242	0.333
GSI	1.636	1.773	0.308	0.799
GSO	0.198	0.276	3.542	0.500
GNE	-1.437	-1.497	3.234	-0.299
GTE	1.734	1.954	1.550	1.132
EM	0.943	0.908	0.199	0.706
EX	0.669	0.605	0.740	0.601
SI	-0.444	-0.463	1	-0.092

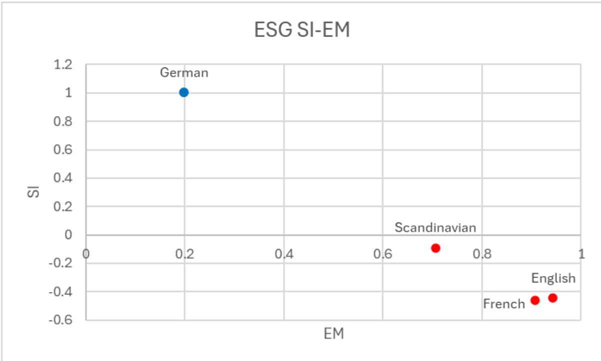
The first panel reports the direct effect and bilateral spillover among four legal origins. GDE, GSI and GSO indicate the group direct, spill-in and spill-out effects, respectively, for each legal origin. GNE is the group net effect measured by the difference between GSO and GSI while GTE is the group total effect measured by the sum of GDE and GSI. EM and SI are an external motivation index the systemic influence index defined in (C.2.16).

We now analyse how dependent is the ith legal origin on external conditions from other legal origins and to what extent the ith legal origin influences or is influenced by the system as a whole. EM_i measures the relative importance and direction of spill-in effects in determining the conditions in the ith legal origin while SI_i captures the systemic influence of the ith legal origin, see (C.2.16). Figure 3.1 displays the coordinate pair (EM_i, SI_i) that will provide a vivid representation of the relative position of the four legal origins in the ESG-SDG network.

The external motivation (EM) is positive across legal origins with English common legal origin recording the highest index (0.94), followed by French civil legal origin (0.91). The market-driven English common law system can be more flexible and adaptable to external ESG strategies that align closely with SDG targets (Magill et al. 2015). French origin consists of a great amount of developing countries with open economy, which also contributes to large GSIs. In contrast, German legal origin has the lowest EM index (0.2). Remarkably, the four legal origins tend to lay along a line from north-west to south-east, since positive spill-ins contribute negatively to a legal origin's net effect. For German legal origin spill-outs dominate spill-ins, which leads to a positive net connectedness with the highest SI. Thus, it becomes the influential net transmitters of ESG impacts. Conversely, English and French legal origins become the passive or beneficial receivers of ESG shocks, mainly from German legal origin, since their spill-ins outperform spill-outs, leading to a negative SI. Again, Scandinavian legal origin also takes an intermediate position in both EM and

SI indices. Our network analysis can unveil that the ESG shock diffuses mostly from German legal origin to English and French legal origins. This demonstrates that the relative position of the legal origins in the dependence-influence space can make an intuitive measure of capability to spur and absorb ESG/SDG spillovers.

Figure 3.1: ESG-SDG network across legal origins



Notes: This figure displays the EM/SI for the four legal origin groups. See also notes to Table 3.3.

Taken together, we find that the ESG-SDG nexus provides support for Hypotheses 1, 2 and 3. This implies that the legal origin theory should be applied to complementary legal frameworks instead of mutually exclusive models so as to provide more comprehensive insights on the network causal effects from ESG metrics to SDG outcomes.

3.4 Robustness Check: Network Analysis of IVA and Individual E/S/G Pillars

Although ESG is constructed as a (time-varying) weighted average of individual E/S/G pillars, all the data are quite noisy and uncertain (Christensen et al. 2022), suggesting that this relationship is still stochastic. In this regard, we consider the following heterogenous panel data model with both (local) spatial and (strong) factor dependence:

$$IVA_{it} = \alpha_i + \rho_i IVA^*_{it} + \beta_{1i}E_{it} + \beta_{2i}S_{it} + \beta_{3i}G_{it} + \boldsymbol{\gamma}_i'\mathbf{f}_t + u_{it},\ i = 1, ..., N,\ t = 1, ..., T \quad (3.4.4)$$

where IVA_{it} is the IVA rating of country i at time t, and similarly for individual scores, E_{it}, S_{it} and G_{it}. $IVA^*_{it} = \Sigma_{j=1}^N w_{ij} IVA_{jt}$ represents the spatial lagged variable with w_{ij} the (i,j)th unit of the $N \times N$ spatial weight matrix, $\mathbf{W}$ with the heterogeneous parameter, ρ_i capturing the spatial spillover. The regressors, E_{it}, S_{it} and G_{it} are assumed to be exogenous with $\boldsymbol{\beta}_{ki}$ for $k = 1, 2, 3$ being heterogeneous parameters. The multi-factor structure consists of unobserved common factors, $\mathbf{f}_t$, and heterogeneous loadings $\boldsymbol{\gamma}_i$. u_{it} is the idiosyncratic error.

We consider the extended MSCI dataset comprising monthly observations of $3,911$ companies across 54 countries, spanning the period from January 2014 to December 2023. We collect IVA as the aggregate ESG rating, along with its three core components: environmental (E), social (S), and governance (G) scores (see Appendix C.1 for further details). Since the MSCI ESG database does not provide country-level ESG ratings, we construct them by averaging the scores of individual firms within each country.[17]

Table 3.5 presents the descriptive statistics of IVA and E/S/G scores (0-10) for English (16 countries), French (25 countries), German (9 countries) and Scandinavian (4 countries) legal origins during January 2014 and December 2023. See also Tables C.3, C.4, C.5 and C.6 in Appendix C.1 for details at the country level. Scandinavian legal origin ranks the top in IVA as well as in individual E/S/G pillars. However, the ranking among English, French and German legal origins is not monotonic. For E and S pillars French law countries have a higher score than German and English counterparts. On the other hand English law countries achieve a higher score for the G pillar. E and G scores are more volatile while Scandinavian legal origin displays the smallest variation in all scores. In sum, the civil law origins tend to outperform the common law origins in terms of IVA and E/S scores, which is mostly consistent with the existing literature, e.g., Liang & Renneboog (2017), though the performance gap between English and French legal origins is almost negligible for IVA.

[17]The aggregate country-level ESG score is likely to be a more stable measure of ESG ratings by eliminating idiosyncratic noises related to individual companies, and reveals a clearer picture of overall ESG practice.

Table 3.5: Descriptive statistics of ESG data based on the legal origin grouping

Variable	Legal origin	Country	Company	Min	Max	Median	Mean	Std.dev
IVA score	English	16	2718	3.500	7.000	4.991	5.009	0.534
	French	25	445	2.920	7.100	5.000	5.020	0.631
	German	9	643	3.267	6.000	5.148	5.036	0.583
	Scandinavian	4	105	5.122	6.511	5.630	5.700	0.272
	Total	54	3911	2.920	7.100	5.083	5.069	0.602
Environmental score	English	16	2718	0.300	9.650	5.283	5.309	1.273
	French	25	445	1.100	10.00	5.855	5.725	1.755
	German	9	643	3.458	8.200	5.550	5.544	0.875
	Scandinavian	4	105	4.917	8.363	6.116	6.124	0.632
	Total	54	3911	0.300	10.00	5.562	5.601	1.454
Social score	English	16	2718	3.307	6.530	4.798	4.758	0.577
	French	25	445	3.600	7.900	5.073	5.084	0.616
	German	9	643	2.907	6.114	5.005	4.922	0.679
	Scandinavian	4	105	4.837	5.867	5.320	5.309	0.246
	Total	54	3911	2.907	7.900	4.988	4.977	0.619
Governance score	English	16	2718	1.200	7.600	5.900	5.634	1.005
	French	25	445	1.140	8.625	4.984	4.846	1.073
	German	9	643	3.200	6.918	5.160	5.115	0.866
	Scandinavian	4	105	4.880	7.704	6.561	6.525	0.607
	Total	54	3911	1.140	8.625	5.353	5.249	1.108

This table reports the descriptive summary of the dataset that contains monthly ESG and E/S/G scores from 54 countries during January 2014 and December 2023, collected from the MSCI database.

To examine the heterogeneous spatial dependence in IVA and the heterogeneous impacts of E/S/G pillars on IVA, we apply the CCEX-2SLS estimator to model (3.4.4) for 54 countries over the period 2014M1-2023M12, and present the group-wise MG estimation results across legal origins in Table 3.6. The spatial coefficients on IVA^* are all positive across legal origins. Spatial spillover is much stronger in Scandinavian and English legal origins than in French and German legal origins. Turning to the coefficients on E/S/G pillars, we find that they are positive and mostly significant. Furthermore, the impacts of S score are shown to be significantly stronger than those of E/G pillars, reflecting that MSCI assigns a higher weight of S pillar in the construction of IVA.[18] As the coefficients on E/S/G pillars cannot be interpreted as marginal effects owing to the presence of the spatial feedback dependence, we conduct a diffusion network analysis by deriving the (causal) network multipliers of IVA with respect to E/S/G pillars and decomposing them into the direct and indirect effects, respectively.

[18] In the current dataset, we find that MSCI applies the time-varying weights to E/S/G pillars (about 20%/50%/30%) in constructing the aggregate IVA rating.

Table 3.6: CCEX-2SLS MG estimation results

	IVA^{*}	E	S	G
English	0.609 (0.418)	0.254 (0.161)	0.341* (0.190)	0.202** (0.096)
French	0.317 (0.735)	0.194 (0.128)	0.333** (0.167)	0.245** (0.105)
German	0.150 (0.421)	0.264* (0.146)	0.328*** (0.120)	0.243** (0.111)
Scandinavian	0.616 (0.803)	0.253*** (0.085)	0.348*** (0.056)	0.212* (0.123)

Notes: We report the Mean Group estimation results for legal origins for the model (3.4.4) using the monthly MSCI ESG data for 54 countries over 2014M1–2023M12. Standard errors are in parentheses. ***, ** and * indicate the significance of the coefficient at the 1%, 5% and 10% level, respectively.

We conduct GCM analysis of the network multipliers of IVA performance with respect to E, S and G scores, which enables us to examine the role of each group in the diffusion of E/S/G impacts across the four legal origins. Table 3.7 reports these results. The aggregate direct effects (the sum of GDEs) dominate the aggregate indirect effects (the sum of GSI or the sum of GSO) for the E pillar (75.5% vs 24.5%), S pillar (76.3% vs 23.7%) and G (75.2% vs 24.8%) pillar, respectively. This observation is opposite to the pattern in the ESG-SDG relationship showing that the indirect effects dominate the direct effects. This indicates that direct impacts within each legal origin can play more significant roles in the diffusion of individual E/S/G shocks in shaping overall IVA ratings.

English legal origin obtains the highest GDE of the E, S and G scores on IVA, whereas the GDE ranking of civil legal origins varies across the individual pillar. As GDE within civil legal origin is lower than GDE within common legal origin, Hypothesis 1 is rejected. Although baseline E score is comparatively lower, the improvement in the environmental performance exerts a more pronounced impact on IVA in English legal origin. By contrast, relatively small improvement can be made in civil legal origin due to a more resilient environmental framework (Eberlein & Matten 2009). The increasing recognition of balancing shareholder values with stakeholder demands in English common legal origin is shifting the focus on the integration of meeting the requirements of investors and regulations.[19] The engagement of activist and ethical investors is a fundamental factors in driving ESG activities within Anglo-Saxon countries (Vuong & Suzuki 2021), which can be more helpful for companies with weak S performance *ex ante* to generate higher IVA (Barko et al. 2022). The continuous revision through case law is evolving the common legal system to construct more robust governance mechanisms for addressing emerging market demands, contributing to its higher effect of G pillar on IVA relative to civil legal system.

[19]The concept of "enlightened shareholder value" introduced in the UK Companies Act in 2006 can serve as a good example.

Next, GSI of E/S/G pillars on IVA to common legal origin is also higher than that to civil legal origin. Indeed, English law countries are main beneficiaries of positive E/S/G influence on ESG mainly from German law countries. This is in line with Hypothesis 2. Institutional investors in common law countries tend to accelerate the trend of increasing stakeholder engagement and ESG-focused investment funds to mitigate risks in corporate reputation (Dyck et al. 2019). The prevalence of independent directors and audit committees also drive compliance with international governance standards in domestic management and enable common law countries to adopt the best E/S/G practices from civil law countries (Armstrong et al. 2010). By contrast, German law countries tend to form a more intimately linked cluster attributed to shared resilient regulatory principles, cultural norms and economic policies (Aguilera & Jackson 2003). Following the precautionary principle, they tend to incorporate stringent E/S/G regulations, leading to less demand for improving their ESG performance through the spill-in channel.

Taken together, English legal origin gets the highest GTE of all E/S/G pillars on IVA, followed by Scandinavian legal origin for E pillar and French legal origin for S/G pillars. By contrast, German legal origin records the lowest GTE of all E/S/G pillars on IVA, mainly due to its negligible GSI from other legal origins. This observation is different from the pattern in the ESG-SDG relationship, indicating that environmental (social/governance) performance in English law countries makes the most significant contribution to improving local IVA.

German legal origin is shown to be systemically most influential as its GSO of E/S/G pillars on IVA dominates other legal origins. As a result, on average, GSO of civil legal origins is stronger than GSO of common legal origin for all E/S/G pillars. The robust ESG systems embedded in the legal framework of German law countries enforce high E/S/G standards in global businesses, particularly manufacturing and automotive industries, that can create a ripple effect that requires the compliance from suppliers and trading partners to maintain the business relationships. On the other hand, tailored to the specific contexts on law, culture and economics, Scandinavian legal origin tends to have significantly localised ESG regulations and activities that are less transferable to other legal origins (Castillo-Merino & Rodríguez-Pérez 2021), as shown by its lowest GSO. Finally, English legal origin relies heavily on voluntary ESG disclosures and individualism, which hinders the transferability of environmental, social and governance practices to civil legal origin that prioritises regulatory compliance and collectivist values.

Finally, we also notice the pronounced heterogeneous spillover patterns across civil law origins. In particular, the spillover for German legal origins takes the opposite pattern to French legal origin: GSI to German legal origin is much smaller than to French origin for E/S/G pillars (0.02 vs 0.12, 0.03 vs 0.15, 0.02 vs 0.1). By contrast GSO from German legal origin dominates GSO from French origin for E/S/G pillars (0.23 vs 0.06, 0.29 vs 0.09, 0.21 vs 0.07). Scandinavian legal origin takes an intermediate position regarding GSI while achieving the highest GDE for E/S pillars, while French legal origin has the highest GDE for G pillar. These results partially support Hypothesis 3. French law system has historically exhibited more significant dependence on EU-level directives than German law system, indicating a greater demand for external E/S/G standards (Börzel & Buzogány 2014). Although both French and German legal originsemphasise state intervention, the former has more centralised control and less corporate autonomy. Such a stricter state-influenced governance system can ensure the adoption and integration of external E/S/G norms, though their E/S/G practices are often perceived as less transferable to other jurisdictions. Scandinavian legal origin combines the elaborate environmental policies from civil law traditions and adaptability in judicial interpretation from common law system. On top of the robust regulatory foundation for social welfare the common law tradition also injects some dynamics in judicial enforcement of social rights in Scandinavian legal origin. For governance Scandinavian legal origin tends to combine strong statutory framework for anti-corruption measures from civil law and judicial independence from common law. All these elements explain Scandinavian intermediate position of E/S/G spillover patterns.

Table 3.7: Group direct, spill-in, spill-out effects across legal origins

Environmental pillar				
	English	French	German	Scandinavian
English	0.362	0.033	0.115	0.007
French	0.045	0.226	0.065	0.005
German	0.011	0.006	0.289	0.002
Scandinavian	0.023	0.016	0.051	0.292
GDE	0.362	0.226	0.289	0.292
GSI	0.155	0.115	0.020	0.090
GSO	0.080	0.055	0.231	0.014
GNE	-0.075	-0.060	0.211	-0.076
GTE	0.517	0.341	0.309	0.382
EM	0.300	0.337	0.064	0.236
EX	0.180	0.195	0.444	0.047
SI	-0.356	-0.286	1	-0.358

Social pillar				
	English	French	German	Scandinavian
English	0.486	0.056	0.143	0.010
French	0.061	0.388	0.081	0.007
German	0.015	0.011	0.359	0.003
Scandinavian	0.031	0.027	0.063	0.401
GDE	0.486	0.388	0.359	0.401
GSI	0.209	0.148	0.029	0.122
GSO	0.107	0.094	0.287	0.020
GNE	-0.102	-0.054	0.258	-0.102
GTE	0.694	0.536	0.388	0.523
EM	0.301	0.276	0.074	0.232
EX	0.180	0.195	0.444	0.047
SI	-0.395	-0.210	1	-0.395

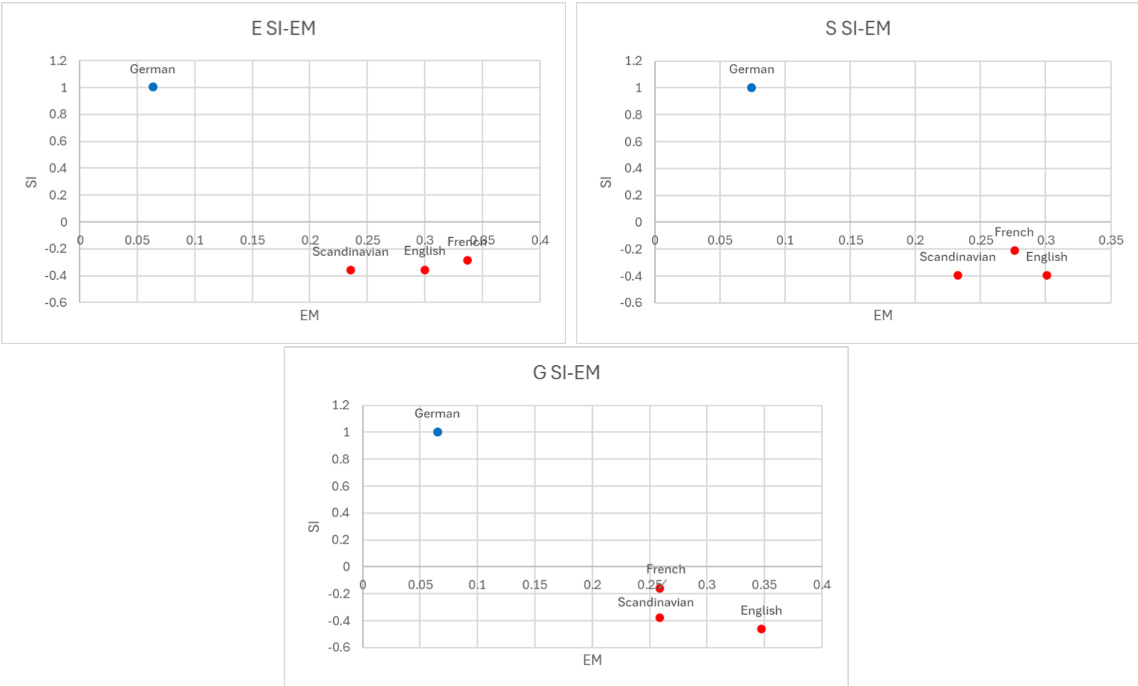
The first panel reports the direct effect and bilateral spillover among four legal origins. GDE, GSI and GSO indicate the group direct, spill-in and spill-out effects, respectively, for each legal origin. GNE is the group net effect measured by the difference between GSO and GSI while GTE is the group total effect measured by the sum of GDE and GSI. EM and SI are an external motivation index the systemic influence index defined in (C.2.16).

Governance pillar				
	English	French	German	Scandinavian
English	0.288	0.041	0.106	0.006
French	0.036	0.286	0.060	0.004
German	0.009	0.008	0.266	0.002
Scandinavian	0.018	0.020	0.047	0.244
GDE	0.288	0.286	0.266	0.244
GSI	0.153	0.100	0.019	0.085
GSO	0.063	0.069	0.213	0.012
GNE	-0.090	-0.031	0.194	-0.073
GTE	0.441	0.386	0.285	0.330
EM	0.347	0.259	0.066	0.259
EX	0.180	0.195	0.444	0.047
SI	-0.463	-0.159	1	-0.378

Figure 3.2 displays the coordinate pair (EM_i, SI_i). The external motivation (EM) is positive across legal origins, with French civil legal origin recording the highest index (0.34), followed by English common legal origin (0.3) for E pillar; while with English common legal origin recording the highest index (0.3 and 0.35), followed by French civil legal origin (0.28 and 0.26) for S and G pillars, respectively. Due to the highly centralised governance systems and globalisation pressures, French civil legal origin tends to adopt external environmental practices. The increasing trend of combined focuses on both shareholder and stakeholder values drives English common legal origin to absorb social and governance norms from other legal origins. In contrast, German legal origin has the lowest EM index across E/S/G pillars (0.06, 0.07, 0.07). The four legal origins tend to lay along a line roughly from north-west to south-east, since positive spill-ins contribute negatively to a legal origin's net effect. For German legal origin spill-outs dominate spill-ins, which leads to a positive net connectedness with the highest SI. Thus, it becomes the influential net transmitters of ESG impacts through E/S/G pillars.

Conversely, English and French legal origins become the beneficial receivers of ESG shocks, mainly from German legal origin, since their spill-ins outperform spill-outs, leading to a negative SI. Scandinavian legal origin takes an intermediate position in EM index. Our network analysis can unveil that the E/S/G shock diffuses mostly from German legal origin to English and French legal origins. This demonstrates that the relative position of the legal origins in the dependence-influence space can make an intuitive measure of capability to spur and absorb E/S/G spillovers.

Figure 3.2: GCM analysis of EM/SI across legal origins for E/S/G



Notes: This figure displays the EM/SI for the four legal origin groups, such as English, French, German and Scandinavian origins. See also table notes to Table 3.6.

Overall, the ESG-SDG nexus supports Hypotheses 1 and 2, in line with both the first and second generations of legal origin theory. On the other hand, the IVA determinants of individual E/S/G pillars support Hypothesis 2 only, advocating the first generation of legal origin theory. These findings challenge the presumption of the binary classification within legal origin theory that one legal origin holds universal superiority over another, which may oversimplify the complex interplay between law systems and socio-economic relationships (Acemoglu & Johnson 2005). The prominent spill-outs from German civil legal origin unveil its essential role as an influential contributor and exporter of superior ESG practices in the system whereas the pronounced spill-ins to common legal origin reveal that they tend to import global ESG standards owing to the flexible and market-driven governance and global supply chain integration. Moreover, both applications provide some support for Hypothesis 3, underscoring additional evidence of the nuanced divergences in how different civil legal origins process E/S/G integration and propagate shocks from ESG to SDG. Such heterogeneity within civil legal origins can challenge the monolithic view of civil law countries, thereby raising the importance of accommodating sub-categorisation in legal origin theory.

3.5 Concluding Remarks

Although ESG can be generally regraded as a sustainable input mechanism designed for promoting SDG outputs, the existing literature remains silent on investigating the network causal relationship from ESG metrics to SDG targets across legal origins. Also, important issues such as local spillovers, global shocks and the parameter heterogeneity are mostly neglected in the literature. To fill this gap, we have developed an integrated panel data model that simultaneously accommodates all three key issues. We first use the CCEX-IV estimator by Chen et al. (2022) to consistently estimate all heterogeneous parameters. Next, we conduct the GCM analysis by Greenwood-Nimmo et al. (2021) and Shin & Thornton (2021), and analyse the network multipliers of SDG with respect to ESG by distinguishing the direct and indirect spillover effects across legal origins. The combined approach is shown to shed lights on the complex interconnected ESG-SDG network.

Using annual SDG Index collected from the SDG Transformation Center and IVA from MSCI Database for 41 countries over 2007-2023, we investigate the network causal relationship from ESG to SDG. By investigating the relative role of each legal origin in terms of respective direct and indirect effects within the system, we find that direct effect of ESG on SDG in civil legal origin is significantly higher than in common legal origin while spill-in effect is stronger in common legal origin. These results provide support to both the first and second generations of legal origin theory. The pronounced heterogeneous spillover patterns are observed across civil legal origins. In particular, spill-out effects from German legal origin dominate while its spill-ins are almost negligible, that renders it to be the most influential ESG shock transmitter in the system. On the other hand, French legal origin takes an opposite pattern while Scandinavian legal origin takes an intermediate position. Finally, the four legal origins lay along a line from north-west to south-east in the (EM, SI) coordinate that provides a vivid representation of their relative position in the ESG-SDG network, and shows that English and French legal origins are the main beneficiaries of ESG shocks, mainly from German legal origin.

As a robustness check, we uncover the determinants of aggregate IVA using the individual E/S/G pillars across legal origins by employing the extended monthly data from MSCI Database for 54 countries over the period January 2014-December 2023. We find that English legal origin obtains the highest GDE of E/S/G pillars on IVA, whereas the GDE ranking of civil legal origins varies across the individual pillar. As group direct effect within civil legal origin is lower than that within common legal origin, this does not support to the second generation of legal origin theory. Group spill-in to common legal origin is still higher than that to civil legal origin. Taken together, English legal origin gets the highest total effects of all E/S/G pillars on IVA. The spillover patterns are still heterogeneous across civil law origins while German legal origin is shown to be systemically most influential.

Overall, the ESG-SDG nexus supports both the first and second generations of legal origin theory whereas the IVA determinants support the first generation of legal origin theory only. These findings challenge the presumption of the binary classification within legal origin theory that one legal origin holds universal superiority over another, which may oversimplify the complex interplay between law systems and socio-economic relationships (Acemoglu & Johnson 2005). As both applications provide some support for additional Hypothesis 3, the monolithic view of civil law countries is being challenged, thereby raising the importance of accommodating sub-categorisation in legal origin theory.

Our work opens several avenues for continuing research. On the methodological side, there is a scope to generalise our approach to the simultaneous equation panel data model that accommodates simultaneity, spatial spillovers, global shocks and parameter heterogeneity. On the empirical side, our work motivates similar studies in other areas of the literature, such as in the network analysis of ESG scores and financial performance/specific SDG across legal origins or industries.

Conclusions

This thesis aims to make contributions to explicitly investigate the fundamental relationship between trade/finance intensities and the business cycle synchronisation (BCS), analyse systematic and noisy components of environmental, social, and governance (ESG) activities, and uncover the network causal relationship from ESG to SDG. In Chapter 1, we developed a simultaneous equation panel data model that jointly controls for spatial spillovers, latent global shocks, simultaneity between BCS and trade/financial intensities, and parameter heterogeneity to analyse the relationship between the 3D BCS and trade/financial intensities using the 2D panel data framework. In Chapter 2, we addressed the complexities in ESG performance due to data noises and uncertainties while aligning with the different ESG disclosure reporting standards between common and civil legal origins by identifying and analysing systematic and noisy components of ESG activities across legal origins through employing the multilevel factor model and applying the data-driven generalised canonical correlation (GCC) approach. We employed both the MSCI and Refinitiv/LSEG datasets in the analysis and found different findings, which point towards the raters' ESG divergence and uncertainty as postulated in the recent literature. In Chapter 3, we have developed an integrated panel data model that simultaneously accommodates the three key issues such as local spillovers, global shocks and the parameter heterogeneity in investigating the network causal relationship from ESG metrics to SDG targets across legal origins. We combined the CCEX-IV estimation and GCM analysis to analyse the network multipliers of SDG with respect to ESG by distinguishing the direct and indirect spillover effects across legal origins.

Therefore, this thesis offers a comprehensive framework for empirical applications of panel data models with a factor structure regarding BCS and ESG activities across legal origins while emphasising the joint accommodation of local spillover effects, global shocks (cross-section dependence) and the parameter heterogeneity (and simultaneity) to reflect these complex relationships in the real world.

This thesis opens several avenues for continuing research on BCS and ESG activities: (i) Regarding BCS determinants, on the empirical side, our results motivate similar and robust studies that employ alternative measures of BCS, trade/financial intensities and the spatial weights, as well as including dynamics and more countries in the sample; on the methodological side, there is scope to generalise our approach using the system 3SLS estimation; (ii) With respect to ESG activities, on the empirical side, our work motivates similar studies in other areas of the literature, such as in the network analysis of ESG scores and financial performance/specific SDG across legal origins or industries; on the methodological side, there is a scope to generalise our approach to the simultaneous equation panel data model that accommodates simultaneity, spatial spillovers, global shocks and parameter heterogeneity.

Appendix A

Appendix to Chapter 1

This Appendix is structured as follows. Section A.1 provides the detailed data construction. Section A.2 shows the classification of EU core and periphery countries. Section A.3 describes a general approach for the construction of the spatial weights matrix among the symmetric country-pairs. Section A.4 presents the additional estimation results. Section A.5 presents the sketch of proofs for the main theoretical results. Section A.6 provides the Monte Carlo simulation results.

A.1 The Data Construction

We provide the data details and their construction with *a priori* expectation about the sign of the impacts. If necessary, we seasonally adjust all the data by applying the X11-ARIMA method.

Key variables

- S_{it} is the level of business cycle synchronisation between the i-th country pair at time t, measured in % by

$$S_{it} = -|g^R_{ht} - g^R_{ft}| \times 100, \tag{A.1.1}$$

where g^R_{ht} and g^R_{ft} are real GDP growth rates of home (h) and foreign (f) countries in the i-th country pair at time t. We collect quarterly real GDP data from the International Financial Statistics (IFS) in IMF. Real GDPs, measured in national currency, are seasonally adjusted, and converted to US dollar with the dollar conversion rate from BIS. Real GDP growth rate is constructed as $g_{jt} = \ln\left(\frac{GDP^R_{jt}}{GDP^R_{j,t-1}}\right)$ for $j = h, f$.

Following Cesa-Bianchi et al. (2019), we decompose GDP growth into systematic and idiosyncratic components as follows:

$$g_{jt} = a_j + \mathbf{F}'_t \boldsymbol{b}_j + \varepsilon_{jt},$$

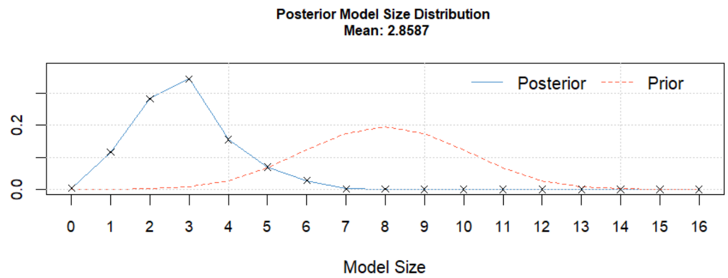
where a_j is the average growth rate, $\mathbf{F}_t$ is the unobserved common factors, $\boldsymbol{b}_j$ is country j's loadings, and ε_{jt} is the idiosyncratic error. Then, we have:

$$S_{it} = -|(a_h - a_f) + \mathbf{F}_t'(\boldsymbol{b}_h - \boldsymbol{b}_f) + (\varepsilon_{ht} - \varepsilon_{ft})| \times 100.$$

- S_{it}^F is the systematic business cycle synchronisation between i-th country pair at time t, given by

$$S_{it}^F = -|\mathbf{F}_t'(\boldsymbol{b}_h - \boldsymbol{b}_f)| \times 100. \tag{A.1.2}$$

The number of common factors is identified by the BIC (Bai & Ng 2002), plotted below:



- S_{it}^{ε} is the idiosyncratic business cycle synchronisation between the i-th country pair at time t, given by

$$S_{it}^{\varepsilon} = -|\varepsilon_{ht} - \varepsilon_{ft}| \times 100. \tag{A.1.3}$$

- T_{it} is the trade intensity between the i-th country pair at time t, measured by

$$T_{it} = \ln\left(\frac{(IMP_{h\leftarrow f,t}^R + EXP_{h\rightarrow f,t}^R) \times GDP_{wt}^R}{GDP_{ht}^R GDP_{ft}^R}\right), \tag{A.1.4}$$

where $IMP_{h\leftarrow f,t}^R = (IMP_{h\leftarrow f,t}^N / MPI_{US}) \times 100$ is the real import of home country from a foreign country, and $EXP_{h\rightarrow f,t}^R = (EXP_{h\rightarrow f,t}^N / XPI_{US}) \times 100$ is the real export of home country to a foreign country, where $IMP_{h\leftarrow f,t}^N$ and $EXP_{h\rightarrow f,t}^N$ are quarterly bilateral import and export measured in millions of current US dollars, and MPI_{US} and XPI_{US} are the US import and export price indices. All the data are measured in millions of US Dollar and collected from Direction of Trade Statistics (DOTS) in IMF. This measure of the trade intensity is widely used in the literature, e.g., Frankel & Rose (1998), Clark & Van Wincoop (2001), Imbs (2004), Gong & Kim (2018).

- K_{it} is the bilateral banking/financial intensity between the i-th country pair at time t, measured by (Gong & Kim 2018)

$$K_{it} = \ln\left(\frac{(Claim_{h\leftarrow f,t} + Claim_{h\rightarrow f,t}) \times GDP^R_{wt}}{GDP^R_{ht} GDP^R_{ft}}\right), \tag{A.1.5}$$

where $Claim_{h\leftarrow f,t}$ and $Claim_{h\rightarrow f,t}$ are banking claims received and provided by home country, respectively. We collect quarterly foreign claims data in millions of US dollar from the consolidated banking statistics in the Bank for International Settlement (BIS) database.

- The exogenous variable in the BCS equation: sim_{it} is size similarity between the i-th country pair at time t, measured by (Mastromarco et al. 2016)

$$sim_{it} = 1 - \left(\frac{GDP^R_{ht}}{GDP^R_{ht} + GDP^R_{ft}}\right)^2 - \left(\frac{GDP^R_{ft}}{GDP^R_{ft} + GDP^R_{ht}}\right)^2. \tag{A.1.6}$$

This indicator ranges between 0 and 0.5. As the higher indicator implies the more different the size of the two countries, its effect on BCS is expected to be negative. Economic size similarity controls for the fact that countries of similar economic size tend to have more synchronised business cycles due to symmetric shocks (Baxter & Kouparitsas 2005). These economies are likely to have factor endowments, economic structures and vulnerabilities in common. Easterly & Levine (2001) provide the insights that the growth patterns of countries with similar characteristics are alike.

- The exogenous variable in the bilateral trade intensity equation: exr_{it} is the absolute real exchange rate fluctuations between the i-th country pair at time t in constant dollar to indicate the competitiveness based on relative price levels, measured by (Böwer & Guillemineau 2006)

$$exr_{it} = |exr_{ht} - exr_{ft}|, \tag{A.1.7}$$

where exr_{ht} (exr_{ft}) is the real exchange rate between the home (foreign) currency and the US dollar. The larger the exchange rate volatility is, the fewer commercial activity there is between the two countries, due to elevated foreign exchange risks, transaction costs and uncertainty (Arize et al. 2000, Clark et al. 2004, Auboin & Ruta 2013). It implies the close connection between exchange rate variation and cross-border trade intensity.

- The exogenous variable in the bilateral financial intensity equation: inr_{it} is the absolute differential of short-term real interest rates adjusted for inflation, measured by (Böwer & Guillemineau 2006)

$$inr_{it} = |inr_{ht} - inr_{ft}|. \tag{A.1.8}$$

Interest rate movements can significantly impact financial intensity through investment decisions, financial institutions' behaviour, monetary policy and macroeconomic stability (Hajilee & Niroomand 2018). Increasing interest rate volatility raises the uncertainty about the cost of borrowing and return on savings, discouraging firms and individuals from participating in the financial market, especially for risk averse investors (Froot & Thaler 1990). The real interest rates are collected from the World Bank database.

Exchange rate volatility and interest rate variation are assumed exogenous in the trade and financial intensity equations, respectively, because they are typically influenced by monetary policy and global financial conditions, which are external to the country-pair interactions in the model (Devereux & Engel 2002). While trade/financial flows may feedback into exchange/interest rates, the short-run impact is often dominated by central bank policies and speculative flows, justifying their exogeneity in a panel setting (Gali & Monacelli 2005).

Exchange rate volatility is not controlled in all the equations. It directly affects trade intensity due to its impact on import/export competitiveness but is less relevant for BCS and financial intensity. While exchange rates can indirectly affect synchronisation via trade, the primary linkage is already captured by bilateral trade intensity. Obstfeld & Rogoff (2000) also document that interest rate differentials are more critical for capital flows than exchange rate volatility. This setup also ensures identification by excluding some exogenous variables from certain equations, avoiding perfect collinearity while maintaining theoretical coherence.

A.2 Classification of EU Core and Periphery Countries

Following economic and institutional criteria common in EU studies (Sapir 2006, Johnston & Regan 2016), core EU members are defined as long-standing, economically advanced economies with strong integration into EU decision-making and financial systems. Austria, Germany, Finland, France, the Netherlands, and Sweden exemplify this group due to their high GDP per capita and stable macroeconomic performance, central role in EU policymaking (e.g., Franco-German leadership), adoption of the euro (except Sweden), and robust financial markets and trade linkages. In contrast, Spain, Greece, Ireland, Italy and Portugal are classified as periphery economies due to their macroeconomic divergence reflected by higher public debt/GDP ratios, vulnerability to sovereign debt crises, and reliance on EU stabilisation mechanisms (e.g., ECB interventions) (De Grauwe 2013), structural imbalances and relatively weaker financial market integration (Jaccard & Smets 2020), and experiences of EU excessive deficit procedures and structural reform pressures (e.g., in labour markets and/or banking sectors).

Regarding the contested role of the UK, some scholars (e.g., Geddes (2013)) argue that the UK occupied an economically core but politically semi-detached position within the EU due to opt-outs (e.g., not adopting the euro or joining Schengen); growing Euroscepticism, leading to Brexit; and divergence from Franco-German leadership on key EU policies. However, most scholars classify the UK as part of the EU's core for the pre-Brexit period due to its economic strength as one of the largest economies in the EU (Copsey & Haughton 2014); political influence as a key player in EU policymaking (Bache et al. 2015); and financial centrality with London as the EU's dominant financial hub (Dyson & Sepos 2010). After Brexit, some scholars, e.g., Martill & Staiger (2018), suggest that the UK has shifted from core to external periphery with looser economic and political ties, indicating that the UK no longer directly shapes EU policies but remains economically interconnected. We acknowledge that the UK's non-adoption of the euro and eventual departure represent institutional divergences and structural discontinuities. Brexit officially took place on 31 January 2020, which is out of our sample period. So we still consider the UK as one of the core members during 1995-2019. To mitigate this structural break, the future research could contain estimation excluding tests for the UK post-Brexit, and year fixed effects to control for Brexit-related shocks.

A.3 The Construction of The Spatial Weights Matrix

S_{it}, specified in (A.1.1), is symmetric unlike directional export or traffic flows. By convention, we do not consider self-flows (i.e., $h \neq f$). Thus, we construct the symmetric dependent variable, S_{it} for $i = 1, ..., N$ with $N = \frac{n(n-1)}{2}$.

Now, we can analyse the relationship between BCS and trade/financial intensities using the simultaneous equation panel data model (1.3.1):[1] Notice, however, that it is not straightforward to construct the spatial weights matrix among the symmetric N country-pairs to capture network proximity, since the dimension of our undirectional data is different from the $n^2 \times 1$ vector of directional traffic flows (including self-flows) considered by LeSage & Pace (2008), who propose constructing the appropriate spatial weights matrix based on the spatial filtering method given by $(\boldsymbol{I}_{n^2} - \rho_o \boldsymbol{W}_o)(\boldsymbol{I}_{n^2} - \rho_d \boldsymbol{W}_d) = (\boldsymbol{I}_{n^2} - \rho_o(\boldsymbol{W} \otimes \boldsymbol{I}_n))(\boldsymbol{I}_{n^2} - \rho_d(\boldsymbol{I}_n \otimes \boldsymbol{W}_d)) = \boldsymbol{I}_{n^2} - \rho_o \boldsymbol{W}_o - \rho_d \boldsymbol{W}_d + \rho_w \boldsymbol{W}_w$, where $\rho_w = -\rho_o \rho_d$, $\boldsymbol{W}_w = \boldsymbol{W} \otimes \boldsymbol{W}$ and $\boldsymbol{W}$ is an $n \times n$ spatial weights matrix among n countries.

To identify the regional determinants of pairwise business cycle synchronisation across 49 US states, Cainelli et al. (2021) adopt a spatial Durbin model in the cross section, where the dependent

[1] See also the factor-based models for symmetric bilateral trade flows analysed by Cheng et al. (2005) and Serlenga & Shin (2007).

variable is measured as the time average of the synchronisation index between state pairs. To build the spatial matrix, they first consider an $n^2 \times n^2$ row-normalised matrix given by $\boldsymbol{W}^* = \boldsymbol{I}_n \otimes \boldsymbol{W}$, where $\boldsymbol{W}$ indicates the typical $n \times n$ first-order contiguity or k-nearest neighbour weight matrix. They do not identify three distinct types of contiguity (origin based $\boldsymbol{W}_o$, destination based $\boldsymbol{W}_o$ and origin-to-destination based $\boldsymbol{W}_w$), because the matrix of bilateral synchronisation indicators among all the state pairs (with $n = 49$) is symmetric. Next, they remove the n cases where the 'origin' and the 'destination' states coincide, obtaining $n(n-1)$ bilateral synchronisation indicators, and transform $\boldsymbol{W}^*$ into the $n(n-1) \times n(n-1)$ matrix $\boldsymbol{W}^{**}$. Finally, they exclude mirrored bilateral synchronisation indicators, and remove the duplicated weights assigned to all possible state pairs from $\boldsymbol{W}^{**}$ by filtering rows and columns of the spatial matrix with respect to the list of unique state pairs to construct the final $n(n-1) \times n(n-1)$ spatial weights matrix, $\boldsymbol{W}^{***}$.

In this paper we propose constructing the spatial weights matrix based on a shared border as follows:

$$\boldsymbol{W}_B = \begin{bmatrix} 0 & w_{12} & \cdots & w_{1N} \\ w_{21} & 0 & \cdots & w_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1} & w_{N2} & \cdots & 0 \end{bmatrix}, \tag{A.3.9}$$

where we assign $w_{ij} = 1, i \neq j$, if the i-th and j-th country pairs share a common country and zero otherwise. This means that those pairs become neighbours only if they share a common country.

Following Shin et al. (2025), we describe a more general alternative approach to constructing the $N \times N$ spatial weights matrix among the symmetric N country-pairs, $\boldsymbol{W}_N$, based on the $n \times n$ distance (or spatial) weights matrix among the n countries, $\mathbf{D}$, given by

$$\mathbf{D} = \begin{bmatrix} 0 & d_{12} & \cdots & d_{1n} \\ d_{21} & 0 & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & 0 \end{bmatrix},$$

where each $d_{kl} = D(k,l)$, $1 \leq k \neq l \leq n$, is a function of the (economic/geographical) distance/similarity between country k and country l. To convert the $n \times n$ matrix $\mathbf{D}$ to the $N \times N$ weights matrix for country pairs, suppose that the i-th country pair is (i_1, i_2) (i.e., consists of countries i_1 and i_2) and the j-th country pair is (j_1, j_2). Shin et al. (2025) propose measuring the distance between these two country pairs as follows:

$$\bar{D}[(i_1, i_2), (j_1, j_2)] = D(i_1, j_1) + D(i_2, j_2). \tag{A.3.10}$$

The main intuition is that the spatial dependence between (i_1, i_2) and (j_1, j_2) pairs can be determined by two factors: similarity on $i_1(j_1)$ and $i_2(j_2)$ dimensions. The more similar between countries i_1 and j_1, and countries i_2 and j_2, the more similar the (i_1, i_2) and (j_1, j_2) pairs such that their spatial dependence becomes stronger. The distance $D(i_1, j_1)$ measures how close j_1 is to origin i_1, while $D(i_2, j_2)$ measures how close j_2 is to destination i_2. If both distances are small, then $\bar{D}[(i_1, i_2), (j_1, j_2)])$ is small so that we expect y_{it} and y_{jt} to be close/similar.

In the general case where the $n \times n$ spatial weights matrix is allowed to be heterogeneous across countries, Shin et al. (2025) propose to measure the distance between (i_1, i_2) and (j_1, j_2) pairs as[2]

$$\bar{D}[(i_1, i_2), (j_1, j_2)] = \frac{\tilde{\boldsymbol{b}}_{i_2}(\boldsymbol{W}^d_{i_1} + \boldsymbol{W}^d_{j_1})\tilde{\boldsymbol{b}}'_{j_2}}{2} + \frac{\boldsymbol{b}_{i_1}(\tilde{\boldsymbol{W}}^d_{i_2} + \tilde{\boldsymbol{W}}^d_{j_2})\boldsymbol{b}'_{j_1}}{2} = \frac{w_{i_1,(i_2,j_2)} + w_{j_1,(i_2,j_2)}}{2} + \frac{\tilde{w}_{i_2,(i_1,j_1)} + \tilde{w}_{j_2,(i_1,j_1)}}{2} \tag{A.3.11}$$

where $\boldsymbol{W}^d_{i_1}$ and $\boldsymbol{W}^d_{j_1}$ are the spatial weights matrices of i_1-th and j_1-th origin countries, $\tilde{\boldsymbol{W}}^d_{i_2}$ and $\tilde{\boldsymbol{W}}^d_{j_2}$ are the spatial weights matrices of i_2-th and j_2-th destination countries, $\underset{1\times M}{\tilde{\boldsymbol{b}}_{i_2}}$ is a zero vector with its i_2-th position being 1 and $\underset{1\times N}{\boldsymbol{b}_{i_1}}$ is a zero vector with its i_1-th position being 1. In the current application with the $n \times n$ (homogeneous) distance matrix, $\mathbf{D}$, among the n countries, the distance between (i_1, i_2) and (j_1, j_2) pairs in (A.3.11) is reduced to

$$\bar{D}[(i_1, i_2), (j_1, j_2)] = d_{i_2,j_2} + d_{i_1,j_1}, \tag{A.3.12}$$

where d_{i_1,j_1} is the (i_1, j_t)-th element of $\mathbf{D}$.

Consider the 4-country example, ordered by China, US, EU and Japan, with 4×4 distance matrix given by

$$\mathbf{D} = \begin{bmatrix} & C & U & E & J \\ C & 0 & d_{12} & d_{13} & d_{14} \\ U & d_{21} & 0 & d_{23} & d_{24} \\ E & d_{31} & d_{32} & 0 & d_{34} \\ J & d_{41} & d_{42} & d_{43} & 0 \end{bmatrix}$$

[2] If $\boldsymbol{W}^d_{i_1} = \boldsymbol{W}^d_{j_1}$, and $\tilde{\boldsymbol{W}}^d_{i_2} = \tilde{\boldsymbol{W}}^d_{j_2}$, then $\bar{D}[(i_1, i_2), (j_1, j_2)] = \tilde{\boldsymbol{b}}_{i_2}(\boldsymbol{W})\tilde{\boldsymbol{b}}'_{j_2} + \boldsymbol{b}_{i_1}(\tilde{\boldsymbol{W}})\boldsymbol{b}'_{j_1} = w_{i_2 j_2} + \tilde{w}_{i_1 j_1}$. Further, if $\boldsymbol{W} = \tilde{\boldsymbol{W}}$, then $\bar{D}[(i_1, i_2), (j_1, j_2)] = \tilde{\boldsymbol{b}}_{i_2}(\boldsymbol{W})\tilde{\boldsymbol{b}}'_{j_2} + \boldsymbol{b}_{i_1}(\boldsymbol{W})\boldsymbol{b}'_{j_1} = w_{i_2 j_2} + w_{i_1 j_1}$.

Then, we need to construct the 6×6 distance matrix among the following 6 pairs:

$$\mathbf{L} = \begin{array}{c} \\ CU \\ CE \\ CJ \\ UE \\ UJ \\ EJ \end{array} \!\!\! \begin{array}{c} \begin{array}{cccccc} CU & CE & CJ & UE & UJ & EJ \end{array} \\ \begin{bmatrix} 0 & \ell_{12} & \ell_{13} & \ell_{14} & \ell_{15} & \ell_{16} \\ \ell_{21} & 0 & \ell_{23} & \ell_{24} & \ell_{25} & \ell_{26} \\ \ell_{31} & \ell_{32} & 0 & \ell_{34} & \ell_{35} & \ell_{36} \\ \ell_{41} & \ell_{42} & \ell_{43} & 0 & \ell_{45} & \ell_{46} \\ \ell_{51} & \ell_{52} & \ell_{53} & \ell_{54} & 0 & \ell_{56} \\ \ell_{61} & \ell_{62} & \ell_{63} & \ell_{64} & \ell_{65} & 0 \end{bmatrix} \end{array}$$

Applying (A.3.12), we obtain:

$$\ell_{12} = d_{UE} = d_{23} = d_{32} = d_{EU}$$

$$\ell_{13} = d_{UJ} = d_{24} = d_{42} = d_{JU}$$

$$\ell_{14} = d_{CE} = d_{13} = d_{31} = d_{EC}$$

$$\ell_{15} = d_{CJ} = d_{14} = d_{41} = d_{JC}$$

$$\ell_{16} = d_{CE} + d_{UJ} = d_{13} + d_{24} = d_{31} + d_{42} = d_{EC} + d_{JU}$$

Therefore,

$$L = \begin{array}{c} \\ CU \\ CE \\ CJ \\ UE \\ UJ \\ EJ \end{array} \!\!\! \begin{array}{c} \begin{array}{cccccc} CU & CE & CJ & UE & UJ & EJ \end{array} \\ \begin{bmatrix} 0 & d_{UE} & d_{UJ} & d_{CE} & d_{CJ} & d_{CE} + d_{UJ} \\ d_{EU} & 0 & d_{EJ} & d_{CU} & d_{CU} + d_{EJ} & d_{CJ} \\ d_{JU} & d_{JE} & 0 & d_{CU} + d_{JE} & d_{CU} & d_{CE} \\ d_{EC} & d_{UC} & d_{UC} + d_{EJ} & 0 & d_{EJ} & d_{UJ} \\ d_{JC} & d_{UC} + d_{JE} & d_{UC} & d_{JE} & 0 & d_{UE} \\ d_{EC} + d_{JU} & d_{JC} & d_{EC} & d_{JU} & d_{EU} & 0 \end{bmatrix} \end{array}$$

which can also be written as

$$\mathbf{L} = \begin{bmatrix} & CU & CE & CJ & UE & UJ & EJ \\ CU & 0 & d_{23} & d_{24} & d_{13} & d_{14} & d_{13}+d_{24} \\ CE & d_{32} & 0 & d_{34} & d_{12} & d_{12}+d_{34} & d_{14} \\ CJ & d_{42} & d_{43} & 0 & d_{12}+d_{43} & d_{12} & d_{13} \\ UE & d_{31} & d_{21} & d_{21}+d_{34} & 0 & d_{34} & d_{24} \\ UJ & d_{41} & d_{21}+d_{43} & d_{21} & d_{43} & 0 & d_{23} \\ EJ & d_{31}+d_{42} & d_{41} & d_{31} & d_{42} & d_{32} & 0 \end{bmatrix}$$

In general, the $N \times N$ distance matrix among symmetric N country-pairs can be written as

$$\mathbf{L} = \begin{bmatrix} 0 & \ell_{12} & \cdots & \ell_{1n} \\ \ell_{21} & 0 & \cdots & \ell_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \ell_{n1} & \ell_{n2} & \cdots & 0 \end{bmatrix}$$

We need to take an inverse distance to construct the final spatial weights matrix, $\boldsymbol{W}_N$. This clearly shows that the two country pairs sharing a common country is given the more weight while the those without sharing a common country is given the less weight (more distance). For comparison we rewrite the spatial weights matrix, $\boldsymbol{W}_B$ defined in (A.3.13) as

$$\boldsymbol{W}_B = \begin{bmatrix} & CU & CE & CJ & UE & UJ & EJ \\ CU & 0 & 1 & 1 & 1 & 1 & 0 \\ CE & 1 & 0 & 1 & 1 & 0 & 1 \\ CJ & 1 & 1 & 0 & 0 & 1 & 1 \\ UE & 1 & 1 & 0 & 0 & 1 & 1 \\ UJ & 1 & 0 & 1 & 1 & 0 & 1 \\ EJ & 0 & 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{A.3.13}$$

We observe that both $\boldsymbol{W}_N$ and $\boldsymbol{W}_B$ assign more weights to the country pairs sharing the common country than those without sharing the common country. But, the main difference lies in that the spatial neighbor is constructed by a (non-sparse) weighted average of all pairs in the former whilst the spatial neighbor is constructed by a (sparse equal weight) average of the selected pairs in the latter. Since the number of pairs sharing common i or j is given by $2(n-1)$, and the zero weight is assigned to the same pairs, the number of pairs with more weights assigned is $2(n-2)$. For example, when $n = 17$, we assign the equal weight to $30 = 2 \times 15$ pairs out of 136 pairs.

There are three options: (i) use $\boldsymbol{W}_N$ and construct the weights w_{ij} as the inverse distance, e.g. $w_{ij} = \frac{\ell_{ij}^{-2}}{\sum_{j=1}^{N} \ell_{ij}^{-2}}$ for $i, j = 1, ..., N$; (ii) use $\boldsymbol{W}_B$ and construct the equal weights $w_{ij} = \frac{1}{2(n-2)}$ for $i, j = 1, ..., N$; (iii) combine $\boldsymbol{W}_B$ and $\boldsymbol{W}_N$ such that we select the neighbours based on the shared border and assign the inverse distances as weights, say $w_{ij} = \frac{\ell_{ij}^{-2}}{\sum_{j=1}^{N} \ell_{ij}^{-2}}$ for $i, j = 1, ..., N$ if $i = g$ or $j = h$, and 0 otherwise. By convention $w_{ij} = 0$ if $i = g$ and $j = h$. For convenience we select the sparse weights based on $\boldsymbol{W}_B$ in the main application.

There are other factors that affect spillovers of the business cycle synchronisation among country pairs, such as trade relationships, financial integration, similar economic policies, etc. Then, we can replace the distance with such economic distance.

A.4 Additional Estimation Results

This section presents the CCEX-2SLS estimation results and the spatial and GCM network analysis of S for the full sample and of S^F using the full and stable samples.

A.4.1 Network multipliers of trade/finance intensities on S using the full sample

Table A.1 displays the descriptive statistics for HDE, HSI and HSO of the full sample that are derived from the highly heterogeneous CCEX-2SLS estimation results for the model (1.3.10). When comparing to Table 1.5, HDEs of the trade intensity $\boldsymbol{\psi}_1$ are more positive (55.15%), though its average is surprisingly negative at -0.67, affected by the outlying results, e.g. Finland-UK (-52.81). Both HSIs and HSOs of trade intensities are positive on average (1.58). The diffusion multipliers of the financial intensity $\boldsymbol{\psi}_2$ for full sample exhibit robust result to the stable sample.

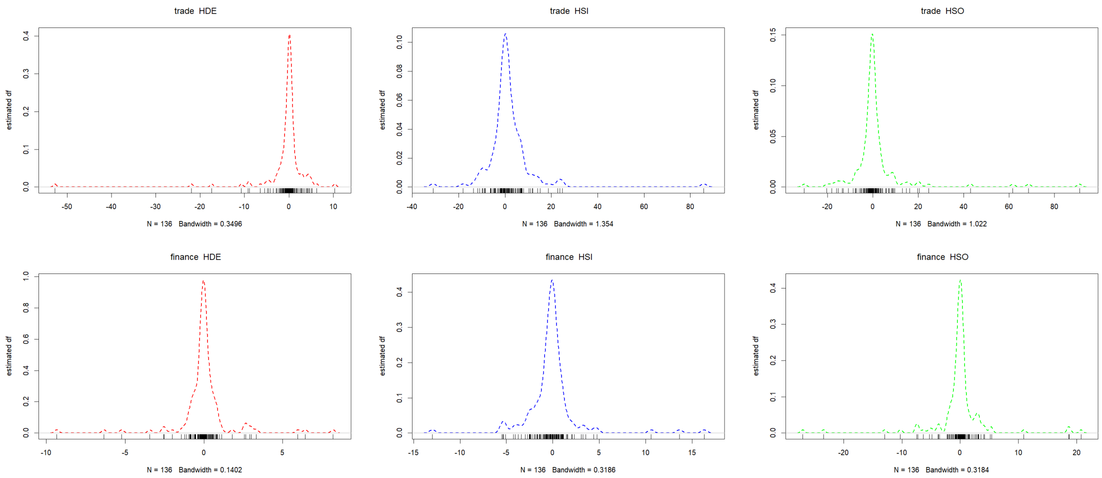
Table A.1: Descriptive statistics for network multipliers of trade/finance intensities on S (full sample)

	$\boldsymbol{\psi}_1$			$\boldsymbol{\psi}_2$		
	HDE	HSI	HSO	HDE	HSI	HSO
Min.	-52.808	-31.075	-30.400	-9.347	-12.964	-27.045
Max.	10.388	85.727	91.040	8.199	16.317	20.761
Median	0.083	0.538	-0.232	0.013	-0.074	-0.026
Mean	-0.673	1.585	1.584	0.027	-0.127	-0.127
SD	5.701	10.113	13.411	1.736	2.863	4.977
$\% > 0$	55.15	55.88	43.38	50.74	42.65	49.26

$\boldsymbol{\psi}_1$ ($\boldsymbol{\psi}_2$) represents the network multipliers of trade (finance) intensity on BCS, S while HDE, HSI and HSO refer to heterogeneous direct, spill-in and spill-out effects, respectively, as described in Section 3.2. See also footnotes to Table 1.2.

The kernel density estimates of HDE, HSI and HSO in Figure A.1 show symmetric distributions centered around zero, with heavy tails. It suggests the use of the heterogeneous coefficient models instead of the restrictive homogeneous model.

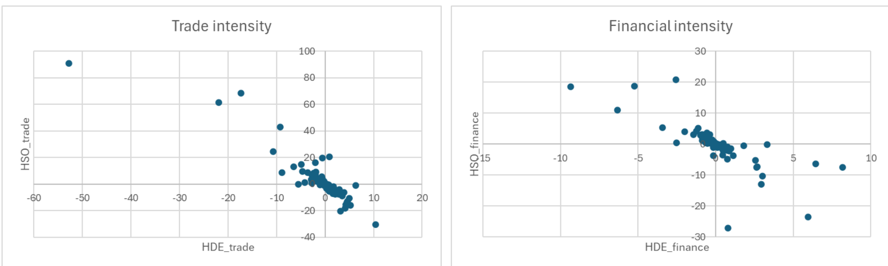
Figure A.1: Kernel density of trade & financial HDE, HSI and HSO on S (full sample)



The top (bottom) panel displays the results for the trade (financial) intensity. See also Table 1.2 footnotes.

Next, given the heterogeneous estimation results, we assign the individual country pair to four cases to identify which country-pairs or groups can contribute to improve or deteriorate the BCS through trade/financial intensities. For trade intensity, we observe case (ii) predominantly followed by case (iii), as evidenced by 54.4% and 42.6% of the sample belonging to cases (ii) and (iii), respectively. However, the respective shares of the sample in case (i) and (iv) are 0.7% and 2.2%. We observe the similar pattern for financial intensity with the proportions of case (i) being 1.5%, case (ii) being 49.3%, case (iii) being 47.8% and case (iv) being 1.5% in the sample. The distributions are shown in Figure A.2, which are aligned with Figure 1.5.

Figure A.2: Network multipliers of trade and finance intensities on S (full sample)



This figure displays the scatter plots of HSO vs. HDE among 136 country-pairs for S. Each country pair is assigned to one of the following four categories: (i) they boost BCS directly through HDE and indirectly through HSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly.

Table A.2 reports the direct, spill-in and spill-out effects of trade/financial intensities on BCS,

S across the six clusters for the full sample. For trade intensity, when compare to the stable sample in Table 1.6, the direct effects for EC-EP cluster become positive, while negative for EC-EC cluster. Summing over the six clusters, we find that an aggregate total effect turns positive (2.572), because an aggregate direct effect is -7.065 and an aggregate indirect spillover effect is 9.637. Turning to the total effect GTE of the trade intensity on BCS in each cluster, we find that it is negative for EC-EC, EP-EP and NEU-NEU clusters. For these three clusters negative direct effect dominate positive spill-ins (mainly from clusters associated with EC and NEU country-pairs). It still implies that the advanced country-pairs are influential transmitters of trade intensity to boost BCS.

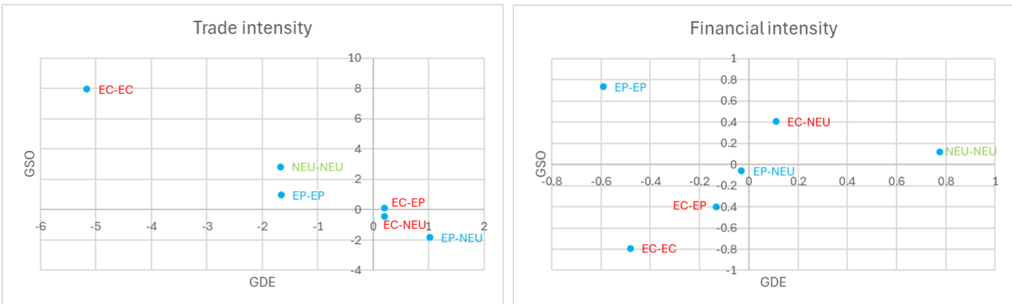
For financial intensity, when compare to the stable sample in Table 1.6, the direct effect for the EP-EP cluster becomes negative. The aggregate total effect turns negative (-0.339), since the aggregate direct effect is -0.349 and the aggregate indirect spillover effect is 0.01. The total effect of the financial intensity on BCS in each cluster, is negative for EC-NEU, EP-EP and EP-NEU clusters. For the EC-NEU cluster negative spill-ins (mainly from clusters associated with EU country-pairs) dominate whereas negative direct effect prevails for EP-EP and EP-NEU clusters. Furthermore, substantial positive (negative) spill-outs are observed in EC-NEU, EP-EP and NEU-NEU (EC-EC and EC-EP) clusters. This implies that the advanced country-pairs are likely to spread out positive shocks to boost BCS, though the intra-EU clusters tend to inhibit BCS (except for EP-EP).

Table A.2: Group direct, spill-in, spill-out effects across the six clusters for S (full sample)

Group Connectedness Matrix - Trade Intensity						
	EC-EC	EC-EP	EC-NEU	EP-EP	EP-NEU	NEU-NEU
EC-EC	-5.159	-0.117	0.198	0.257	-1.145	1.563
EC-EP	3.516	0.199	-0.340	0.692	-0.027	1.160
EC-NEU	2.938	0.564	0.201	-0.255	-0.509	0.218
EP-EP	0.965	-0.367	0.051	-1.656	-0.190	0.417
EP-NEU	0.433	0.165	-0.582	0.472	1.022	-0.529
NEU-NEU	0.101	-0.114	0.244	-0.178	0.035	-1.672
GDE	-5.159	0.199	0.201	-1.656	1.022	-1.672
GSI	0.757	5.001	2.955	0.876	-0.040	0.088
GSO	7.953	0.132	-0.429	0.988	-1.835	2.830
GTE	-4.402	5.2	3.156	-0.78	0.982	-1.584
GNE	7.196	-4.870	-3.384	0.112	-1.795	2.742
Group Connectedness Matrix - Financial Intensity						
	EC-EC	EC-EP	EC-NEU	EP-EP	EP-NEU	NEU-NEU
EC-EC	-0.481	0.002	0.090	0.654	-0.096	0.150
EC-EP	-0.013	-0.133	0.088	0.751	0.153	-0.248
EC-NEU	-0.605	-0.424	0.111	-0.101	-0.173	0.279
EP-EP	-0.283	0.059	0.094	-0.592	0.063	-0.003
EP-NEU	0.159	-0.069	0.111	-0.141	-0.029	-0.061
NEU-NEU	-0.049	0.036	0.022	-0.429	-0.006	0.775
GDE	-0.481	-0.133	0.111	-0.592	-0.029	0.775
GSI	0.800	0.732	-1.025	-0.070	-0.002	-0.425
GSO	-0.791	-0.397	0.406	0.734	-0.058	0.116
GTE	0.319	0.599	-0.914	-0.662	-0.031	0.35
GNE	-1.591	-1.128	1.430	0.804	-0.056	0.541

We divide 17 countries into the 3 groups as EU core (EC), EU periphery (EP) and non-EU (NEU) countries, and construct the 6 clusters, including EC-EC, EC-EP, EC-NEU, EP-EP, EP-NEU and NEU-NEU. GDE, GSI and GSO refer to group direct, spill-in and spill-out effects, respectively. GTE is the group total effect, measured by the sum of GDE and GSI. GNE is the group net effect, measured by the difference between GSO and GSI.

Figure A.3: GCM analysis of GDE/GSO across the six clusters for S (full sample)



We now discuss the GCM results associated with trade intensities for the full sample in Figure A.3. Regarding trade intensities, the EC-EC cluster changes to an indirect BCS booster but direct BCS inhibitor. The EC-EP cluster becomes a BCS booster directly. The EP-EP cluster maintains the role as a direct BCS inhibitor while also becomes a slightly indirect BCS booster. Regarding financial intensities, the EC-EP cluster changes to a BCS inhibitor both directly and indirectly. The EP-EP clusters shifts from case (ii) in stable sample to case (iii) in full sample, becoming the direct BCS inhibitor but an indirect BCS booster. The EP-NEU cluster turns into the (direct and indirect) BCS inhibitor.

A.4.2 Network multipliers of trade/finance intensities on S^F

Now, we discuss the descriptive statistics of network measures for the systematic component of BCS, S^F presented in Table A.3. These results are generally similar to the results of S using the stable sample in Table 1.5. The differences are: (i) HSOs of the trade/financial intensities, $\boldsymbol{\psi}_1/\boldsymbol{\psi}_2$ are more positive for the stable sample. (ii) On average, the HDE of $\boldsymbol{\psi}_2$ remains negative for both full and stable samples, while the mean of spillovers becomes positive for the stable sample.

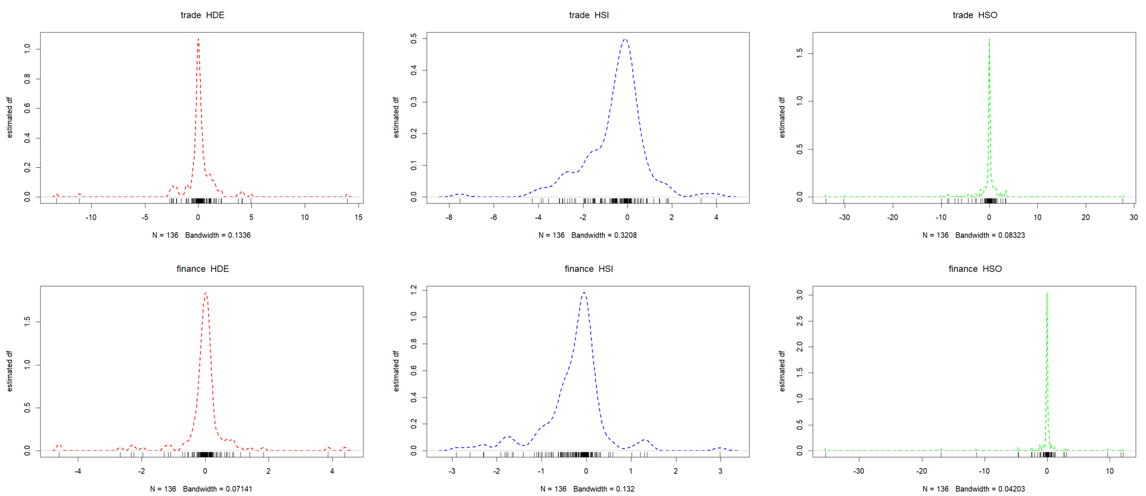
Table A.3: Descriptive statistics of GCM analysis for S^F

	Panel A: full sample			Panel B: stable sample		
$\boldsymbol{\psi}_1$	HDE	HSI	HSO	HDE	HSI	HSO
Min.	-13.294	-7.516	-33.929	-2.540	-1.999	-7.860
Max.	13.959	3.973	27.679	4.100	1.420	3.419
Median	0.041	-0.246	0.009	0.035	-0.046	0.007
Mean	0.082	-0.570	-0.570	0.089	-0.164	-0.164
SD	2.218	1.400	4.941	0.909	0.527	1.573
$\% > 0$	55.88	30.88	54.41	55.81	37.98	54.26
$\boldsymbol{\psi}_2$	HDE	HSI	HSO	HDE	HSI	HSO
Min.	-4.597	-2.902	-35.390	-2.673	-0.794	-10.762
Max.	4.385	2.978	12.149	1.831	2.151	11.084
Median	0.006	-0.126	-0.006	0.012	0.011	0.003
Mean	-0.042	-0.281	-0.281	-0.011	0.082	0.082
SD	0.933	0.733	3.976	0.482	0.319	1.728
$\% > 0$	50	27.94	44.12	50.39	31.62	51.94

See also footnotes to Table 1.2.

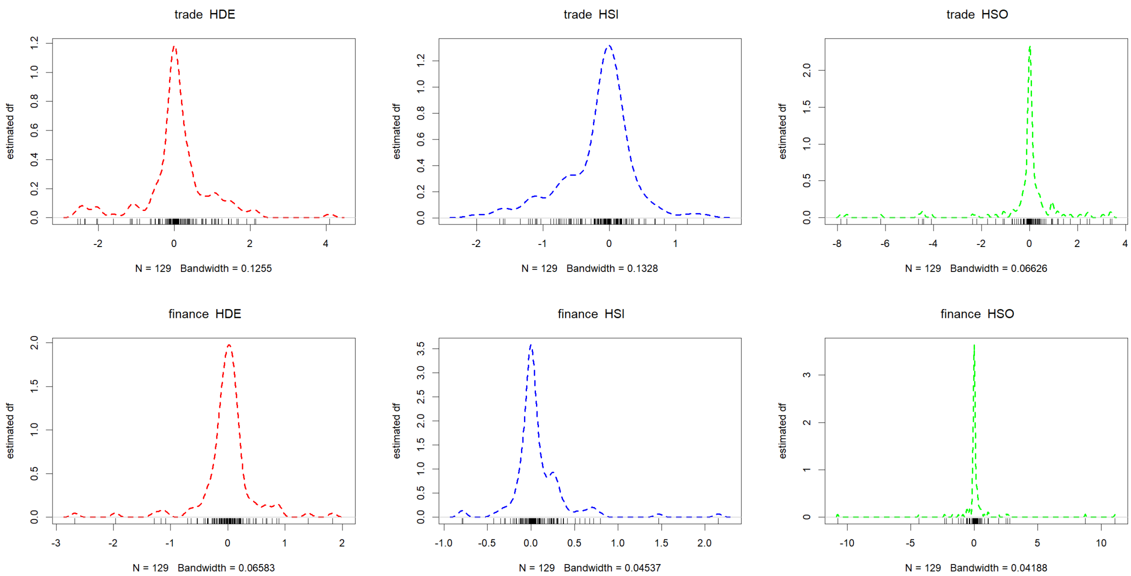
The kernel density estimates of HDE, HSI and HSO in Figures A.4 and A.5 for the full and stable samples clearly suggest the importance of the heterogeneous coefficients models.

Figure A.4: Kernel density of trade & finance HDE, HSI and HSO on S^F (full sample)



The top (bottom) panel displays the results for the trade (financial) intensity. See also footnotes to Table 1.2.

Figure A.5: Kernel density of trade & finance HDE, HSI and HSO on S^F (stable sample)



The top (bottom) panel displays the results for the trade (financial) intensity. See also Table 1.2 footnotes.

Next, given the heterogeneous estimation results, we assign the individual country pair to four cases to identify which country-pairs or groups can contribute to improve or deteriorate the BCS through trade/financial intensities. For trade intensity, we observe case (i) predominantly followed by case (ii), as evidenced by 32.4% and 23.5% of the sample belonging to cases (i) and (ii), respectively. The shares of the sample in case (iii) and (iv) are both 22.1%. However, we observe a different pattern for financial intensity with the proportions of case (i) being 24.3%, case (ii) being 25.7%, case (iii) being 19.9% and case (iv) being 30.2% in the sample. The distributions are shown in Figure A.6. This is not exactly the same as the result for S in Figure 1.5, which indicates that the impacts of direct and spill-out effects on BCS through trade/financial intensities can be different for S and S^F.

Figure A.6: Network multipliers of trade and finance intensities on S^F (full sample)

This figure displays the scatter plots of HSO vs. HDE among 136 country-pairs for S^F. Each country pair is assigned to one of the following four categories: (i) they boost BCS directly through HDE and indirectly through HSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly.

Table A.4 reports the direct, spill-in and spill-out effects of trade/financial intensities on systemic BCS, S^F across the six clusters for the full sample. In comparison with stable result of S for trade intensity in Table 1.6, the negative direct effects for the NEU-NEU cluster become more significant. Summing over the six clusters, we find that an aggregate total effect remains negative (-4.07), because an aggregate direct effect (-1.91) and an aggregate indirect spillover effect (-2.16) are both negative. Turning to the total effect GTE of the trade intensity on BCS in each cluster, we find that it is positive for EC-EC cluster only. For EC-EP cluster negative direct effect dominates positive spill-ins (mainly from the NEU cluster) while negative spill-ins prevail for the EP-NEU cluster (mainly from clusters associated with EP country pairs). It still implies that the advanced country-pairs are influential transmitters of trade intensity to boost BCS while the clusters associated with the less developed country-pairs may transmit adverse shocks and inhibit BCS. For financial intensity, when compare to the stable sample for S, the direct effects of EC-NEU, EP-EP and NEU-NEU clusters become negative, while positive of the EP-NEU cluster. The aggregate total effect turns negative (-2.68), since the aggregate direct effect is -1.57 and the aggregate indirect spillover effect is -1.11. The total effect of the financial intensity on BCS in each cluster, turns negative for EC-EP, EP-EP and NEU-NEU clusters, where negative direct effect prevails with negative spill-ins (mainly from clusters associated with EP country pairs). Furthermore, substantial positive (negative) spill-outs are observed in EC-EC and EP-NEU (EC-EP and EP-EP) clusters.

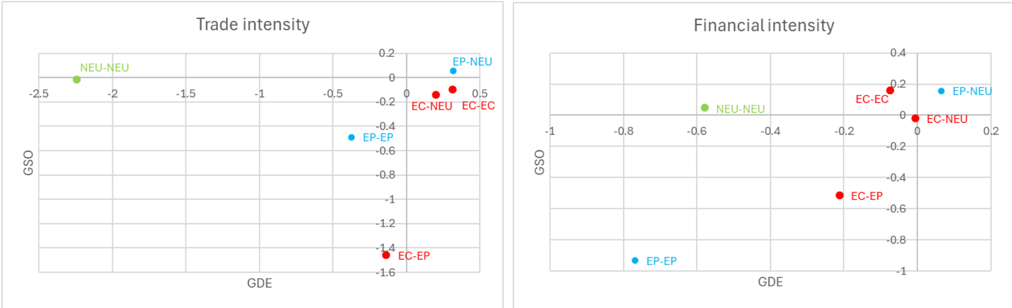
Table A.4: Group direct, spill-in, spill-out effects across the six clusters for S^F (full sample)

Group Connectedness Matrix - Trade Intensity						
	EC-EC	EC-EP	EC-NEU	EP-EP	EP-NEU	NEU-NEU
EC-EC	0.317	-0.102	-0.017	-0.011	-0.001	-0.113
EC-EP	0.113	-0.134	-0.068	-0.182	0.028	0.193
EC-NEU	-0.071	-0.398	0.201	-0.032	-0.039	-0.142
EP-EP	-0.015	-0.119	-0.025	-0.373	0.003	0.210
EP-NEU	-0.073	-0.503	-0.004	-0.145	0.317	-0.169
NEU-NEU	-0.055	-0.337	-0.027	-0.120	0.066	-2.238
GDE	0.317	-0.134	0.201	-0.373	0.317	-2.238
GSI	-0.244	0.084	-0.683	0.054	-0.894	-0.473
GSO	-0.101	-1.460	-0.141	-0.490	0.056	-0.020
GTE	0.073	-0.05	-0.482	-0.319	-0.577	-2.711
GNE	0.143	-1.545	0.543	-0.544	0.950	0.453
Group Connectedness Matrix - Financial Intensity						
	EC-EC	EC-EP	EC-NEU	EP-EP	EP-NEU	NEU-NEU
EC-EC	-0.073	0.048	0.008	0.009	0.004	-0.018
EC-EP	0.049	-0.211	-0.011	-0.356	0.044	0.079
EC-NEU	0.006	0.016	-0.005	-0.057	0.021	-0.038
EP-EP	0.029	-0.212	-0.011	-0.768	0.014	0.065
EP-NEU	0.048	-0.302	-0.018	-0.278	0.064	-0.044
NEU-NEU	0.025	-0.066	0.011	-0.250	0.075	-0.578
GDE	-0.073	-0.211	-0.005	-0.768	0.064	-0.578
GSI	0.051	-0.197	-0.051	-0.115	-0.593	-0.205
GSO	0.157	-0.515	-0.022	-0.933	0.157	0.045
GTE	-0.022	-0.408	-0.056	-0.883	-0.529	-0.783
GNE	0.107	-0.319	0.030	-0.818	0.750	0.250

We divide 17 countries into the 3 groups as EU core (EC), EU periphery (EP) and non-EU (NEU) countries, and construct the 6 clusters, including EC-EC, EC-EP, EC-NEU, EP-EP, EP-NEU and NEU-NEU. GDE, GSI and GSO refer to group direct, spill-in and spill-out effects, respectively. GTE is the group total effect, measured by the sum of GDE and GSI. GNE is the group net effect, measured by the difference between GSO and GSI.

We now discuss the GCM results associated with trade/financial intensities for the full sample of S^F in Figure A.7 and compare the result with the stable sample of S in Figure 1.6. In terms of trade intensities, the EC-EC cluster turns into a direct BCS booster but indirect BCS inhibitor. The negative spill-outs of EC-NEU and EP-EP clusters get stronger and they become the direct BCS booster but indirect BCS inhibitor, and the BCS inhibitor directly and indirectly, respectively. The EP-NEU cluster shifts from case (ii) to case (i) as a direct and indirect BCS booster. Finally, the NEU-NEU cluster exerts less positive spill-outs and serves as the indirect BCS booster only. Next, we turn to the GCM results associated with financial intensities. The EC-EC cluster maintains its role as the direct BCS inhibitor while becomes the indirect BCS booster. The EC-EP cluster becomes the BCS inhibitor both directly and indirectly. The direct and indirect effects of the EC-NEU cluster both shrink and become negligible. On the contrary, the EP-NEU cluster becomes the direct and indirect BCS booster. Finally, the NEU-NEU cluster shifts from case (i) for S to case (iii) for S^F using the stable sample, becoming the direct BCS inhibitor but slightly indirect BCS booster.

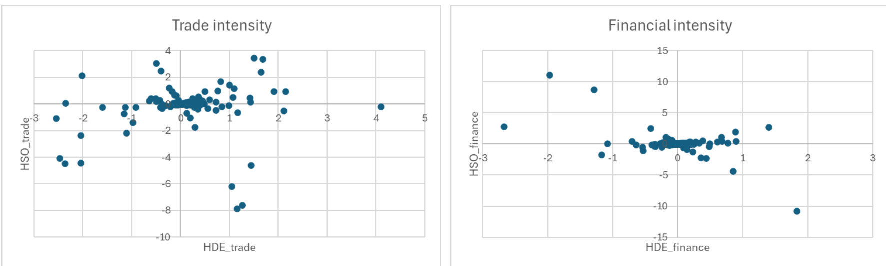
Figure A.7: GCM analysis of GDE/GSO across the six clusters for S^F (full sample)



Notes: This figure displays the GDE/GSO across the six clusters. Each cluster is assigned to one of the following four cases: (i) they boost BCS directly through GDE and indirectly through GSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly.

Next, we assign the stable individual country pair to four cases to identify which country-pairs or groups can contribute to improve or deteriorate the BCS through trade/financial intensities. We observe similar patterns in Figure A.8 to full sample in Figure A.6.

Figure A.8: Network multipliers of trade and finance intensities on S^F (stable sample)



This figure displays the scatter plots of HSO vs. HDE among 129 country-pairs for S^F. Each country pair is assigned to one of the following four cases: (i) they boost BCS directly through HDE and indirectly through HSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly.

Table A.5 reports the direct, spill-in and spill-out effects of trade/financial intensities on systemic BCS, S^F across the six clusters for the stable sample. In comparison with stable result of S (Table 1.6) for trade intensity, the direct effects for the EC-EC cluster becomes negative, while positive for the EP-EP cluster. Summing over the six clusters, we find that an aggregate total effect remains negative (-0.476). Turning to the total effect GTE of the trade intensity on BCS in each cluster, we find that it is negative for EC-EC, EC-EP and NEU-NEU clusters where both direct effects and spill-ins (mainly from the EC-EP cluster) are negative. For financial intensity, when compare to the stable sample for S, the direct effects of EC-NEU and NEU-NEU clusters become negative, while positive of the EC-EP and EP-NEU cluster. The aggregate total effect remains positive (0.187). The total effect of the financial intensity on BCS in each cluster, turns negative for the NEU-NEU cluster while turns positive for the EC-NEU and EP-NEU clusters. For the NEU-NEU cluster negative direct effect dominates positive spill-ins (mainly from clusters associated with EU country-pairs). For the EC-NEU and EP-NEU clusters, the positive spill-ins mainly come from clusters associated with EU country-pairs.

Table A.5: Group direct, spill-in, spill-out effects across the six clusters for S^F (stable sample)

Group Connectedness Matrix - Trade Intensity						
	EC-EC	EC-EP	EC-NEU	EP-EP	EP-NEU	NEU-NEU
EC-EC	-0.086	-0.068	-0.019	-0.025	-0.027	-0.009
EC-EP	-0.021	-0.136	-0.023	0.000	0.050	-0.030
EC-NEU	0.027	-0.138	0.201	-0.005	-0.039	0.076
EP-EP	-0.009	-0.114	-0.028	0.138	0.059	-0.011
EP-NEU	0.033	-0.242	-0.004	-0.012	0.317	-0.021
NEU-NEU	0.026	-0.125	-0.010	0.003	0.047	-0.251
GDE	-0.086	-0.136	0.201	0.138	0.317	-0.251
GSI	-0.149	-0.024	-0.078	-0.103	-0.247	-0.058
GSO	0.056	-0.687	-0.084	-0.039	0.090	0.005
GTE	-0.235	-0.16	0.123	0.035	0.07	-0.309
GNE	0.204	-0.663	-0.006	0.064	0.337	0.064
Group Connectedness Matrix - Financial Intensity						
	EC-EC	EC-EP	EC-NEU	EP-EP	EP-NEU	NEU-NEU
EC-EC	-0.168	0.013	0.022	-0.027	0.016	0.013
EC-EP	0.020	0.110	-0.015	-0.049	0.041	0.029
EC-NEU	0.029	0.023	-0.005	-0.009	0.021	-0.001
EP-EP	0.034	0.050	-0.011	0.005	0.025	0.027
EP-NEU	0.074	0.077	-0.018	-0.053	0.064	-0.019
NEU-NEU	0.040	0.034	0.009	-0.021	0.049	-0.242
GDE	-0.168	0.110	-0.005	0.005	0.064	-0.242
GSI	0.037	0.026	0.062	0.126	0.061	0.111
GSO	0.197	0.197	-0.012	-0.159	0.153	0.048
GTE	-0.131	0.136	0.057	0.131	0.125	-0.131
GNE	0.160	0.171	-0.074	-0.285	0.092	-0.063

We divide 17 countries into the 3 groups as EU core (EC), EU periphery (EP) and non-EU (NEU) countries, and construct the 6 clusters, including EC-EC, EC-EP, EC-NEU, EP-EP, EP-NEU and NEU-NEU. GDE, GSI and GSO refer to group direct, spill-in and spill-out effects, respectively. GTE is the group total effect, measured by the sum of GDE and GSI. GNE is the group net effect, measured by the difference between GSO and GSI.

We now discuss the GCM results associated with trade/financial intensities for the stable sample of S^F in Figure A.9 and compare the result with the stable sample of S in Figure 1.6. In terms of trade intensities, the EC-EC cluster turns from a (direct and indirect) BCS booster to an indirect BCS booster but direct BCS inhibitor. The negative spill-outs of EC-NEU cluster get stronger and this cluster becomes the direct BCS booster but indirect BCS inhibitor. The EP-EP cluster maintains the role as a slightly indirect BCS inhibitor while also becomes a direct BCS booster. The EP-NEU cluster shifts from case (ii) to case (i) as a direct and indirect BCS booster. Finally, the

NEU-NEU cluster exerts less positive spill-outs and serves as the indirect BCS booster only. Next, we turn to the GCM results associated with financial intensities. The EC-EC cluster maintains its role as the direct BCS inhibitor while becomes the indirect BCS booster. The EC-EP cluster changes to a BCS booster both directly and indirectly. On the contrary, the EC-NEU cluster becomes the direct and indirect BCS inhibitor. The EP-NEU cluster turns into the (direct and indirect) BCS booster. Finally, the NEU-NEU cluster shifts from case (i) for S to case (iii) for S^F using the stable sample, becoming the direct BCS inhibitor but indirect BCS booster.

Figure A.9: GCM analysis of GDE/GSO across the six clusters for S^F (stable sample)

Notes: This figure displays the GDE/GSO across the six clusters. Each cluster is assigned to one of the following four cases: (i) they boost BCS directly through GDE and indirectly through GSO; (ii) they boost BCS directly but inhibit it indirectly; (iii) they inhibit BCS directly but boost it indirectly; and (iv) they inhibit BCS both directly and indirectly.

A.5 A Sketch of The Proofs of The Asymptotic Distributions of The Individual And Mean-group Estimators

We first provide a sketch for the proof of the asymptotic distribution of the individual estimator presented in (1.3.5).

Note that by (1.3.3) and (1.3.4), we have

$$\begin{aligned}\hat{\boldsymbol{\delta}}_{1i} =&(\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i})^{-1}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{y}}_{1i} = (\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i})^{-1}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\big(\tilde{\mathbf{Z}}_{1i}\boldsymbol{\delta}_{1i} + \tilde{\mathbf{e}}_{1i}\big)\\ =&\boldsymbol{\delta}_{1i} + (\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i})^{-1}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{e}}_{1i}\\ =&\boldsymbol{\delta}_{1i} + \left(\frac{1}{T}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i}\right)^{-1}\left(\frac{1}{T}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{e}}_{1i}\right).\end{aligned} \tag{A.5.14}$$

Similar to the proof of Theorem 1 in Chen et al. (2022), we can show that for each i, $1 \leq i \leq N$, there exists a symmetric nonsingular matrix $\mathbf{\Xi}_{1i}$ such that

$$\frac{1}{T}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{Z}}_{1i} \xrightarrow{p} \mathbf{\Xi}_{1i} \tag{A.5.15}$$

as $(N,T) \to \infty$ and $T/N^2 \to 0$. Furthermore, under regularity conditions similar to Chen et al. (2022), we have

$$E\left(\frac{1}{\sqrt{T}}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{e}}_{1i}\right) = o\left(1\right), \tag{A.5.16}$$

and there exists a positive definite matrix $\mathbf{\Theta}_{1i}$ such that

$$Var\left(\frac{1}{\sqrt{T}}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{e}}_{1i}\right) \longrightarrow \mathbf{\Theta}_{1i}, \tag{A.5.17}$$

and

$$\frac{1}{\sqrt{T}}\tilde{\mathbf{Z}}_{1i}'\mathbf{\Pi}_{1i}\tilde{\mathbf{e}}_{1i} \xrightarrow{d} N\left(\mathbf{0}, \mathbf{\Theta}_{1i}\right). \tag{A.5.18}$$

Combining (A.5.14), (A.5.15), and (A.5.18), we have

$$\sqrt{T}(\hat{\boldsymbol{\delta}}_{1i} - \boldsymbol{\delta}_{1i}) \xrightarrow{d} N\left(\mathbf{0}, \mathbf{\Xi}_{1i}^{-1}\mathbf{\Theta}_{1i}\mathbf{\Xi}_{1i}^{-1}\right). \tag{A.5.19}$$

For the asymptotic distribution of the mean-group estimator, notice that under the random-coefficient model, $\boldsymbol{\delta}_{1i} = \boldsymbol{\delta}_1 + \boldsymbol{\varepsilon}_{\delta_1,i}$ with $\boldsymbol{\varepsilon}_{\delta_1,i} \sim \text{i.i.d.}(\mathbf{0}, \mathbf{\Omega}_{\delta_1})$, we have

$$\begin{aligned}
\hat{\boldsymbol{\delta}}_{1,MG} - \boldsymbol{\delta}_1 =& \frac{1}{N}\sum_{i=1}^{N}\hat{\boldsymbol{\delta}}_{1i} - \boldsymbol{\delta}_1 \\
=& \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\boldsymbol{\delta}}_{1i} - \boldsymbol{\delta}_{1i}\right) + \frac{1}{N}\sum_{i=1}^{N}\left(\boldsymbol{\delta}_{1i} - \boldsymbol{\delta}_1\right) \\
=& \frac{1}{N}\sum_{i=1}^{N}\left(\hat{\boldsymbol{\delta}}_{1i} - \boldsymbol{\delta}_{1i}\right) + \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{\varepsilon}_{\delta_1,i}.
\end{aligned} \tag{A.5.20}$$

With similar arguments to the proof of Theorem 2 in Chen et al. (2022), we can show that

$$\frac{1}{\sqrt{N}}\sum_{i=1}^{N}\left(\hat{\boldsymbol{\delta}}_{1i} - \boldsymbol{\delta}_{1i}\right) = o_p(1), \tag{A.5.21}$$

$$\frac{1}{\sqrt{N}}\sum_{i=1}^{N}\boldsymbol{\varepsilon}_{\delta_1,i} \xrightarrow{d} N\left(\mathbf{0}, \mathbf{\Omega}_{\delta_1}\right), \tag{A.5.22}$$

as $(N, T) \to \infty$. Combining (A.5.20)–(A.5.22), we have

$$\sqrt{N}\left(\hat{\boldsymbol{\delta}}_{1,MG} - \boldsymbol{\delta}_1\right) \xrightarrow{d} N\left(\mathbf{0}, \boldsymbol{\Omega}_{\delta_1}\right). \tag{A.5.23}$$

A.6 Monte Carlo Simulations

A.6.1 Data generating process

We construct the simultaneous equation model with spatial effects and common factors as follows:

$$\begin{aligned} y_{1it} &= \rho_{1i} y_{1it}^* + \gamma_{1i} y_{2it} + \beta_{11i} x_{1it} + \beta_{12i} x_{2it} + \boldsymbol{\lambda}_{1i}' \mathbf{f}_t + l_1 u_{1it}, \\ y_{2it} &= \rho_{2i} y_{2it}^* + \gamma_{2i} y_{1it} + \beta_{21i} x_{3it} + \beta_{22i} x_{4it} + \boldsymbol{\lambda}_{2i}' \mathbf{f}_t + l_2 u_{2it}, \\ x_{qit} &= \boldsymbol{\phi}_{qi}' \mathbf{f}_{xt} + m_q v_{qit}, \quad q = 1, 2, 3, 4, \end{aligned} \tag{A.6.24}$$

where $y_{1it}^* = \sum_{j=1}^N w_{ij} y_{1jt}$, $y_{2it}^* = \sum_{j=1}^N w_{ij} y_{2jt}$, $\mathbf{f}_t = (f_{1t}, f_{2t})'$, $\boldsymbol{\lambda}_{pi} = (\lambda_{p1i}, \lambda_{p2i})'$ for $p = 1, 2$, and $\mathbf{f}_{xt} = (f_{1t}, f_{3t})'$, $\boldsymbol{\phi}_{qi} = (\phi_{q1i}, \phi_{q2i})'$ for $q = 1, 2, 3, 4$.

We set the numbers of exogenous regressors and unobserved factors in each simultaneous equation as two. We partially follow the model setting in Lu (2022) who assumes identical factors in both y and x equations, while here we consider two specifications of the data-generating process (DGP) in (A.6.24). Specifically, Case 1 (DGP1): y_{pit} and x_{qit} share the same factors, i.e., $f_{2t} = f_{3t}$; Case 2 (DGP2): f_{2t} and f_{3t} are generated differently. The factors follow an AR(1) process:

$$f_{rt} = \varphi_{f_r} f_{r,t-1} + \varepsilon_{f_{rt}}, \; t = 1, \ldots, T; \; r = 1, 2, 3,$$

where $\varphi_{f_r} = 0.5$ and $\varepsilon_{f_{rt}} \sim IDN(0, 1 - \varphi_{f_r}^2)$. The factor loadings, $\boldsymbol{\lambda}_{pi}$ and $\boldsymbol{\phi}_{qi}$ follow IIDN(0,1) and IIDN(0,0.5), respectively. Next, we generate the heterogeneous parameters by the random coefficient model:

$$\begin{aligned} \rho_{pi} &= \rho_p + \varepsilon_{\rho_{pi}} = 0.5 + \varepsilon_{\rho_{pi}}, & \gamma_{pi} &= \gamma_p + \varepsilon_{\gamma_{pi}} = 0.1 + \varepsilon_{\gamma_{pi}}, \\ \beta_{11i} &= \beta_{11} + \varepsilon_{\beta_{11i}} = 1 + \varepsilon_{\beta_{11i}}, & \beta_{12i} &= \beta_{12} + \varepsilon_{\beta_{12i}} = 2 + \varepsilon_{\beta_{12i}}, \\ \beta_{21i} &= \beta_{21} + \varepsilon_{\beta_{21i}} = 2 + \varepsilon_{\beta_{21i}}, & \beta_{22i} &= \beta_{22} + \varepsilon_{\beta_{22i}} = 1 + \varepsilon_{\beta_{22i}}, \end{aligned}$$

for $i = 1, \ldots, N$, with $\varepsilon_{\rho_{pi}} \sim IIDU(-0.3, 0.3)$, $\varepsilon_{\gamma_{pi}} \sim IIDN(0, 0.2)$, $\varepsilon_{\varphi_{pi}} \sim IIDN(0, 0.1)$, $\varepsilon_{\beta_{11i}} \sim IIDN(0, 0.5)$, $\varepsilon_{\beta_{12i}} \sim IIDN(0, 0.3)$, $\varepsilon_{\beta_{21i}} \sim IIDN(0, 0.3)$, and $\varepsilon_{\beta_{22i}} \sim IIDN(0, 0.3)$.

We generate the idiosyncratic errors, u_{pit} for $p = 1, 2$ and v_{qit} for $q = 1, 2, 3, 4$, to be cross-sectionally heteroskedastic and serially correlated as follows:

$$u_{pit} = \psi_{u_{pi}} u_{pi,t-1} + \sigma_{pi}(1 - \psi_{u_{pi}}^2)^{0.5} \varepsilon_{u_{pit}},\ p = 1, 2$$

where $\psi_{u_{1i}} = 0.5$, $\psi_{u_{2i}} = 0.4$, $\sigma_{pi}^2 \sim IIDU(0.5, 1)$, $\varepsilon_{u_{pit}} \sim IIDN(0, 1)$ and

$$v_{qit} = \psi_{v_{qi}} v_{qi,t-1} + \varepsilon_{v_{qit}},\ q = 1, 2, 3, 4,$$

where $\psi_{v_{qi}} = 0.5$ and $\varepsilon_{v_{qit}} \sim IIDN(0, 1 - \psi_{v_{qi}}^2)$. For convenience we set the signal-to-noise ratio coefficients as $l_p = 1, m_q = 1$.

Following Baltagi & Deng (2015), we construct a spatial weights matrix, $\boldsymbol{W}_h$, based on the standard h-ahead-and-h-behind neighbour specification. The diagonal elements are set as zero and only the $h/2$ off-diagonal elements immediately before and after the diagonal are nonzero with equal weight $1/h$. We consider $h = 6$, and the spatial weight matrix is row-sum normalised.[3] Each experiment is replicated 1,000 times for each (N, T) pair with $N = \{20, 50, 100\}$ and $T = \{20, 50, 100\}$.

A.6.2 Simulation results

The finite sample performances of individual and mean group estimators of the parameters, $\hat{\boldsymbol{\delta}}_i = (\hat{\rho}_{1i}, \hat{\gamma}_{1i}, \hat{\beta}_{11i}, \hat{\beta}_{12i}, \hat{\rho}_{2i}, \hat{\gamma}_{2i}, \hat{\beta}_{21i}, \hat{\beta}_{22i})'$, are evaluated in terms of bias and RMSE (multiplied by 100). As a benchmark, we also compute the infeasible 2SLS estimator, which uses the true factors, $\mathbf{f}_t$, to defactorise the equations. As the simulation results are qualitatively similar for DGP1 and DGP2, we focus on the results for DGP2 with different factors for y and x.

We first analyse the simulation results for the individual estimator, reported in Table A.6. The biases and RMSEs of the CCEX-2SLS individual estimator are relatively smaller than those of the CCE-2SLS counterpart, especially when both N and T are small, although the gap becomes smaller for as N and T increase, indicating that the efficiency gain from applying the CCE estimator is not attainable. RMSEs of the individual estimator decrease sharply with T, in line with the theoretical prediction that the individual estimator is $\sqrt{T}$-consistent. Furthermore, as the sample size increases, the values of bias and RMSE of the CCEX-2SLS individual estimator get closer to those of the infeasible estimator that employs the true factors in defactorisation.

Table A.7 presents the simulation results for the mean-group estimator, which are qualitatively similar to those for the individual estimator. Again, biases and RMSEs of the CCEX-2SLS estimator

[3] We have also employed $h = 4, 8, 0.3N$, and obtained qualitatively similar results.

are relatively smaller than those of the CCE-2SLS counterpart, especially when both N and T are small. RMSE of the MG estimator decreases sharply with N, in line with the theoretical prediction that the MG estimator is $\sqrt{N}$-consistent. As the sample size increases, bias and RMSE of the CCEX-2SLS MG estimator become closer to those of the infeasible estimator. Overall, we recommend the use of the simpler CCEX-2SLS estimator over the CCE-2SLS estimator.

Table A.6: Finite sample performance of individual estimators

$\rho = 0.5, h = 6$		Bias($\times 100$)								RMSE($\times 100$)							
	N	ρ_{1i}	γ_{1i}	β_{11i}	β_{12i}	ρ_{2i}	γ_{2i}	β_{21i}	β_{22i}	ρ_{1i}	γ_{1i}	β_{11i}	β_{12i}	ρ_{2i}	γ_{2i}	β_{21i}	β_{22i}
		T=20															
CCE-2SLS	20	4.74	-1.05	-4.89	-10.71	0.72	-0.61	-9.86	-5.88	18.15	19.74	26.08	47.52	17.74	21.21	45.10	25.82
	50	-0.15	-0.40	-2.10	-3.94	0.78	-0.20	-4.01	-2.00	8.75	12.78	18.72	28.83	6.95	11.32	29.42	15.29
	100	2.42	0.24	-1.57	-1.98	0.10	0.04	-2.08	-0.97	5.18	6.87	12.11	20.29	6.01	6.79	22.22	10.49
CCEX-2SLS	20	0.90	-1.00	-4.37	-10.04	0.55	-0.49	-9.83	-4.89	10.11	14.94	23.85	45.01	11.16	17.02	45.24	23.25
	50	0.17	-0.38	-1.65	-3.89	0.31	-0.16	-3.95	-1.97	7.60	12.89	15.81	28.08	6.71	9.89	29.15	14.81
	100	0.24	-0.19	-1.40	-2.07	0.10	0.01	-1.97	-1.01	5.76	6.83	11.41	20.01	4.64	6.58	21.06	10.38
Infeasible	20	0.82	-0.90	-4.27	-9.99	0.49	-0.45	-9.82	-4.89	9.67	14.67	23.81	44.96	10.57	16.42	44.88	22.53
	50	0.17	-0.37	-2.00	-3.86	0.25	-0.17	-3.08	-1.89	9.96	10.07	15.80	28.00	6.48	7.63	29.26	14.20
	100	0.14	-0.19	-1.52	-1.99	0.10	-0.02	-1.96	-0.99	5.68	6.80	11.38	20.29	4.08	6.43	20.84	10.28
		T=50															
CCE-2SLS	20	0.60	-1.04	-4.85	-10.03	0.33	-1.04	-9.59	-5.30	18.76	10.41	23.81	46.07	16.00	10.42	44.14	26.31
	50	0.59	-0.37	-2.05	-3.95	0.27	-0.27	-4.00	-1.86	7.78	6.28	15.80	27.12	8.01	6.68	28.85	14.44
	100	0.01	-0.22	-0.99	-2.02	0.09	-0.15	-1.97	-1.04	4.15	4.64	10.82	20.58	3.97	3.82	20.01	10.90
CCEX-2SLS	20	0.52	-1.11	-4.75	-9.96	0.67	-0.98	-9.56	-4.87	10.00	11.30	23.32	44.71	9.06	10.54	43.60	24.22
	50	0.33	-0.32	-2.09	-3.94	0.24	-0.32	-3.94	-1.94	7.15	5.43	15.99	28.06	6.70	6.45	28.78	14.65
	100	0.02	-0.16	-0.99	-1.99	0.08	-0.15	-1.97	-1.04	4.43	4.28	10.67	20.25	2.78	3.87	19.93	10.12
Infeasible	20	0.51	-1.06	-4.76	-9.95	0.67	-0.44	-9.61	-4.83	9.48	11.24	23.32	44.65	9.48	9.66	43.51	23.02
	50	0.31	-0.30	-2.08	-3.98	0.19	-0.31	-3.04	-1.68	7.00	5.42	16.09	28.05	6.76	6.18	28.73	14.04
	100	0.01	-0.16	-1.02	-1.98	0.08	-0.14	-1.97	-1.00	4.29	3.71	10.76	20.56	2.75	3.80	20.34	10.13
		T=100															
CCE-2SLS	20	0.68	-0.82	-4.84	-10.35	0.89	-0.95	-9.54	-5.24	15.97	7.42	22.81	47.45	16.52	7.12	44.96	25.48
	50	-0.01	-0.45	-2.00	-4.03	0.13	-0.43	-3.96	-1.98	7.58	5.10	14.82	29.27	7.49	5.10	28.35	15.63
	100	-0.03	-0.22	-1.00	-2.00	0.08	-0.21	-1.96	-0.97	6.48	4.27	10.46	20.73	5.24	3.45	20.04	10.39
CCEX-2SLS	20	0.49	-0.74	-4.98	-10.29	0.86	-0.95	-9.49	-4.20	9.71	6.58	22.47	46.59	10.44	6.84	45.00	23.16
	50	0.13	-0.44	-1.97	-4.00	0.32	-0.36	-3.97	-1.96	5.92	5.63	14.59	28.64	7.10	5.32	28.35	14.73
	100	0.02	-0.19	-0.98	-1.97	0.15	-0.20	-1.93	-0.97	5.27	3.79	10.38	20.06	4.64	3.73	19.60	10.20
Infeasible	20	0.24	-0.86	-4.90	-9.17	0.86	-0.80	-9.48	-4.80	9.19	6.79	22.47	44.98	10.04	6.83	43.88	22.57
	50	0.17	-0.42	-1.96	-3.94	0.26	-0.31	-3.96	-1.91	6.66	5.34	14.45	28.33	6.29	5.02	28.36	14.33
	100	0.01	-0.18	-0.96	-1.93	0.16	-0.20	-1.92	-0.96	4.73	3.50	10.14	20.61	5.05	3.77	19.87	10.06

Table A.7: Finite sample performance of mean-group estimators

$\rho = 0.5, h = 6$		Bias($\times$100)								RMSE($\times$100)							
	N	ρ_{1i}	γ_{1i}	β_{11i}	β_{12i}	ρ_{2i}	γ_{2i}	β_{21i}	β_{22i}	ρ_{1i}	γ_{1i}	β_{11i}	β_{12i}	ρ_{2i}	γ_{2i}	β_{21i}	β_{22i}
		T=20															
CCE-2SLS	20	-2.44	-0.98	-4.91	-10.70	-3.33	-0.55	-9.95	-5.08	16.79	5.55	20.72	44.60	17.84	4.55	43.56	23.10
	50	0.30	-0.38	-1.79	-4.00	0.33	-0.36	-3.99	-2.01	2.69	3.14	12.78	28.32	2.90	2.61	28.28	14.33
	100	0.19	-0.18	-0.91	-2.01	0.16	-0.10	-1.99	-1.01	1.74	2.02	9.13	20.07	1.80	1.40	19.69	10.07
CCEX-2SLS	20	0.78	-0.92	-4.54	-10.01	0.81	-0.53	-9.66	-4.97	4.15	5.04	20.08	44.83	4.30	4.41	43.36	22.35
	50	0.32	-0.39	-1.78	-4.00	0.32	-0.33	-3.98	-2.00	2.65	3.04	12.68	28.13	2.33	2.61	28.36	14.35
	100	0.18	-0.16	-0.91	-2.01	0.17	-0.09	-1.96	-1.01	1.89	1.79	9.10	20.05	1.79	1.19	19.67	10.06
Infeasible	20	0.75	-0.94	-4.52	-10.01	0.76	-0.52	-9.65	-4.95	3.95	4.97	20.67	44.80	4.11	4.40	43.20	22.38
	50	0.30	-0.37	-1.73	-3.99	0.31	-0.35	-3.98	-1.99	2.60	2.77	12.60	28.23	2.43	2.60	27.79	14.49
	100	0.18	-0.16	-0.91	-2.00	0.17	-0.10	-1.96	-1.01	1.82	1.74	9.25	20.04	1.77	1.15	19.63	10.06
		T=50															
CCE-2SLS	20	-2.76	-0.91	-4.90	-10.07	-2.79	-0.76	-9.94	-5.04	16.58	4.65	21.81	45.21	18.11	4.10	44.52	22.66
	50	0.29	-0.36	-1.93	-3.98	0.33	-0.31	-3.96	-1.98	2.56	2.78	13.68	28.19	2.61	2.41	27.99	14.08
	100	0.16	-0.18	-0.97	-1.99	0.17	-0.15	-1.98	-0.99	1.80	1.90	9.71	19.96	1.80	1.63	19.84	10.00
CCEX-2SLS	20	0.74	-0.86	-4.85	-10.02	0.76	-0.75	-9.91	-5.00	3.84	4.40	22.00	44.88	3.65	4.24	44.38	22.48
	50	0.34	-0.36	-1.94	-3.97	0.34	-0.31	-3.95	-1.98	2.64	2.74	13.72	28.10	2.55	2.35	27.97	14.05
	100	0.17	-0.18	-0.97	-1.99	0.17	-0.16	-1.98	-0.99	1.74	1.89	9.67	19.92	1.78	1.63	19.80	10.00
Infeasible	20	0.73	-0.86	-4.40	-10.00	0.74	-0.72	-9.91	-4.99	3.47	4.26	22.03	44.78	3.91	3.95	44.35	22.43
	50	0.34	-0.37	-1.95	-3.97	0.33	-0.30	-3.95	-1.99	2.63	2.76	13.83	28.12	2.53	2.36	27.97	14.05
	100	0.18	-0.19	-0.97	-1.99	0.17	-0.16	-1.98	-1.00	1.74	1.80	9.67	19.92	1.78	1.63	19.75	10.00
		T=100															
CCE-2SLS	20	-2.63	-0.81	-4.97	-9.97	-2.77	-0.89	-9.69	-4.97	16.66	4.70	22.15	44.75	17.07	4.31	44.51	22.54
	50	0.28	-0.38	-1.97	-3.97	0.31	-0.22	-3.99	-1.95	2.49	2.71	13.96	28.16	2.78	2.34	28.19	13.88
	100	0.17	-0.19	-0.98	-1.99	0.17	-0.18	-1.97	-0.99	1.80	1.94	9.69	19.95	1.86	1.78	19.94	9.96
CCEX-2SLS	20	0.81	-0.64	-4.93	-9.97	0.74	-0.86	-9.94	-4.95	4.14	4.52	22.12	44.67	3.92	4.14	44.45	22.25
	50	0.30	-0.34	-1.97	-3.97	0.34	-0.24	-3.93	-1.96	2.35	2.71	13.97	28.08	2.62	2.08	28.16	13.95
	100	0.16	-0.19	-0.97	-1.99	0.17	-0.17	-1.97	-0.99	1.70	1.93	9.64	19.94	1.80	1.80	19.96	9.98
Infeasible	20	0.75	-0.62	-4.93	-9.94	0.78	-0.89	-9.94	-4.91	3.47	4.46	22.09	44.50	3.52	4.25	44.48	22.04
	50	0.31	-0.30	-1.97	-3.96	0.33	-0.20	-3.92	-1.95	2.31	2.63	13.96	28.02	3.95	2.10	28.18	13.12
	100	0.16	-0.19	-0.97	-1.99	0.16	-0.17	-1.96	-0.99	1.72	1.97	9.58	19.84	1.83	1.79	19.93	9.99

Appendix B

Appendix to Chapter 2

This Appendix is structured as follows. Section B.1 provides the detailed data construction. Section B.2 presents the estimation algorithms.

B.1 The Data Construction

IVA analyses each firm's risk exposure, measuring the extent to which its core business is at risk of incurring unanticipated losses. The data are normalised by the most relevant and available factors such as sales or production levels. The environmental score of IVA rates the companies based on the following issues: carbon emissions, product carbon footprint, energy efficiency, insurance against climate change risk, water stress, biodiversity and land use, raw material sourcing, financing environmental impact, toxic emissions and waste, packaging material and waste, electronic waste, opportunities in clean tech, opportunities in green building, opportunities in renewable energy, etc. Labour management, human capital development, health and safety, supply-chain labour standards, controversial sourcing, product safety and quality, chemical safety, privacy and data security, responsible investing, insuring health and demographic risk, opportunities in health and nutrition, access to communications, access to healthcare, etc. are evaluated in the social score. The government score is based on the sum of deductions derived from Key Metrics included in the Corporate Governance (including Board, Pay, Ownership & Control, and Accounting) and Corporate Behaviour (including Business Ethics and Tax Transparency) themes.

MSCI IVA is a strategic assessment rather than a simple summation, emphasising financial materiality and industry context. It does not treat all ESG issues equally. Instead, it identifies key ESG issues per industry based on quantitative analysis of environmental and social externalities (MSCI 2024). MSCI uses publicly available data (corporate reports, regulatory filings, NGO reports) and third-party sources (e.g., CDP, ILO, World Bank). Analysts assess controversies and management quality rather than just aggregating raw ESG scores (MSCI 2024).

The data are converted to a relative rating by assigning the company with the best performance in a given category an AAA (6) rating while giving the company with the worst performance a CCC (0) rating. The categorical scores are converted to the weighted average scores between 0 and 10, where the weights are given by the leader companies with AA (8.571-10) and AA (7.143-8.571), the average firms with A (5.714-7.143), BBB (4.286-5.714) and BB (2.857-4.286), and the laggard companies with B (1.429-2.857) and CCC (0-1.429).

We collect monthly ESG data from the MSCI ESG dataset over Jan. 2014–Dec. 2023. Table B.1 reports the summary of IVA, E, S and G scores of 3,911 companies from 54 countries.

For robustness check, we also collect annual ESG data from the Refinitiv/LSEG dataset over 2002-2023. The scores range between 0 and 100, spilt into four quartiles that indicate the relative ESG performance and insufficient degree of transparency in reporting material ESG data publicly. Scores within the four quartiles, 0-25, 25-50, 50-75 and 75-100, respectively correspond to four rankings such as poor, satisfactory, good and excellent. Table B.2 reports the summary of ESG, E, S and G scores of 2,306 companies from 60 countries.

Table B.1: The summary of IVA, E, S and G scores of 3911 companies over Jan. 2014–Dec. 2023 from the MSCI Database

		IVA			E			S			G		
Country	N	Mean	SD	Mid	Mean	SD	Mid	Mean	SD	Mid	Mean	SD	Mid
Argentina	4	4.9	0.6	4.9	6.3	1.4	6.4	4.5	1.5	4.2	4.9	1.8	5.0
Australia	146	5.2	1.1	5.2	5.4	2.5	5.1	5.1	1.6	4.9	6.4	1.8	6.7
Austria	18	5.3	0.8	5.2	5.8	1.9	5.4	5.2	1.2	5.0	5.8	1.4	6.0
Belgium	18	5.2	0.8	5.2	6.4	2.1	6.0	4.9	1.0	5.1	5.5	1.7	5.6
Bermuda	18	4.4	0.9	4.5	3.6	2.1	3.5	4.1	1.4	3.9	6.2	1.7	6.3
Brazil	45	4.7	1.2	4.7	5.8	2.2	6.0	4.8	1.5	4.9	4.0	1.4	3.9
Canada	171	5.0	1.0	5.0	4.9	2.2	4.7	4.6	1.7	4.8	5.9	1.6	6.0
Chile	22	4.9	0.8	4.9	4.9	1.9	4.9	5.2	1.3	5.1	4.7	1.2	4.8
China	69	3.8	1.0	3.9	4.1	2.1	4.1	3.6	1.5	3.7	4.5	1.8	4.3
Colombia	6	5.0	0.8	5.2	5.0	1.7	5.4	5.5	1.2	5.4	4.3	1.2	4.3
Costa Rica	1	6.0	0.5	6.0	6.9	1.2	6.3	5.9	0.8	5.7	5.9	0.7	5.8
Czechia	7	5.6	0.9	5.4	6.2	2.0	5.9	5.5	1.0	5.2	5.3	1.3	5.5
Denmark	23	5.6	0.8	5.7	5.5	1.8	5.1	5.3	1.6	5.4	6.6	1.2	6.5
Egypt	1	4.8	0.3	4.8	2.9	1.9	2.4	4.8	0.7	4.5	5.6	0.7	5.7
Finland	18	5.9	0.9	5.8	5.9	1.6	5.6	5.3	1.9	5.2	7.1	1.4	7.2
France	85	5.6	0.9	5.5	6.7	1.8	6.6	5.4	1.5	5.3	5.6	1.7	5.7
Germany	61	5.3	1.0	5.4	6.4	2.1	6.2	4.6	1.7	4.6	5.4	2.0	5.7
Greece	3	4.7	0.9	4.7	7.0	2.2	7.1	5.0	1.4	4.8	3.9	1.4	3.8
Hong Kong	89	4.6	1.2	4.7	5.3	1.9	5.2	4.5	1.8	4.5	4.5	1.8	4.3
Hungary	4	5.1	0.6	4.9	5.2	1.8	4.8	5.5	1.1	5.4	4.6	1.0	4.9
India	55	4.2	1.1	4.3	4.9	2.0	4.8	3.9	1.6	4.0	4.3	1.9	4.3
Indonesia	22	4.2	1.0	4.3	3.7	2.2	3.5	4.9	1.6	5.1	3.9	1.6	3.8
Ireland	27	5.5	1.1	5.6	5.7	2.1	6.0	5.0	1.5	4.9	6.6	1.6	6.7
Israel	8	4.8	0.9	5.0	4.2	1.8	4.0	4.5	1.3	4.8	6.0	1.5	6.2
Italy	25	5.2	1.0	5.0	6.0	2.4	6.4	4.9	1.4	4.7	5.0	1.6	5.1
Japan	312	4.9	0.9	4.9	5.5	1.9	5.5	5.1	1.5	5.1	4.5	1.7	4.3
Korea	115	4.5	0.9	4.6	4.9	1.9	4.9	4.5	1.5	4.5	4.4	1.7	4.4
Luxembourg	25	5.2	0.8	5.1	6.8	2.2	6.4	5.0	1.4	4.9	5.2	1.6	5.2
Macao	5	4.4	0.7	4.3	4.9	1.4	5.2	4.3	0.8	4.4	4.2	1.2	4.4
Malaysia	49	4.7	1.0	4.9	4.7	2.5	4.6	4.6	1.5	4.7	5.1	1.8	5.4
Mexico	35	4.3	1.4	4.3	5.1	2.4	5.2	4.6	1.8	4.5	3.5	1.8	3.3
Morocco	2	5.1	0.7	4.9	8.0	1.4	8.4	5.6	0.7	5.6	3.7	1.6	3.2
Namibia	2	5.6	0.5	5.5	7.5	2.0	7.2	4.8	0.7	4.8	6.6	1.0	6.4
Netherlands	58	5.5	1.2	5.4	6.9	2.1	7.0	5.1	1.9	5.0	5.3	1.9	5.5
New Zealand	12	5.6	0.9	5.6	7.4	1.7	7.6	4.9	1.2	5.1	6.3	1.8	6.4
Nigeria	1	5.2	0.8	5.2	3.9	1.9	3.5	5.3	0.6	5.3	4.9	1.6	5.5
Norway	19	5.7	0.8	5.6	6.7	1.9	6.7	5.2	1.4	5.0	6.7	1.3	6.9
Panama	1	5.2	0.3	5.2	4.7	1.6	4.0	5.2	0.4	5.1	5.4	0.9	5.4
Paraguay	1	6.0	0.5	5.9	9.9	0.2	10.0	5.5	0.7	5.7	6.2	0.5	6.1
Peru	5	4.7	0.9	4.7	3.4	2.1	2.3	5.3	1.1	5.2	4.7	1.4	4.6
Philippines	12	4.0	0.8	4.0	4.4	2.2	4.5	4.5	1.5	4.6	3.2	1.7	3.1
Poland	16	4.6	0.8	4.8	4.5	2.4	4.0	4.4	1.6	4.3	5.5	1.5	5.6
Portugal	5	5.9	1.3	5.4	6.7	1.9	6.8	5.6	1.4	5.1	5.6	1.5	5.6

		IVA			E			S			G		
Country	N	Mean	SD	Mid	Mean	SD	Mid	Mean	SD	Mid	Mean	SD	Mid
Romania	1	5.2	0.5	5.2	5.0	1.9	4.3	4.8	0.4	4.7	5.8	0.9	6.0
Singapore	34	5.2	1.0	5.1	5.5	2.2	5.3	5.1	1.7	5.1	5.3	1.7	5.3
Slovakia	2	5.3	0.5	5.4	5.7	1.7	5.6	5.4	0.8	5.2	5.1	1.3	5.4
South Africa	64	5.1	0.9	5.1	5.6	2.4	5.0	4.6	1.4	4.7	6.3	1.5	6.3
Spain	32	5.9	1.3	5.7	7.1	2.2	7.4	5.9	1.5	5.7	5.7	1.6	5.8
Sweden	45	5.6	0.9	5.7	6.4	1.9	6.0	5.4	1.6	5.3	5.8	1.7	6.1
Switzerland	55	5.5	1.0	5.4	5.9	2.2	6.0	4.9	1.5	4.9	6.5	1.6	6.6
Thailand	23	4.8	0.8	4.8	5.1	2.0	5.0	5.8	1.9	5.7	3.9	1.5	3.9
Turkey	15	4.3	0.8	4.3	4.1	2.6	3.7	5.4	1.6	5.0	3.7	1.5	3.7
UK	264	5.5	1.1	5.4	6.3	2.3	6.3	4.9	1.6	4.8	6.4	1.9	6.7
USA	1755	4.8	1.0	4.7	5.0	2.3	5.0	4.4	1.6	4.4	5.5	1.7	5.5

Table B.2: The summary of ESG, E, S and G scores of 2306 companies over 2002–2023 from the Refinitiv/LSEG Database

		ESG			E			S			G		
Country	N	Mean	SD	Mid	Mean	SD	Mid	Mean	SD	Mid	Mean	SD	Mid
Australia	110	43.8	22.3	41.5	37.8	26.0	33.2	43.8	23.7	40.0	55.6	22.2	56.1
Austria	13	49.1	18.0	49.8	51.6	24.8	57.3	50.8	20.7	48.0	53.9	20.8	54.9
Belgium	17	46.6	20.2	48.9	51.2	25.5	51.1	48.1	23.7	46.2	50.7	23.0	51.3
Bermuda	13	39.8	17.8	38.5	33.0	17.7	27.0	37.7	17.3	31.4	59.6	21.8	63.1
Brazil	39	53.0	20.6	56.5	52.8	21.5	52.7	59.2	22.0	62.9	53.7	20.8	56.4
Canada	97	43.6	21.9	42.6	41.9	27.9	38.8	44.6	23.3	41.8	53.7	21.7	54.9
Cayman Islands	1	32.6	17.4	30.4	13.6	15.0	8.1	35.3	20.4	36.0	67.4	13.0	71.3
Chile	14	37.2	24.7	34.2	39.7	27.8	36.2	42.1	25.2	42.2	46.7	22.2	47.4
China	75	33.2	19.3	31.3	36.8	25.7	32.2	30.6	19.2	27.6	50.9	20.7	52.1
Colombia	5	45.3	23.5	50.4	41.4	26.4	41.0	55.1	19.8	58.5	51.9	19.9	54.4
Czech Republic	2	40.6	14.0	38.1	57.2	13.8	49.0	46.3	15.3	45.7	48.9	14.9	50.0
Denmark	22	44.3	21.1	45.5	45.4	24.8	48.0	45.0	24.7	46.5	49.2	22.4	50.7
Egypt	5	27.9	18.1	24.6	22.9	21.6	16.7	26.5	15.8	23.3	43.7	21.5	44.3
Finland	23	54.6	21.3	59.7	60.9	25.7	68.7	55.5	22.9	57.5	52.7	22.9	52.5
France	68	58.1	21.2	62.3	63.3	25.2	70.0	62.4	23.4	66.4	54.6	22.1	57.0
Germany	63	53.0	24.5	54.4	54.2	28.5	58.1	56.3	26.0	59.1	54.0	23.0	54.8
Greece	11	49.5	21.0	47.8	52.5	25.9	52.3	51.3	25.9	48.8	53.4	20.5	55.7
Hong Kong	62	35.6	21.9	32.6	36.9	26.8	30.0	38.7	22.8	36.2	48.4	21.0	49.7
Hungary	4	53.8	22.6	59.1	59.2	22.2	68.7	61.0	21.4	67.4	54.2	20.7	54.2
India	62	46.1	22.0	47.0	44.2	25.0	44.5	52.7	21.7	50.7	48.1	24.4	46.8
Indonesia	23	48.2	21.3	51.1	42.5	24.4	35.3	55.3	21.9	55.4	54.9	21.8	59.8
Ireland	20	47.2	20.2	47.6	44.5	25.7	41.2	50.8	22.0	49.3	54.2	21.2	56.3
Israel	7	44.5	21.9	40.2	48.4	26.6	57.6	51.8	25.6	46.7	46.5	20.6	43.3
Italy	20	56.0	24.5	58.8	57.0	29.0	61.6	60.9	26.3	68.7	56.3	24.8	59.5
Japan	290	43.0	21.4	43.9	49.4	26.6	52.0	37.9	24.0	35.4	49.8	23.1	49.4
Jersey	2	34.3	23.4	31.6	41.9	19.4	38.7	41.9	19.3	39.0	48.1	23.8	46.9
Jordan	1	47.1	13.3	49.4	56.7	15.4	58.3	49.0	11.9	52.6	52.1	11.4	50.0

		ESG			E			S			G		
Country	N	Mean	SD	Mid	Mean	SD	Mid	Mean	SD	Mid	Mean	SD	Mid
Korea	63	49.8	23.1	55.5	54.8	26.0	63.3	50.7	25.6	54.7	51.1	23.1	51.2
Kuwait	4	32.2	17.7	29.8	29.1	18.3	23.4	28.3	22.1	19.7	54.9	20.6	56.9
Luxembourg	6	50.5	22.3	51.3	50.5	24.3	45.0	54.3	25.6	49.1	51.1	23.7	46.1
Macau	3	32.9	24.3	25.3	34.6	31.2	28.7	31.8	27.8	13.1	65.4	9.7	67.2
Malaysia	30	38.7	21.9	40.0	36.3	23.7	35.0	41.8	23.4	37.8	54.2	20.2	54.4
Mexico	17	48.2	22.8	51.0	46.5	28.2	45.4	50.5	25.8	54.1	51.4	23.4	52.2
Morocco	2	44.7	16.0	50.4	37.2	20.9	27.3	45.1	16.2	47.3	59.3	16.3	59.9
Netherlands	24	58.6	20.5	62.5	56.6	26.1	60.0	65.1	22.9	70.3	54.4	22.8	57.8
New Zealand	9	45.9	18.9	45.3	37.4	25.7	36.3	43.9	20.3	42.1	60.7	20.7	64.7
Nigeria	1	29.1	5.6	29.8	21.2	6.8	16.6	28.4	8.5	27.5	42.8	5.3	43.3
Norway	17	50.7	21.6	54.7	49.3	26.7	52.0	53.8	24.5	56.5	53.3	22.7	53.0
Oman	1	32.7	17.8	31.7	49.9	12.2	45.6	29.7	23.2	38.3	56.2	17.1	50.0
Panama	1	20.4	1.3	20.1	7.6	0.9	7.6	31.3	3.2	31.7	25.1	4.1	21.7
Peru	1	40.9	25.1	42.1	59.9	17.6	64.1	42.1	18.3	34.7	59.2	16.8	71.7
Philippines	17	39.2	22.5	39.1	36.7	24.1	33.9	41.2	24.5	39.2	53.4	23.0	56.2
Poland	16	38.5	21.3	38.0	40.1	25.6	34.5	40.4	23.6	38.7	54.8	20.9	58.2
Portugal	7	56.7	21.7	61.2	56.0	28.8	66.7	59.8	25.3	64.2	51.7	23.7	52.0
Puerto Rico	1	35.0	6.8	34.8	27.0	14.8	18.2	38.7	9.6	38.8	43.0	6.0	43.3
Qatar	1	35.5	22.6	31.5	33.9	25.6	18.2	35.1	21.9	20.7	66.9	8.1	61.7
Russia	1	33.8	22.3	36.5	39.5	23.2	41.3	47.8	20.0	55.5	28.1	21.6	18.3
Saudi Arabia	3	30.5	17.9	29.0	34.4	24.8	20.8	27.5	18.6	22.6	46.0	16.2	46.4
Singapore	26	39.4	21.8	36.8	37.7	26.6	32.7	41.4	22.9	39.7	51.7	23.2	52.1
South Africa	48	52.1	18.4	53.8	50.2	22.9	50.8	57.0	19.3	58.9	53.6	20.8	53.0
Spain	28	62.1	21.4	67.4	67.2	24.5	73.2	69.5	24.8	78.0	54.3	22.9	56.6
Sweden	38	55.8	19.7	57.8	55.3	27.5	61.5	60.8	22.6	67.1	55.1	21.8	56.5
Switzerland	53	49.2	23.6	49.7	51.6	26.6	52.4	52.4	26.0	52.2	52.9	22.8	53.6
Taiwan	78	42.2	24.9	42.3	45.4	26.0	44.5	43.1	28.1	39.9	51.1	22.7	51.8
Thailand	16	47.5	22.2	51.8	49.8	25.7	53.6	56.3	24.9	58.8	52.3	19.6	54.9
Turkey	20	48.5	23.6	52.7	53.8	29.3	59.5	55.9	24.2	55.2	53.4	19.4	56.0
Ukraine	1	29.4	20.1	27.5	18.8	24.4	2.9	26.5	31.2	14.0	48.7	7.3	50.0
The Emirates	1	26.7	20.0	24.5	33.2	12.5	26.7	32.2	18.8	24.0	33.0	21.6	20.8
UK	175	51.4	20.2	52.3	50.1	25.7	49.7	52.8	22.1	53.4	57.7	21.3	59.9
USA	528	45.6	22.0	45.4	42.1	26.7	39.3	49.4	22.5	47.9	53.8	22.2	55.6

Table B.3 reports the correlation matrix between MSCI and Refinitiv cross-section average data on the annual frequency over 2014—2023.

Table B.3: The correlation matrix between MSCI and Refinitiv CSA data

Legal origin	Variable	R_ESG	R_E	R_S	R_G	M_IVA	M_E	M_S	M_G
English	R_ESG	1							
	R_E	0.997	1						
	R_S	0.995	0.997	1					
	R_G	0.995	0.993	0.995	1				
	M_IVA	0.926	0.909	0.889	0.898	1			
	M_E	0.964	0.952	0.941	0.953	0.958	1		
	M_S	0.823	0.816	0.782	0.774	0.920	0.830	1	
	M_G	0.117	0.082	0.051	0.053	0.397	0.143	0.568	1
French	R_ESG	1							
	R_E	0.996	1						
	R_S	0.991	0.997	1					
	R_G	0.990	0.983	0.985	1				
	M_IVA	0.816	0.805	0.767	0.757	1			
	M_E	0.918	0.908	0.876	0.876	0.907	1		
	M_S	0.809	0.764	0.736	0.813	0.822	0.815	1	
	M_G	-0.416	-0.411	-0.452	-0.509	0.111	-0.244	-0.204	1
German	R_ESG	1							
	R_E	0.991	1						
	R_S	0.993	0.999	1					
	R_G	0.982	0.975	0.968	1				
	M_IVA	0.755	0.687	0.698	0.719	1			
	M_E	0.956	0.935	0.947	0.899	0.803	1		
	M_S	0.967	0.936	0.935	0.966	0.867	0.932	1	
	M_G	-0.272	-0.361	-0.365	-0.239	0.352	-0.226	-0.038	1
Scandinavian	R_ESG	1							
	R_E	0.992	1						
	R_S	0.894	0.914	1					
	R_G	0.973	0.973	0.817	1				
	M_IVA	0.809	0.811	0.667	0.768	1			
	M_E	0.713	0.681	0.489	0.677	0.947	1		
	M_S	0.577	0.570	0.290	0.699	0.512	0.553	1	
	M_G	0.611	0.663	0.770	0.506	0.593	0.342	-0.138	1

Note: We convert the monthly MSCI data to annual frequency by taking the 12-month moving-average. Then we estimate the correlation coefficients between the cross-section averages (CSA) of ESG and E/S/G data from MSCI (M) and Refinitiv (R) across legal origins over 2014–2023.

B.2 The GCC Estimation Algorithm

Let $y_{ijt} = ESG_{ijt}$. Stacking (2.2.1) over time period t, we can write the model as

$$\boldsymbol{Y}_{ij} = \boldsymbol{G}\boldsymbol{\gamma}_{ij} + \boldsymbol{F}_i\boldsymbol{\lambda}_{ij} + \boldsymbol{e}_{ij} = \boldsymbol{K}_i\boldsymbol{\theta}_{ij} + \boldsymbol{e}_{ij} \tag{B.2.1}$$

where $\underset{T\times 1}{\boldsymbol{Y}_{ij}} = [y_{ij1}, ..., y_{ijT}]'$, $\underset{T\times 1}{\boldsymbol{e}_{ij}} = [e_{ij1}, ..., e_{ijT}]'$, $\underset{T\times r_0}{\boldsymbol{G}} = [\boldsymbol{G}_1, ..., \boldsymbol{G}_T]'$, $\underset{T\times r_i}{\boldsymbol{F}_i} = [\boldsymbol{F}_{i1}, ..., \boldsymbol{F}_{iT}]'$, $\boldsymbol{\theta}_{ij} = \left[\boldsymbol{\gamma}'_{ij}, \boldsymbol{\lambda}'_{ij}\right]'$ and $\boldsymbol{K}_i = [\boldsymbol{G}, \boldsymbol{F}_i]$. For each group i we have:

$$\boldsymbol{Y}_i = \boldsymbol{G}\boldsymbol{\gamma}'_i + \boldsymbol{F}_i\boldsymbol{\lambda}'_i + \boldsymbol{e}_i = \boldsymbol{K}_i\boldsymbol{\theta}'_i + \boldsymbol{e}_i,\ i = 1, ..., R \tag{B.2.2}$$

where $\underset{T\times N_i}{\boldsymbol{Y}_i} = [\boldsymbol{Y}_{i1}, \boldsymbol{Y}_{i2}, \ldots, \boldsymbol{Y}_{iN_i}]$, $\boldsymbol{e}_i = [\boldsymbol{e}_{i1}, \boldsymbol{e}_{i2}, \ldots, \boldsymbol{e}_{iN_i}]$ and $\underset{N_i\times(r_0+r_i)}{\boldsymbol{\theta}_i} = [\boldsymbol{\gamma}_i, \boldsymbol{\lambda}_i]$. Notice that the CCA does not always identify the global factors in the presence of common local/regional factors. To address this important issue, Lin and Shin (2024) propose the GCC approach based on the construction of the following $T(R-1)R/2 \times \sum_{l=1}^{R}(r_0 + r_l)$ system-wide matrix:

$$\boldsymbol{\Phi} = \begin{bmatrix} \boldsymbol{K}_1 & -\boldsymbol{K}_2 & \boldsymbol{0} & \boldsymbol{0} & \ldots & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{K}_1 & \boldsymbol{0} & -\boldsymbol{K}_3 & \boldsymbol{0} & \ldots & \boldsymbol{0} & \boldsymbol{0} \\ & & & \vdots & & & \\ \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} & \ldots & \boldsymbol{K}_{R-1} & -\boldsymbol{K}_R \end{bmatrix} \tag{B.2.3}$$

Estimation of global factors and loadings We first obtain the PC estimate of $\boldsymbol{K}_i$ for each group i, denoted $\widehat{\boldsymbol{K}}_i$, by $\sqrt{T}$ times the $r_{\max}$ eigenvectors of $\boldsymbol{Y}_i\boldsymbol{Y}'_i$ corresponding to the $r_{\max}$ largest eigenvalues, where $r_{\max} \geq \max_{i=1,...,R}\{r_0 + r_i\}$. We construct the $TR(R-1)/2 \times Rr_{\max}$ matrix, $\widehat{\boldsymbol{\Phi}}$ by replacing $\boldsymbol{K}_i$ with $\widehat{\boldsymbol{K}}_i$ in (B.2.3), and evaluate the singular value decomposition (SVD) of $\widehat{\boldsymbol{\Phi}}$ given by $\widehat{\boldsymbol{\Phi}} = \widehat{\boldsymbol{P}}\widehat{\boldsymbol{\Delta}}\widehat{\boldsymbol{Q}}'$, where $\widehat{\boldsymbol{P}}$ and $\widehat{\boldsymbol{Q}}$ are the $TR(R-1)/2 \times Rr_{\max}$ and $Rr_{\max} \times Rr_{\max}$ orthonormal matrices, and $\widehat{\boldsymbol{\Delta}}$ is the $Rr_{\max} \times Rr_{\max}$ diagonal matrix consisting of the singular values in *ascending order*. Next, we construct the $T \times Rr_0$ matrix, $\widehat{\boldsymbol{\Psi}} = \left[\widehat{\boldsymbol{K}}_1\widehat{\boldsymbol{Q}}_1^{r_0}, \ldots, \widehat{\boldsymbol{K}}_R\widehat{\boldsymbol{Q}}_R^{r_0}\right]$, where $\widehat{\boldsymbol{Q}}^{r_0} = \left[\widehat{\boldsymbol{Q}}_1^{r_0\prime}, \ldots, \widehat{\boldsymbol{Q}}_R^{r_0\prime}\right]'$ is the first r_0 columns of $\widehat{\boldsymbol{Q}}$. We consider the eigen-decomposition, $T^{-1}\widehat{\boldsymbol{\Psi}}\widehat{\boldsymbol{\Psi}}' = \widehat{\boldsymbol{L}}\widehat{\boldsymbol{\Xi}}\widehat{\boldsymbol{L}}'$ where $\widehat{\boldsymbol{L}}$ is a $T \times T$ orthonormal matrix and $\widehat{\boldsymbol{\Xi}}$ is a $T \times T$ diagonal matrix consisting of the eigenvalues in *descending order*. The consistent estimator of the global factors can be obtained as $\sqrt{T}$ times the r_0 vectors of $\widehat{\boldsymbol{L}}$ corresponding to the r_0 largest eigenvalues given by $\widehat{\boldsymbol{G}} = \frac{1}{\sqrt{T}}\widehat{\boldsymbol{\Psi}}\widehat{\boldsymbol{\Psi}}'\widehat{\boldsymbol{J}}^{r_0} = \frac{1}{\sqrt{T}}\left(\sum_{i=1}^{R}\widehat{\boldsymbol{K}}_i\widehat{\boldsymbol{Q}}_i^{r_0}\widehat{\boldsymbol{Q}}_i^{r_0\prime}\widehat{\boldsymbol{K}}'_i\right)\widehat{\boldsymbol{J}}^{r_0}$ where $\widehat{\boldsymbol{J}}^{r_0} = \widehat{\boldsymbol{L}}^{r_0}\left(\widehat{\boldsymbol{\Xi}}^{r_0}\right)^{-1}$, $\widehat{\boldsymbol{L}}^{r_0}$ collects the first r_0 columns of $\widehat{\boldsymbol{L}}$ and $\widehat{\boldsymbol{\Xi}}^{r_0}$ is an $r_0 \times r_0$ diagonal matrix consisting of the r_0 largest eigenvalues of $T^{-1}\widehat{\boldsymbol{\Psi}}\widehat{\boldsymbol{\Psi}}'$ in *descending order*. The global factor loadings can then be estimated by $\widehat{\boldsymbol{\Gamma}}_i = T^{-1}\boldsymbol{Y}'_i\widehat{\boldsymbol{G}}$.

Estimation of local factors and loadings For each group $i = 1, ..., R$, the local factors can be consistently estimated by $\sqrt{T}$ times the r_i eigenvectors of $\widehat{\boldsymbol{Y}}_i \widehat{\boldsymbol{Y}}_i'$ corresponding to the r_i largest eigenvalues, denoted $\widehat{\boldsymbol{F}}_i$, where $\widehat{\boldsymbol{Y}}_i = \boldsymbol{Y}_i - \widehat{\boldsymbol{G}}\widehat{\boldsymbol{\Gamma}}_i'$. The local factor loadings can be estimated by $\widehat{\boldsymbol{\Lambda}}_i = T^{-1}\widehat{\boldsymbol{Y}}_i'\widehat{\boldsymbol{F}}_i$.

The GCC criterion for identifying the number of global/local factors Using the diagonal matrix, $\widehat{\boldsymbol{\Delta}}$ from the SVD of $\widehat{\boldsymbol{\Phi}}$ ($\widehat{\boldsymbol{\Phi}} = \widehat{\boldsymbol{P}}\widehat{\boldsymbol{\Delta}}\widehat{\boldsymbol{Q}}'$), we estimate the number of global factors consistently by

$$\hat{r}_{0,GCC} = \underset{k=0,\ldots,r_{\max}}{\operatorname{argmax}} \frac{\hat{\delta}_{k+1}^2}{\hat{\delta}_k^2} \tag{B.2.4}$$

where $\hat{\delta}_1, \ldots, \hat{\delta}_{Rr_{\max}}$ are the diagonal elements of $\widehat{\boldsymbol{\Delta}}$ in *ascending order*. To handle the case with $r_0 = 0$, we set the mock singular value as $\hat{\delta}_0^2 = \left(C_{\underline{N}T} R r_{\max}\right)^{-1} \sum_{k=1}^{Rr_{\max}} \hat{\delta}_k^2$. Given $\hat{r}_0$, we can consistently estimate global factors and loadings, denoted $\widehat{\boldsymbol{G}}$ and $\widehat{\boldsymbol{\Gamma}}_i$. Then, the number of local factors, r_i can be consistently estimated by applying the existing approximate factor model to $\widehat{\boldsymbol{Y}}_i = \boldsymbol{Y}_i - \widehat{\boldsymbol{G}}\widehat{\boldsymbol{\Gamma}}_i'$ for $i = 1, ..., R$, e.g., Bai & Ng (2002) and Ahn & Horenstein (2013).

Appendix C

Appendix to Chapter 3

This Appendix is structured as follows. Section C.1 provides the detailed data construction. Section C.2 presents the estimation algorithms.

C.1 The Data Construction

In our research, we collected SDG data from three widely-used sources: the World Bank, the UN Statistics Division, and the SDG Transformation Center. We ultimately selected the SDG Index from the SDG Transformation Center as our primary SDG data source. The selection was based on the following rationale: first, we excluded the World Bank as the main source because it does not provide original SDG data; instead, its SDG data are directly derived from the World Development Indicators (WDI). As stated in the World Bank database's official documentation, "*Relevant indicators are drawn from the World Development Indicators, reorganised according to the goals and targets of the Sustainable Development Goals (SDGs). These indicators may help to monitor SDGs, but they are not always the official indicators for SDG monitoring.*" This statement confirms that the World Bank's SDG data are secondary in nature, and cannot be treated as a comprehensive measurement data resource. Second, the UN Statistics Division (UNSD) SDG indicators are widely recognised data source for tracking progress on the United Nations' Sustainable Development Goals (SDGs). However, they also have several limitations. The UNSD SDG indicators have methodological inconsistencies, for instance, the 17 goals include a mix of binary, continuous, and composite metrics, making direct comparisons difficult. Additionally, data reporting is often delayed, and some indicators are not collected annually. There are also significant data gaps, as many countries lack complete and consistent reporting. Some data are obtained from model-based estimates rather than actual observations, reducing accuracy and comparability across nations. After careful evaluation, we selected the SDG Index from the SDG Transformation Center as our main data source, as it integrates official SDG indicators while providing an overall SDG score, making it the most suitable dataset for our analysis.

The SDG Index provides an overall assessment of countries' progress toward the 17 Sustainable Development Goals (SDGs) by measuring their distance to targets using the most up-to-date data available for all 193 UN member states. The SDG index includes 98 global indicators and 27 additional indicators for OECD countries due to better data coverage. The methodology involves four key steps: (1) Indicator selection, where official UN SDG indicators are prioritised, supplemented by other reliable sources when necessary; (2) Normalisation, where raw data are rescaled on a 0–100 scale, with 100 representing full achievement of the SDG target and 0 representing the worst performance; (3) Aggregation, where indicators are first averaged within each SDG, and then across all 17 goals to compute the overall SDG Index score, ensuring equal weighting across goals; and (4) Trend analysis, which tracks progress over time. The SDG Index primarily uses official data sources from organisations such as the UN Statistics Division, WHO, FAO, OECD, and World Bank, while also incorporating non-official sources like household surveys, civil society reports, and peer-reviewed studies to fill data gaps. To address missing data, the index includes countries with at least 80 percentage data coverage and avoids imputations except in rare cases.

Our ESG rating is based on the Intangible Value Assessment (IVA) provide by MSCI ESG. IVA analyses each firm's risk exposure, measuring the extent to which its core business is at risk of incurring unanticipated losses. The data are normalised by the most relevant and available factors such as sales or production levels. The environmental score of IVA rates the companies based on the following issues: carbon emissions, product carbon footprint, energy efficiency, insurance against climate change risk, water stress, biodiversity and land use, raw material sourcing, financing environmental impact, toxic emissions and waste, packaging material and waste, electronic waste, opportunities in clean tech, opportunities in green building, opportunities in renewable energy, etc. Labour management, human capital development, health and safety, supply-chain labour standards, controversial sourcing, product safety and quality, chemical safety, privacy and data security, responsible investing, insuring health and demographic risk, opportunities in health and nutrition, access to communications, access to healthcare, etc. are evaluated in the social score. The government score is based on the sum of deductions derived from Key Metrics included in the Corporate Governance (including Board, Pay, Ownership & Control, and Accounting) and Corporate Behaviour (including Business Ethics and Tax Transparency) themes.

The data are then converted to a relative rating by assigning the company with the best performance in a given category an AAA (6) rating while giving the company with the worst performance a CCC (0) rating. The categorical scores are converted to the weighted average scores between 0 and

10, where the weights are given by the leader companies with AA (8.571-10) and AA (7.143-8.571), the average firms with A (5.714-7.143), BBB (4.286-5.714) and BB (2.857-4.286), and the laggard companies with B (1.429-2.857) and CCC (0-1.429).

Regarding Section 3.3.3, we collect annual SDG and IVA data of for 41 countries over 2007-2023 from the SDG Transformation Center and MSCI datasets, respectively. Detailed descriptive summaries on SDG and ESG data are reported in Tables C.1 and C.2.

Regarding Section 3.4, we collect monthly ESG data of 3911 companies for 54 countries over 2014M1-2023M12 from the MSCI ESG dataset. Detailed descriptive summaries on IVA and E/S/G data are reported in Tables C.3, C.4, C.5 and C.6, respectively.

Table C.1: SDG by country

ID	Country	Legal origin	Min	Max	Median	Mean	SD	Q25	Q50	Q75
1	Australia	English	72.4	76.9	75.2	74.6	1.6	73.0	75.2	75.9
2	Austria	German	80.0	83.8	82.5	82.2	1.2	81.3	82.5	83.0
3	Belgium	French	74.5	80.0	77.9	77.6	1.8	76.3	77.9	79.1
4	Brazil	French	69.6	73.9	72.6	72.2	1.3	71.2	72.6	73.1
5	Canada	English	75.3	78.8	77.2	77.1	1.1	76.2	77.2	77.9
6	Chile	French	73.2	78.3	76.4	76.0	1.7	74.4	76.4	77.7
7	China	German	62.4	70.9	67.6	67.0	3.0	64.5	67.6	69.6
8	Czechia	German	77.3	82.2	80.5	80.0	1.4	79.2	80.5	81.0
9	Denmark	Scandinavian	80.8	85.0	83.3	83.2	1.3	82.2	83.3	84.1
10	Egypt	French	65.4	69.1	66.9	67.1	1.2	66.4	66.9	67.6
11	Finland	Scandinavian	83.0	86.4	85.3	85.2	1.0	84.8	85.3	85.7
12	France	French	77.4	82.9	80.5	80.5	1.8	78.8	80.5	82.3
13	Germany	German	78.6	83.4	81.8	81.3	1.6	79.7	81.8	82.6
14	Greece	French	73.3	78.7	76.3	76.3	1.7	75.2	76.3	77.8
15	Hungary	German	77.6	80.7	79.0	79.2	0.8	78.6	79.0	79.6
16	India	English	53.8	64.0	58.4	58.5	3.5	55.8	58.4	61.6
17	Indonesia	French	60.2	69.4	64.1	64.7	3.3	62.0	64.1	67.9
18	Ireland	English	75.4	78.7	77.6	77.5	0.9	77.1	77.6	78.1
19	Israel	English	69.2	73.8	71.9	71.8	1.6	70.8	71.9	73.2
20	Italy	French	74.6	79.4	77.9	77.5	1.5	76.3	77.9	78.8
21	Japan	German	77.0	79.9	78.5	78.4	0.9	77.9	78.5	79.1
22	Korea	German	73.5	77.3	75.6	75.6	1.1	74.7	75.6	76.5
23	Luxembourg	French	71.8	77.5	74.7	74.5	1.8	72.8	74.7	75.7
24	Malaysia	English	63.0	69.3	66.8	66.2	2.0	64.8	66.8	67.8
25	Mexico	French	64.1	69.3	67.2	67.1	1.6	66.0	67.2	68.6
26	Morocco	French	62.7	70.9	68.0	67.6	2.6	65.9	68.0	69.9
27	Netherlands	French	74.2	79.2	77.7	77.2	1.5	76.1	77.7	77.9
28	New Zealand	English	75.5	78.8	76.3	76.5	0.8	75.9	76.3	76.8
29	Norway	Scandinavian	78.8	82.2	81.2	80.9	1.0	80.3	81.2	81.6
30	Philippines	French	59.9	67.5	63.1	63.4	2.5	61.4	63.1	65.8
31	Poland	French	76.3	81.7	79.1	79.1	1.7	77.4	79.1	80.6
32	Portugal	French	74.1	80.2	77.9	77.9	1.7	76.9	77.9	79.3
33	Singapore	English	67.6	71.4	68.8	68.8	0.9	68.4	68.8	69.0
34	South Africa	English	57.7	63.4	61.1	60.9	1.9	59.6	61.1	62.4
35	Spain	French	75.8	80.7	78.1	78.3	1.6	77.0	78.1	79.7
36	Sweden	Scandinavian	84.4	85.9	85.1	85.2	0.4	84.8	85.1	85.4
37	Switzerland	German	76.5	80.1	78.1	78.1	1.1	77.1	78.1	78.8
38	Thailand	English	68.7	74.7	72.1	71.6	1.9	69.9	72.1	72.9
39	Turkey	French	66.6	70.5	69.0	69.0	1.1	68.5	69.0	69.9
40	UK	English	77.2	82.2	80.4	80.3	1.6	79.5	80.4	81.4
41	USA	English	71.1	74.5	73.1	73.1	1.0	72.6	73.1	73.6
	Total		53.8	86.4	76.3	74.6	6.7	69.6	76.3	79.3

This table contains descriptive summary of annual SDG scores from 41 countries during 2007 and 2023 from SDG Transformation Center.

Table C.2: MSCI IVA by country (SDG application)

ID	Country	Legal origin	Min	Max	Median	Mean	SD	Q25	Q50	Q75
1	Australia	English	49.1	56.6	50.8	51.3	2.2	49.7	50.8	52.0
2	Austria	German	48.7	55.9	50.9	51.8	2.5	49.8	50.9	54.7
3	Belgium	French	48.1	57.3	51.9	52.5	2.9	50.7	51.9	54.8
4	Brazil	French	45.7	58.8	49.6	51.1	4.0	48.0	49.6	54.5
5	Canada	English	44.8	56.5	49.4	49.4	3.2	46.4	49.4	51.1
6	Chile	French	36.7	53.3	48.4	47.3	4.9	46.9	48.4	50.2
7	China	German	27.9	38.6	35.5	34.4	3.6	31.0	35.5	36.7
8	Czechia	German	48.7	56.9	51.4	51.8	2.5	50.2	51.4	52.3
9	Denmark	Scandinavian	50.9	64.1	54.6	55.4	3.6	52.5	54.6	57.2
10	Egypt	French	31.4	52.5	43.6	42.0	6.0	36.5	43.6	45.3
11	Finland	Scandinavian	52.9	63.0	58.0	57.9	2.8	56.2	58.0	59.8
12	France	French	52.2	64.0	55.9	57.2	4.3	53.7	55.9	61.7
13	Germany	German	49.7	61.5	52.4	54.5	4.6	51.0	52.4	60.4
14	Greece	French	39.2	57.5	48.4	47.7	4.5	44.2	48.4	50.1
15	Hungary	German	37.2	61.9	50.6	50.6	6.2	48.4	50.6	54.1
16	India	English	39.0	50.6	43.1	44.1	3.8	41.5	43.1	46.7
17	Indonesia	French	31.4	47.7	41.6	40.9	4.4	39.1	41.6	43.8
18	Ireland	English	46.5	56.2	48.8	49.5	2.5	47.9	48.8	50.1
19	Israel	English	31.6	47.7	44.1	43.3	4.1	43.0	44.1	45.5
20	Italy	French	46.0	55.7	50.0	50.2	2.8	48.2	50.0	52.0
21	Japan	German	44.2	56.8	48.9	50.0	4.1	46.7	48.9	54.7
22	Korea	German	35.1	55.5	44.3	44.3	5.3	41.9	44.3	46.9
23	Luxembourg	French	47.1	62.0	49.0	51.0	3.9	48.0	49.0	53.1
24	Malaysia	English	38.0	51.8	42.8	43.2	3.6	41.2	42.8	43.5
25	Mexico	French	38.1	46.9	43.4	43.3	2.0	42.6	43.4	44.2
26	Morocco	French	17.0	60.2	45.2	41.5	10.8	35.4	45.2	47.0
27	Netherlands	French	51.6	63.1	53.1	55.6	4.1	52.3	53.1	58.2
28	New Zealand	English	44.5	62.2	54.1	53.6	4.1	52.5	54.1	54.5
29	Norway	Scandinavian	51.4	63.9	54.0	56.0	4.2	52.7	54.0	58.4
30	Philippines	French	19.0	48.2	40.5	37.5	7.8	31.5	40.5	41.9
31	Poland	French	32.9	49.8	46.6	45.6	4.2	45.3	46.6	48.1
32	Portugal	French	47.4	59.5	50.8	52.2	3.4	50.0	50.8	54.3
33	Singapore	English	45.1	53.3	47.8	48.6	2.4	47.1	47.8	50.4
34	South Africa	English	47.2	58.6	49.5	51.7	4.0	48.7	49.5	55.0
35	Spain	French	51.8	62.7	54.2	55.9	3.7	52.5	54.2	59.2
36	Sweden	Scandinavian	51.6	62.4	54.6	56.0	3.3	53.6	54.6	58.8
37	Switzerland	German	51.0	59.6	52.8	54.1	2.7	51.9	52.8	56.5
38	Thailand	English	38.5	49.9	46.3	46.2	2.6	46.0	46.3	47.2
39	Turkey	French	37.8	54.5	43.6	43.5	3.5	42.7	43.6	44.1
40	UK	English	50.5	58.9	53.7	54.7	3.2	51.9	53.7	58.0
41	USA	English	42.1	51.8	47.1	47.2	2.9	44.7	47.1	49.5
	Total		17.0	64.1	49.7	49.1	6.9	45.3	49.7	53.3

This table reports the descriptive summary of the dataset that contains annual IVA scores from 41 countries during 2007 and 2023, collected from the MSCI database. To match with the scale of SDG data (0-100), we multiple the country-average IVA data by 10.

Table C.3: IVA by country (MSCI dataset)

ID	Country	Legal origin	Company	Min	Max	Median	Mean	SD	Q25	Q50	Q75
1	Argentina	French	4	4.5	5.5	4.8	4.9	0.2	4.7	4.8	5.0
2	Australia	English	146	4.9	5.8	5.2	5.2	0.3	5.0	5.2	5.4
3	Austria	German	18	4.8	5.8	5.3	5.3	0.2	5.2	5.3	5.5
4	Belgium	French	18	4.8	5.8	5.1	5.2	0.3	5.0	5.1	5.4
5	Bermuda	English	18	4.1	5.1	4.3	4.4	0.3	4.2	4.3	4.7
6	Brazil	French	45	4.5	5.1	4.6	4.7	0.2	4.6	4.6	4.7
7	Canada	English	171	4.6	5.6	4.9	5.0	0.3	4.7	4.9	5.1
8	Chile	French	22	4.4	5.3	5.0	4.9	0.2	4.8	5.0	5.1
9	China	German	69	3.3	4.5	3.8	3.8	0.4	3.5	3.8	4.0
10	Colombia	French	6	4.5	5.5	5.1	5.0	0.2	4.9	5.1	5.1
11	Costa Rica	French	1	5.4	7.1	6.0	6.0	0.5	5.5	6.0	6.3
12	Czechia	German	7	5.1	6.0	5.6	5.6	0.2	5.5	5.6	5.7
13	Denmark	Scandinavian	23	5.1	6.0	5.5	5.6	0.2	5.4	5.5	5.8
14	Egypt	French	1	3.8	5.3	4.8	4.8	0.3	4.6	4.8	5.0
15	Finland	Scandinavian	18	5.3	6.5	5.9	5.9	0.3	5.8	5.9	6.0
16	France	French	85	5.3	6.1	5.5	5.6	0.2	5.5	5.5	5.7
17	Germany	German	61	5.0	5.8	5.2	5.3	0.2	5.1	5.2	5.4
18	Greece	French	3	3.8	5.8	4.6	4.7	0.6	4.0	4.6	5.2
19	Hong Kong	English	89	4.1	5.4	4.6	4.6	0.4	4.3	4.6	4.7
20	Hungary	German	4	4.7	5.5	5.1	5.1	0.2	5.0	5.1	5.3
21	India	English	55	3.9	4.5	4.1	4.2	0.1	4.1	4.1	4.2
22	Indonesia	French	22	3.9	4.5	4.2	4.2	0.1	4.1	4.2	4.4
23	Ireland	English	27	5.3	6.1	5.5	5.5	0.2	5.4	5.5	5.6
24	Israel	English	8	4.4	5.3	4.8	4.8	0.2	4.7	4.8	4.9
25	Italy	French	25	4.8	5.6	5.1	5.2	0.2	5.0	5.1	5.3
26	Japan	German	312	4.6	5.4	4.8	4.9	0.2	4.8	4.8	5.0
27	Korea	German	115	4.1	4.8	4.5	4.5	0.2	4.4	4.5	4.6
28	Luxembourg	French	25	4.9	5.8	5.1	5.2	0.2	5.0	5.1	5.3
29	Macao	French	5	2.9	5.4	4.5	4.4	0.5	4.1	4.5	4.7
30	Malaysia	English	49	4.3	5.3	4.6	4.7	0.3	4.4	4.6	4.9
31	Mexico	French	35	4.1	4.7	4.3	4.3	0.2	4.2	4.3	4.4
32	Morocco	French	2	4.5	6.3	4.8	5.1	0.5	4.7	4.8	5.4
33	Namibia	English	2	5.0	6.8	5.5	5.6	0.4	5.5	5.5	5.6
34	Netherlands	French	58	5.3	5.9	5.5	5.5	0.2	5.4	5.5	5.6
35	New Zealand	English	12	5.2	6.3	5.6	5.6	0.3	5.4	5.6	5.9
36	Nigeria	English	1	3.5	7.0	5.2	5.2	0.8	5.0	5.2	5.4
37	Norway	Scandinavian	19	5.2	6.4	5.6	5.7	0.3	5.5	5.6	5.9
38	Panama	French	1	4.7	5.7	5.2	5.2	0.3	5.0	5.2	5.4
39	Paraguay	French	1	4.9	6.6	5.9	6.0	0.5	5.6	5.9	6.4
40	Peru	French	5	4.4	5.2	4.7	4.7	0.2	4.6	4.7	4.8
41	Philippines	French	12	3.7	4.4	4.0	4.0	0.1	4.0	4.0	4.1
42	Poland	French	16	4.1	4.9	4.7	4.6	0.2	4.5	4.7	4.8
43	Portugal	French	5	5.3	6.6	5.9	5.9	0.4	5.6	5.9	6.1
44	Romania	French	1	4.3	6.1	5.2	5.2	0.5	4.9	5.2	5.5

ID	Country	Legal origin	Company	Min	Max	Median	Mean	SD	Q25	Q50	Q75
45	Singapore	English	34	4.8	5.7	5.1	5.2	0.2	5.0	5.1	5.2
46	Slovakia	German	2	4.6	5.8	5.5	5.3	0.3	5.1	5.5	5.6
47	South Africa	English	64	4.8	5.6	5.0	5.1	0.2	4.9	5.0	5.2
48	Spain	French	32	5.7	6.3	5.9	5.9	0.2	5.8	5.9	6.0
49	Sweden	Scandinavian	45	5.5	5.9	5.6	5.6	0.1	5.6	5.6	5.7
50	Switzerland	German	55	5.0	5.9	5.5	5.5	0.2	5.3	5.5	5.6
51	Thailand	English	23	4.5	5.4	4.8	4.8	0.2	4.6	4.8	4.9
52	Turkey	French	15	4.0	4.5	4.3	4.3	0.1	4.3	4.3	4.4
53	UK	English	264	5.2	6.0	5.5	5.5	0.3	5.3	5.5	5.6
54	USA	English	1755	4.4	5.3	4.8	4.8	0.3	4.5	4.8	4.9
	Total		3911	2.9	7.1	5.1	5.1	0.6	4.7	5.1	5.5

This table reports the descriptive summary of the dataset that contains monthly IVA scores from 54 countries during January 2014 and December 2023, collected from the MSCI database.

Table C.4: E by country (MSCI dataset)

ID	Country	Legal origin	Company	Min	Max	Median	Mean	SD	Q25	Q50	Q75
1	Argentina	French	4	5.4	7.1	6.3	6.3	0.4	6.0	6.3	6.6
2	Australia	English	146	5.1	6.2	5.3	5.4	0.3	5.2	5.3	5.5
3	Austria	German	18	4.8	6.7	5.7	5.8	0.5	5.5	5.7	6.3
4	Belgium	French	18	5.7	7.3	6.3	6.4	0.4	6.1	6.3	6.6
5	Bermuda	English	18	2.9	4.7	3.4	3.6	0.4	3.3	3.4	3.7
6	Brazil	French	45	5.3	6.5	5.8	5.8	0.3	5.6	5.8	6.2
7	Canada	English	171	4.6	5.5	4.9	4.9	0.3	4.7	4.9	5.2
8	Chile	French	22	3.8	5.6	5.0	4.9	0.4	4.5	5.0	5.1
9	China	German	69	3.5	4.9	4.2	4.1	0.4	3.7	4.2	4.4
10	Colombia	French	6	3.9	6.7	4.8	5.0	0.6	4.6	4.8	5.2
11	Costa Rica	French	1	5.8	9.5	6.3	6.9	1.2	6.0	6.3	8.1
12	Czechia	German	7	5.0	8.0	6.1	6.2	0.7	5.9	6.1	6.6
13	Denmark	Scandinavian	23	4.9	6.6	5.3	5.5	0.5	5.2	5.3	6.0
14	Egypt	French	1	1.1	8.6	2.4	2.9	1.9	1.1	2.4	4.9
15	Finland	Scandinavian	18	5.5	6.2	5.9	5.9	0.2	5.8	5.9	6.0
16	France	French	85	6.1	7.4	6.7	6.7	0.3	6.6	6.7	7.0
17	Germany	German	61	6.0	6.9	6.4	6.5	0.3	6.3	6.4	6.7
18	Greece	French	3	5.9	8.1	7.0	7.0	0.5	6.7	7.0	7.4
19	Hong Kong	English	89	4.4	6.2	5.2	5.3	0.5	4.9	5.2	5.6
20	Hungary	German	4	4.0	6.1	5.3	5.2	0.5	5.2	5.3	5.5
21	India	English	55	4.5	5.3	4.8	4.9	0.2	4.7	4.8	5.0
22	Indonesia	French	22	3.3	4.4	3.7	3.7	0.3	3.5	3.7	3.8
23	Ireland	English	27	5.1	6.6	5.6	5.7	0.4	5.4	5.6	6.0
24	Israel	English	8	3.3	5.6	3.8	4.2	0.8	3.6	3.8	4.9
25	Italy	French	25	5.3	7.0	5.8	6.0	0.5	5.7	5.8	6.4
26	Japan	German	312	5.2	5.9	5.6	5.5	0.2	5.4	5.6	5.7
27	Korea	German	115	4.6	5.4	4.9	4.9	0.2	4.7	4.9	5.0
28	Luxembourg	French	25	6.0	7.7	6.8	6.8	0.4	6.4	6.8	6.9
29	Macao	French	5	2.8	6.1	5.1	4.9	0.9	4.6	5.1	5.4
30	Malaysia	English	49	3.7	6.3	4.3	4.7	0.9	3.9	4.3	5.7
31	Mexico	French	35	4.7	5.8	5.0	5.1	0.3	4.9	5.0	5.4
32	Morocco	French	2	6.2	9.5	7.8	8.0	0.9	7.4	7.8	8.3
33	Namibia	English	2	4.4	9.7	7.5	7.5	1.4	7.3	7.5	8.3
34	Netherlands	French	58	6.5	7.5	6.8	6.9	0.3	6.7	6.8	7.1
35	New Zealand	English	12	6.9	8.3	7.3	7.4	0.3	7.2	7.3	7.7
36	Nigeria	English	1	0.3	8.2	3.5	3.9	1.9	3.2	3.5	4.9
37	Norway	Scandinavian	19	5.6	8.4	6.5	6.7	0.6	6.3	6.5	6.9
38	Panama	French	1	3.1	7.6	4.0	4.7	1.6	3.4	4.0	5.4
39	Paraguay	French	1	9.2	10.0	10.0	9.9	0.2	10.0	10.0	10.0
40	Peru	French	5	2.5	4.4	3.3	3.4	0.4	3.1	3.3	3.5
41	Philippines	French	12	4.0	4.8	4.4	4.4	0.2	4.2	4.4	4.6
42	Poland	French	16	3.6	6.1	4.4	4.5	0.7	4.0	4.4	5.0
43	Portugal	French	5	5.7	8.0	6.6	6.7	0.7	6.1	6.6	7.3
44	Romania	French	1	2.4	8.6	4.3	5.0	1.9	3.4	4.3	6.5

ID	Country	Legal origin	Company	Min	Max	Median	Mean	SD	Q25	Q50	Q75
45	Singapore	English	34	4.9	6.4	5.4	5.5	0.4	5.1	5.4	5.8
46	Slovakia	German	2	4.5	8.2	5.0	5.7	1.3	4.8	5.0	6.3
47	South Africa	English	64	5.3	6.2	5.5	5.6	0.2	5.4	5.5	5.7
48	Spain	French	32	6.4	7.9	7.0	7.1	0.4	6.8	7.0	7.3
49	Sweden	Scandinavian	45	5.9	7.0	6.4	6.5	0.3	6.2	6.4	6.8
50	Switzerland	German	55	5.4	6.3	5.9	5.9	0.2	5.8	5.9	6.0
51	Thailand	English	23	4.3	5.9	5.1	5.1	0.4	4.8	5.1	5.6
52	Turkey	French	15	3.5	5.0	4.0	4.1	0.5	3.8	4.0	4.7
53	UK	English	264	5.8	6.9	6.2	6.3	0.3	6.1	6.2	6.5
54	USA	English	1755	4.6	5.5	5.0	5.0	0.3	4.8	5.0	5.2
	Total		3911	0.3	10.0	5.6	5.6	1.5	4.8	5.6	6.5

This table reports the descriptive summary of the dataset that monthly environmental scores from 54 countries during January 2014 and December 2023, collected from the MSCI database.

Table C.5: S by country (MSCI dataset)

ID	Country	Legal origin	Company	Min	Max	Median	Mean	SD	Q25	Q50	Q75
1	Argentina	French	4	3.7	5.2	4.7	4.5	0.4	4.2	4.7	4.8
2	Australia	English	146	4.7	5.3	5.1	5.1	0.2	5.0	5.1	5.2
3	Austria	German	18	4.6	5.8	5.3	5.2	0.3	5.0	5.3	5.4
4	Belgium	French	18	4.4	5.5	5.0	4.9	0.3	4.7	5.0	5.2
5	Bermuda	English	18	3.5	5.1	3.8	4.1	0.5	3.7	3.8	4.6
6	Brazil	French	45	4.1	5.1	4.9	4.8	0.2	4.8	4.9	4.9
7	Canada	English	171	4.4	5.0	4.6	4.6	0.2	4.5	4.6	4.8
8	Chile	French	22	4.4	5.9	5.3	5.2	0.4	4.9	5.3	5.5
9	China	German	69	2.9	4.6	3.5	3.6	0.5	3.1	3.5	3.9
10	Colombia	French	6	4.9	6.4	5.4	5.5	0.4	5.2	5.4	5.8
11	Costa Rica	French	1	5.1	7.9	5.7	5.9	0.8	5.3	5.7	6.2
12	Czechia	German	7	5.0	6.1	5.5	5.5	0.2	5.4	5.5	5.6
13	Denmark	Scandinavian	23	4.9	5.6	5.3	5.3	0.2	5.1	5.3	5.4
14	Egypt	French	1	3.6	6.3	4.5	4.8	0.7	4.3	4.5	5.3
15	Finland	Scandinavian	18	4.9	5.9	5.2	5.3	0.3	5.1	5.2	5.7
16	France	French	85	5.0	5.8	5.4	5.4	0.2	5.2	5.4	5.5
17	Germany	German	61	4.2	5.2	4.6	4.6	0.3	4.4	4.6	4.8
18	Greece	French	3	3.8	6.2	5.2	5.0	0.7	4.3	5.2	5.5
19	Hong Kong	English	89	3.7	5.5	4.6	4.5	0.5	4.1	4.6	4.8
20	Hungary	German	4	4.9	6.1	5.6	5.5	0.4	5.3	5.6	5.9
21	India	English	55	3.3	4.7	3.9	3.9	0.4	3.6	3.9	4.4
22	Indonesia	French	22	4.1	5.7	5.0	4.9	0.4	4.6	5.0	5.2
23	Ireland	English	27	4.7	5.4	4.9	5.0	0.2	4.8	4.9	5.1
24	Israel	English	8	4.0	5.3	4.4	4.5	0.4	4.2	4.4	4.6
25	Italy	French	25	4.5	5.6	4.9	4.9	0.3	4.7	4.9	5.1
26	Japan	German	312	4.6	5.5	5.1	5.1	0.3	4.8	5.1	5.2
27	Korea	German	115	4.1	5.0	4.4	4.5	0.2	4.3	4.4	4.6
28	Luxembourg	French	25	4.7	5.6	5.0	5.0	0.2	4.9	5.0	5.1
29	Macao	French	5	3.9	5.0	4.3	4.3	0.3	4.1	4.3	4.5
30	Malaysia	English	49	3.6	5.2	4.7	4.6	0.5	4.1	4.7	4.9
31	Mexico	French	35	4.0	5.3	4.5	4.6	0.4	4.3	4.5	5.0
32	Morocco	French	2	4.9	6.7	5.7	5.6	0.5	5.2	5.7	6.0
33	Namibia	English	2	4.2	6.5	4.5	4.8	0.5	4.4	4.5	5.4
34	Netherlands	French	58	4.7	5.7	5.0	5.1	0.3	4.9	5.0	5.3
35	New Zealand	English	12	4.6	5.2	4.9	4.9	0.2	4.8	4.9	5.0
36	Nigeria	English	1	4.5	6.5	5.3	5.3	0.6	4.8	5.3	5.8
37	Norway	Scandinavian	19	4.8	5.8	5.1	5.2	0.3	5.0	5.1	5.5
38	Panama	French	1	4.6	6.1	5.1	5.2	0.4	5.0	5.1	5.5
39	Paraguay	French	1	4.1	6.6	5.7	5.5	0.7	5.0	5.7	6.0
40	Peru	French	5	4.4	6.3	5.2	5.3	0.5	4.9	5.2	5.7
41	Philippines	French	12	3.9	5.0	4.5	4.5	0.3	4.2	4.5	4.7
42	Poland	French	16	4.0	4.7	4.4	4.4	0.2	4.2	4.4	4.5
43	Portugal	French	5	5.1	6.4	5.5	5.6	0.4	5.4	5.5	6.0
44	Romania	French	1	4.2	5.3	4.7	4.8	0.4	4.4	4.7	5.2

ID	Country	Legal origin	Company	Min	Max	Median	Mean	SD	Q25	Q50	Q75
45	Singapore	English	34	4.8	5.7	5.1	5.1	0.2	5.0	5.1	5.3
46	Slovakia	German	2	4.6	5.9	5.5	5.4	0.4	5.1	5.5	5.8
47	South Africa	English	64	4.2	5.1	4.6	4.6	0.3	4.4	4.6	4.9
48	Spain	French	32	5.5	6.5	5.9	5.9	0.3	5.7	5.9	6.2
49	Sweden	Scandinavian	45	5.1	5.9	5.4	5.4	0.2	5.3	5.4	5.5
50	Switzerland	German	55	4.5	5.5	4.9	4.9	0.3	4.6	4.9	5.2
51	Thailand	English	23	5.2	6.5	5.9	5.8	0.4	5.4	5.9	6.1
52	Turkey	French	15	4.8	5.9	5.4	5.4	0.3	5.1	5.4	5.6
53	UK	English	264	4.6	5.2	4.9	4.9	0.2	4.8	4.9	5.0
54	USA	English	1755	4.2	4.8	4.4	4.4	0.2	4.2	4.4	4.6
	Total		3911	2.9	7.9	5.0	5.0	0.6	4.6	5.0	5.4

This table reports the descriptive summary of the dataset that contains monthly social scores from 54 countries during January 2014 and December 2023, collected from the MSCI database.

Table C.6: G by country (MSCI dataset)

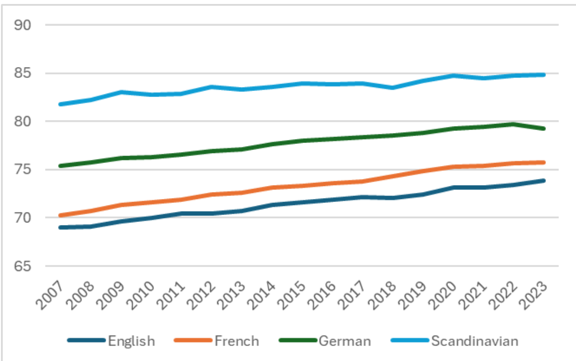
ID	Country	Legal origin	Company	Min	Max	Median	Mean	SD	Q25	Q50	Q75
1	Argentina	French	4	3.6	8.6	4.6	4.9	1.2	4.2	4.6	4.9
2	Australia	English	146	5.9	7.1	6.4	6.4	0.3	6.1	6.4	6.5
3	Austria	German	18	4.9	6.2	5.9	5.8	0.3	5.6	5.9	6.0
4	Belgium	French	18	4.6	5.9	5.5	5.5	0.3	5.4	5.5	5.7
5	Bermuda	English	18	5.6	6.8	6.3	6.2	0.3	6.0	6.3	6.3
6	Brazil	French	45	3.1	5.2	3.9	4.0	0.5	3.6	3.9	4.3
7	Canada	English	171	5.3	6.9	5.9	5.9	0.5	5.6	5.9	6.5
8	Chile	French	22	4.1	5.4	4.8	4.7	0.3	4.5	4.8	5.0
9	China	German	69	3.8	6.2	4.4	4.5	0.5	4.3	4.4	4.5
10	Colombia	French	6	3.2	5.7	4.5	4.3	0.6	4.0	4.4	4.7
11	Costa Rica	French	1	4.6	7.8	5.8	5.9	0.7	5.4	5.8	6.5
12	Czechia	German	7	3.5	6.0	5.5	5.3	0.6	5.1	5.5	5.7
13	Denmark	Scandinavian	23	5.9	7.7	6.5	6.6	0.4	6.3	6.5	6.8
14	Egypt	French	1	4.0	6.7	5.7	5.6	0.7	5.3	5.7	6.1
15	Finland	Scandinavian	18	5.8	7.6	7.3	7.1	0.4	6.8	7.3	7.4
16	France	French	85	5.1	6.2	5.5	5.6	0.3	5.4	5.5	5.7
17	Germany	German	61	4.9	5.8	5.4	5.4	0.2	5.2	5.4	5.5
18	Greece	French	3	2.5	5.5	3.7	3.9	0.9	3.2	3.7	4.4
19	Hong Kong	English	89	3.8	5.1	4.4	4.5	0.3	4.2	4.4	4.8
20	Hungary	German	4	3.4	5.3	4.7	4.6	0.4	4.4	4.7	4.9
21	India	English	55	3.2	5.8	4.2	4.3	0.6	4.1	4.2	4.7
22	Indonesia	French	22	2.7	5.8	3.4	3.9	0.9	3.1	3.4	4.6
23	Ireland	English	27	5.8	7.1	6.7	6.6	0.4	6.4	6.7	6.9
24	Israel	English	8	5.2	6.7	6.1	6.0	0.4	5.7	6.1	6.3
25	Italy	French	25	4.4	5.5	5.0	5.0	0.3	4.8	5.0	5.3
26	Japan	German	312	3.7	6.8	4.1	4.5	0.9	3.9	4.1	5.2
27	Korea	German	115	3.4	6.4	4.4	4.4	0.6	4.0	4.4	4.6
28	Luxembourg	French	25	4.8	6.1	5.1	5.2	0.4	5.0	5.1	5.5
29	Macao	French	5	1.1	5.7	4.2	4.2	0.8	3.6	4.1	5.0
30	Malaysia	English	49	4.5	6.7	5.1	5.1	0.5	4.8	5.1	5.4
31	Mexico	French	35	3.0	3.8	3.5	3.5	0.2	3.3	3.5	3.7
32	Morocco	French	2	1.6	5.2	3.7	3.7	1.0	3.3	3.7	4.3
33	Namibia	English	2	5.5	7.6	6.6	6.6	0.6	6.0	6.6	7.0
34	Netherlands	French	58	4.7	6.1	5.3	5.3	0.3	5.2	5.3	5.5
35	New Zealand	English	12	5.2	7.1	6.3	6.3	0.4	6.1	6.3	6.5
36	Nigeria	English	1	1.2	7.1	5.5	4.9	1.6	4.0	5.5	6.2
37	Norway	Scandinavian	19	5.2	7.3	6.8	6.7	0.4	6.5	6.8	7.0
38	Panama	French	1	3.4	6.8	5.4	5.4	0.9	4.8	5.4	6.1
39	Paraguay	French	1	5.1	7.4	6.1	6.2	0.5	5.8	6.1	6.4
40	Peru	French	5	3.6	5.8	4.7	4.7	0.5	4.5	4.7	5.0
41	Philippines	French	12	2.5	4.6	3.2	3.2	0.5	2.9	3.2	3.4
42	Poland	French	16	4.1	7.0	5.7	5.5	0.8	4.9	5.7	6.2
43	Portugal	French	5	4.6	6.7	5.4	5.6	0.5	5.2	5.4	6.0
44	Romania	French	1	3.9	7.0	6.1	5.8	0.9	5.5	6.0	6.5

ID	Country	Legal origin	Company	Min	Max	Median	Mean	SD	Q25	Q50	Q75
45	Singapore	English	34	4.9	6.0	5.3	5.3	0.3	5.1	5.3	5.6
46	Slovakia	German	2	3.2	6.2	5.3	5.1	0.8	4.6	5.3	5.6
47	South Africa	English	64	5.6	7.2	6.3	6.3	0.3	6.1	6.3	6.4
48	Spain	French	32	4.6	6.6	5.8	5.7	0.4	5.5	5.8	5.9
49	Sweden	Scandinavian	45	4.9	6.2	5.8	5.8	0.3	5.6	5.8	6.0
50	Switzerland	German	55	5.7	6.9	6.6	6.5	0.3	6.2	6.6	6.7
51	Thailand	English	23	3.3	4.9	4.0	3.9	0.4	3.5	4.0	4.2
52	Turkey	French	15	2.6	5.1	3.7	3.7	0.7	3.3	3.7	4.3
53	UK	English	264	5.9	7.0	6.4	6.4	0.3	6.1	6.4	6.5
54	USA	English	1755	4.7	6.8	5.5	5.5	0.6	4.9	5.5	6.0
	Total		3911	1.1	8.6	5.4	5.2	1.1	4.5	5.4	6.1

This table reports the descriptive summary of the dataset that contains monthly governance scores from 54 countries during January 2014 and December 2023, collected from the MSCI database.

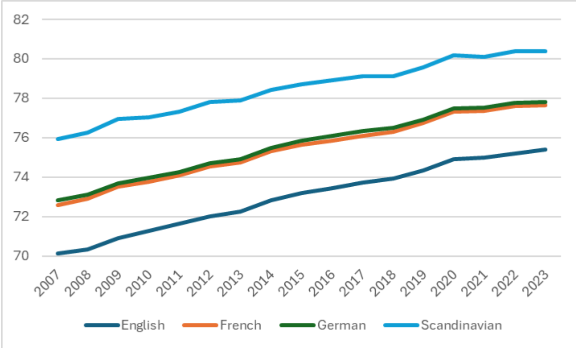
The time series plots of SDG, SDG^* and IVA across legal origins are provided in Figures C.1, C.2 and C.3, respectively. Both SDG and SDG^* show a smooth trend though SDG^* of French and German legal origins are quite similar. SDG^* presents a steeper slope for all the legal origins due to the impact of trade weight. Scandinavian legal origin tops the list, followed by German, French and English legal origins. The IVA data are more volatile, suffering from significant drops in the earlier period, going through a relatively stable period and exhibiting an upward trend after the pandemic peak in 2021. Scandinavian legal origin remains as the best IVA performer, whereas the rankings of the other legal origins alternate.

Figure C.1: SDG by legal origin



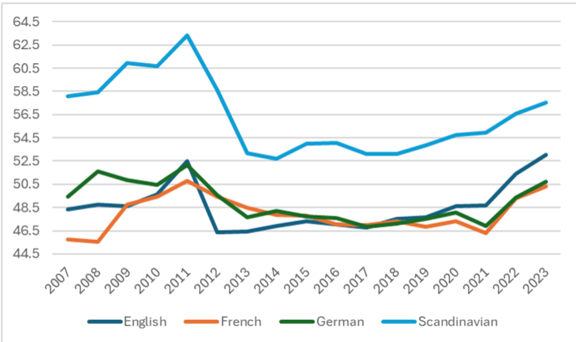
Notes: This figure plots the annual SDG data across legal origins over 2007-2023.

Figure C.2: SDG^* by legal origin



Notes: This figure plots the annual SDG^* data across legal origins over 2007-2023.

Figure C.3: IVA by legal origin



Notes: This figure plots the annual IVA data across legal origins over 2007-2023.

C.2 Estimation Algorithms

Let $y_{it} = SDG_{it}$ and $\mathbf{x}_{it} = ESG_{it}$ in Section 3.3 and $y_{it} = IVA_{it}$ and $\mathbf{x}_{it} = (E_{it}, S_{it}, G_{it})'$ in Section 4. Rewrite (3.3.1) and (3.4.4) as

$$y_{it} = \alpha_i + \rho_i y^*_{it} + \boldsymbol{\beta}'_i \mathbf{x}_{it} + \boldsymbol{\gamma}'_i \mathbf{f}_t + u_{it}, \;\; i = 1, ..., N, \;\; t = 1, ..., T \tag{C.2.1}$$

C.2.1 The CCEX-IV estimator

Stacking the individual regression (C.2.1) over $t = 1, ..., T$, we have:

$$\mathbf{y}_i = \rho_i \mathbf{y}^*_i + \mathbf{x}_i \boldsymbol{\beta}_i + \mathbf{e}_i = \mathbf{Z}_i \boldsymbol{\delta}_i + \mathbf{e}_i, \;\; i = 1, ..., N, \tag{C.2.2}$$

where $\mathbf{y}_i = (y_{i1}, ..., y_{iT})'$, $\mathbf{y}^*_i = (y^*_{i1}, ..., y^*_{iT})'$, $\mathbf{x}_i = (\mathbf{x}_{i1}, ..., \mathbf{x}_{iT})'$ and $\mathbf{Z}_i = (y^*_i, \mathbf{x}_i)$ with $\boldsymbol{\delta}_i = (\rho_i, \boldsymbol{\beta}'_i)'$. We outline the CCEX-IV estimation algorithm as follows:

Step 1: Factor proxies and defactorisation: We construct the factor proxies by the cross-section average of regressors given by $\hat{\mathbf{f}}_t = (1, \bar{\mathbf{x}}_t')'$ with $\bar{\mathbf{x}}_t = \frac{1}{N}\sum_{i=1}^N \mathbf{x}_{it}$. To deal with the correlation between regressors and unobserved factors, we construct the $T \times T$ de-factorisation matrix, $\mathbf{M}_{\hat{f}} = \boldsymbol{I}_T - \hat{\mathbf{f}}(\hat{\mathbf{f}}'\hat{\mathbf{f}})^{-1}\hat{\mathbf{f}}'$ with $\hat{\mathbf{f}} = (\hat{\mathbf{f}}_1, \ldots, \hat{\mathbf{f}}_T)'$, and pre-multiply both sides of (C.2.2) by $\mathbf{M}_{\hat{f}}$ to obtain:

$$\tilde{\mathbf{y}}_i = \rho_i \tilde{\mathbf{y}}_i^* + \tilde{\mathbf{x}}_i \boldsymbol{\beta}_i + \tilde{\mathbf{e}}_i = \tilde{\mathbf{Z}}_i \boldsymbol{\delta}_i + \tilde{\mathbf{e}}_i, \tag{C.2.3}$$

where $\tilde{\mathbf{y}}_i = \mathbf{M}_{\hat{f}}\mathbf{y}_i$, $\tilde{\mathbf{y}}_i^* = \mathbf{M}_{\hat{f}}\mathbf{y}_i^*$, $\tilde{\mathbf{x}}_i = \mathbf{M}_{\hat{f}}\mathbf{x}_i$, $\tilde{\mathbf{Z}}_i = \mathbf{M}_{\hat{f}}\mathbf{Z}_i$, and $\tilde{\mathbf{e}}_i = \mathbf{M}_{\hat{f}}\mathbf{e}_i$.

Step 2: Construction of internal IVs and individual CCEX-IV estimator: To address endogeneity due to the spatial dependence, we obtain the set of instruments by $\underset{NT\times\tau}{\mathbf{H}} = (\mathbf{H}_1', \ldots, \mathbf{H}_T')'$ where $\mathbf{H}_t = (\mathbf{x}_t, \boldsymbol{W}\mathbf{x}_t, \ldots, \boldsymbol{W}^r\mathbf{x}_t)$ is an $N \times \tau$ IV matrix with $\tau = (r+1)k$ and r is a positive integer of the spatial lag order. We then de-factorise the IVs as

$$\underset{T\times\tau}{\tilde{\mathbf{H}}_i} = \mathbf{M}_{\hat{f}}(\boldsymbol{I}_T \otimes \mathbf{b}_i')\mathbf{H}, \ i = 1, ..., N \tag{C.2.4}$$

which can be written as $\tilde{\mathbf{H}}_i = (\boldsymbol{I}_T \otimes \mathbf{b}_i')(\mathbf{M}_{\hat{f}} \otimes \boldsymbol{I}_N)\mathbf{H} = (\mathbf{M}_{\hat{f}} \otimes 1)(\boldsymbol{I}_T \otimes \mathbf{b}_i')\mathbf{H} = \mathbf{M}_{\hat{f}}(\mathbf{I_T} \otimes \mathbf{b}_i')\mathbf{H}$, where $\mathbf{b}_i$ is an $N \times 1$ column vector with the i-th entry being 1 and 0 otherwise. The individual CCEX-IV estimator is given by

$$\hat{\boldsymbol{\delta}}_i = (\tilde{\mathbf{Z}}_i' \boldsymbol{\Pi}_i \tilde{\mathbf{Z}}_i)^{-1} \tilde{\mathbf{Z}}_i' \boldsymbol{\Pi}_i \tilde{\mathbf{y}}_i, \ i = 1, ..., N, \tag{C.2.5}$$

where $\boldsymbol{\Pi}_i = \tilde{\mathbf{H}}_i(\tilde{\mathbf{H}}_i'\tilde{\mathbf{H}}_i)^{-1}\tilde{\mathbf{H}}_i'$. The individual variance estimator is consistently estimated by

$$\hat{\boldsymbol{\Omega}}_i = Cov(\boldsymbol{\delta}_i) = \left(\frac{\tilde{\mathbf{Z}}_i'\boldsymbol{\Pi}_i\tilde{\mathbf{Z}}_i}{T}\right)^{-1} \left(\frac{\tilde{\mathbf{Z}}_i'\tilde{\mathbf{H}}_i}{T}\right) \left(\frac{\tilde{\mathbf{H}}_i'\tilde{\mathbf{H}}_i}{T}\right)^{-1} \hat{\boldsymbol{\Sigma}}_i \left(\frac{\tilde{\mathbf{H}}_i'\tilde{\mathbf{H}}_i}{T}\right)^{-1} \left(\frac{\tilde{\mathbf{H}}_i'\tilde{\mathbf{Z}}_i}{T}\right) \left(\frac{\tilde{\mathbf{Z}}_i'\boldsymbol{\Pi}_i\tilde{\mathbf{Z}}_i}{T}\right)^{-1}, \tag{C.2.6}$$

where $\hat{\boldsymbol{\Sigma}}_i$ is the robust Newey & West (1987) estimator given by

$$\hat{\boldsymbol{\Sigma}}_i = \hat{\boldsymbol{\Sigma}}_{i,0} + \sum_{h=1}^{p_T}\left(1 - \frac{h}{p_T+1}\right)(\hat{\boldsymbol{\Sigma}}_{i,h} + \hat{\boldsymbol{\Sigma}}_{i,h}'),$$

where $\hat{\boldsymbol{\Sigma}}_{i,h} = \sum_{t=h+1}^T \hat{e}_{it}\hat{e}_{i,t-h}\tilde{\mathbf{H}}_{it}'\tilde{\mathbf{H}}_{i,t-h}/T$, p_T is the bandwidth of the Bartlett kernel, $\hat{\mathbf{e}}_i = \mathbf{M}_{\hat{F}}(\tilde{\mathbf{y}}_i - \tilde{\mathbf{Z}}_i\hat{\boldsymbol{\delta}}_i) = (\hat{e}_{i1}, \ldots, \hat{e}_{iT})'$ with the $\tau \times 1$ vector $\tilde{\mathbf{H}}_{it}$ being the transpose of the t-th row of $\tilde{\mathbf{H}}_i$.

Furthermore, the mean group CCEX-2SLS estimator is given by

$$\hat{\boldsymbol{\delta}}_{MG} = \frac{1}{N}\sum_{i=1}^N \hat{\boldsymbol{\delta}}_i. \tag{C.2.7}$$

The consistent mean group variance estimator is given by (e.g., Pesaran (2006)),

$$\hat{\boldsymbol{\Omega}}_{MG} = Cov(\boldsymbol{\delta}_{MG}) = \frac{1}{N-1}\sum_{i=1}^{N}(\hat{\boldsymbol{\delta}}_i - \hat{\boldsymbol{\delta}}_{MG})(\hat{\boldsymbol{\delta}}_i - \hat{\boldsymbol{\delta}}_{MG})'. \tag{C.2.8}$$

C.2.2 Network multipliers and the GCM analysis

Following Shin & Thornton (2021) and Mastromarco et al. (2023), we turn to the development of network analysis capable of highlighting the spatial/network interactions captured by the model (C.2.1). Based on a sequence of network connectedness matrices that can be interpreted as output network matrices resulting from the input network matrix, $\boldsymbol{W}$ and the heterogeneous coefficients, we propose a comprehensible method for the presentation of results to analyse the systemic dependence and importance of particular nodes within a network. For these practical network-oriented measures, we need only $\sqrt{T}$-consistent estimators of the individual heterogeneous parameters. A pooled or mean group estimator will net out heterogeneous signs and, therefore, fail to reveal the relative importance of individual nodes beyond what is assumed *ex ante* via the spatial weight matrix, $\boldsymbol{W}$.

Stacking the individual regressions, (C.2.1) over $i = 1, ..., N$:

$$\boldsymbol{y}_t = \boldsymbol{P}\boldsymbol{W}\boldsymbol{y}_t + \boldsymbol{B}\boldsymbol{x}_t + \boldsymbol{e}_t, \quad \text{with } \boldsymbol{e}_t = \boldsymbol{\alpha} + \boldsymbol{\Lambda}\mathbf{f}_t + \boldsymbol{u}_t, \tag{C.2.9}$$

where $\boldsymbol{y}_t = (y_{1t}, ..., y_{Nt})'$, $\boldsymbol{x}_t = (\boldsymbol{x}'_{1t}, ..., \boldsymbol{x}'_{Nt})'$, $\boldsymbol{f}_t = (f_{1t}, ..., f_{rt})'$, $\boldsymbol{\Lambda} = (\boldsymbol{\lambda}_1, ..., \boldsymbol{\lambda}_N)'$, $\boldsymbol{W}$ is an $N \times N$ spatial weights matrix. $\boldsymbol{P} = diag(\rho_1, ..., \rho_N)$ and $\boldsymbol{B} = diag(\boldsymbol{\beta}'_1, ..., \boldsymbol{\beta}'_N)$ are diagonal matrices consisting of the heterogeneous parameters.

To measure the direct and indirect effects, we consider the following transformation of (1.3.9):

$$\boldsymbol{y}_t = (\boldsymbol{I}_N - \boldsymbol{P}\mathbf{W})^{-1}(\boldsymbol{B}\boldsymbol{x}_t + \boldsymbol{e}_t), \tag{C.2.10}$$

where $(\boldsymbol{I}_N - \boldsymbol{P}\mathbf{W})^{-1}$ links the dependent variable to the regressors $\boldsymbol{x}_t$ that describes interdependencies among different individual countries. We construct the heterogeneous direct, spill-in and spill-out effects of $\boldsymbol{x}_t$ for the i-th country as follows:

- Heterogeneous direct effect (HDE): the direct effect of $\boldsymbol{x}_{it}$ on y_{it} is given by the i-th diagonal element of $(\boldsymbol{I}_N - \boldsymbol{P}\boldsymbol{W})^{-1}\boldsymbol{B}$ for $i = 1, ..., N$.

- Heterogeneous spill-in effect (HSI): the sum of the effects of $\boldsymbol{x}_t$ from all the other countries on y_{it} is given by the ith row-sum minus the i-th diagonal element of $(\boldsymbol{I}_N - \boldsymbol{P}\boldsymbol{W})^{-1}\boldsymbol{B}$ for $i = 1, ..., N$.

- Heterogeneous spill-out effect (HSO): the sum of the effects of $\boldsymbol{x}_{it}$ on $\boldsymbol{y}_t$ of all the other countries is given by the ith column-sum minus the ith diagonal element of $(\boldsymbol{I}_N - \boldsymbol{PW})^{-1}\boldsymbol{B}$ for $i = 1, ..., N$.

- Heterogeneous net effect (HNE): a net influence of the ith country in the system, given by the difference between HSO and HSI of the ith country, i.e., $HNE_i = HSO_i - HSI_i$ for $i = 1, ..., N$.

Denote $\boldsymbol{\psi} = (\boldsymbol{I}_N - \boldsymbol{PW})^{-1}\boldsymbol{B}_k$ as the network multipliers of y_{it} with respect to the hth regressor, x_{hjt} for $i, j = 1, ..., N$ and $h = 1, ..., H$. Then, we can write $\boldsymbol{\psi}$ as an $N \times N$ connectedness matrix:

$$\underset{N\times N}{\boldsymbol{\psi}} = \begin{bmatrix} \psi_{1\leftarrow 1} & \cdots & \psi_{1\leftarrow N_1} & \psi_{1\leftarrow N_1+1} & \cdots & \psi_{1\leftarrow N_1+N_2} & \cdots & \psi_{1\leftarrow N} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \psi_{N_1\leftarrow 1} & \cdots & \psi_{N_1\leftarrow N_1} & \psi_{N_1\leftarrow N_1+1} & \cdots & \psi_{N_1\leftarrow N_1+N_2} & \cdots & \psi_{N_1\leftarrow N} \\ \psi_{N_1+1\leftarrow 1} & \cdots & \psi_{N_1+1\leftarrow N_1} & \psi_{N_1+1\leftarrow N_1+1} & \cdots & \psi_{N_1+1\leftarrow N_1+N_2} & \cdots & \psi_{N_1+1\leftarrow N} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \psi_{N_1+N_2\leftarrow 1} & \cdots & \psi_{N_1+N_2\leftarrow N_1} & \psi_{N_1+N_2\leftarrow N_1+1} & \cdots & \psi_{N_1+N_2\leftarrow N_1+N_2} & \cdots & \psi_{N_1+N_2\leftarrow N} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \psi_{N\leftarrow 1} & \cdots & \psi_{N\leftarrow N_1} & \psi_{N\leftarrow N_1+1} & \cdots & \psi_{N\leftarrow N_1+N_2} & \cdots & \psi_{N\leftarrow N} \end{bmatrix}. \tag{C.2.11}$$

Using (1.3.11), we can develop the network approach at two extremes: (i) complete aggregation, where the $N(N-1)$ bilateral linkages among N individual countries are aggregated into the single (spillover) index (Diebold & Yılmaz 2014), and (ii) no aggregation, where the $N(N-1)$ bilateral linkages are studied at the individual country level. To avoid the processing constraints, we follow the GCM approach advanced by Greenwood-Nimmo et al. (2021) and consider an intermediate level of aggregation. Suppose there are R groups, each with N_r for $1 \le r \le R$ where $N_1 + \ldots + N_R = N$. Consider the (k, l)-th block, $\mathbf{B}_{k\leftarrow l}$, $k, l = 1, ..., R$, given by

$$\underset{(N_k\times N_l)}{\mathbf{B}_{k\leftarrow l}} = \begin{bmatrix} \psi_{\tilde{N}_k+1\leftarrow\tilde{N}_l+1} & \cdots & \psi_{\tilde{N}_k+1\leftarrow\tilde{N}_l+N_l} \\ \vdots & \ddots & \vdots \\ \psi_{\tilde{N}_k+N_k\leftarrow\tilde{N}_l+1} & \cdots & \psi_{\tilde{N}_k+N_k\leftarrow\tilde{N}_l+N_l}, \end{bmatrix}, \tag{C.2.12}$$

where $\tilde{N}_k = \sum_{j=1}^{k-1} N_j$ for $k = 2, ..., R$, and $\tilde{N}_1 = 0$. We then normalise the sum of the elements of $\mathbf{B}_{k\leftarrow l}$ by the average number of country pairs in the k-th and l-th groups:

$$\phi_{k\leftarrow l} = \frac{1}{0.5(N_k + N_l)}\boldsymbol{\iota}'_{N_k}\mathbf{B}_{k\leftarrow l}\boldsymbol{\iota}_{N_l}, \tag{C.2.13}$$

where $\boldsymbol{\iota}_{N_k}$ is an $N_k \times 1$ column vector of ones. Then, we can construct the following $R \times R$

connectedness matrix at the group level:

$$\underset{(R\times R)}{\mathbf{C}_R} = \begin{bmatrix} \phi_{1\leftarrow 1} & \phi_{1\leftarrow 2} & \cdots & \phi_{1\leftarrow R} \\ \phi_{2\leftarrow 1} & \phi_{2\leftarrow 2} & \cdots & \phi_{2\leftarrow R} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{R\leftarrow 1} & \phi_{R\leftarrow 2} & \cdots & \phi_{R\leftarrow R} \end{bmatrix}. \tag{C.2.14}$$

Using (1.3.14), it is straightforward to construct the direct, spill-in and spill-out effects at the group level as

$$GDE_i = \phi_{i\leftarrow i};\;\; GSI_i = \sum_{j=1,j\neq i}^{R} \phi_{i\leftarrow j};\;\; GSO_i = \sum_{j=1,j\neq i}^{R} \phi_{j\leftarrow i},\; i = 1,...,N. \tag{C.2.15}$$

We construct the group net effect (GNE) by the difference between GSO and GSI, which enables us to distinguish between net-transmitting and net-receiving groups. Furthermore, we measure the total effects within the group as $GTE_i = GDE_i + GSI_i$.

Finally, we follow Shin & Thornton (2021) and construct the External Motivation (EM), External Contagion (EX) and Systemic Influence (SI) indices by

$$EM_i = \frac{GSI_i}{ATOT_{i\leftarrow\bullet}};\;\; EX_i = \frac{GSO_i}{ACTOT_{\bullet\leftarrow j}};\;\; SI_i = \frac{GNE_i}{TNP},\; i = 1,...,N \tag{C.2.16}$$

where $ATOT_{i\leftarrow\bullet} = \sum_{j=1}^{R} |\phi_{i\leftarrow j}|$ is the absolute row-sum for ith group, $ACTOT_{\bullet\leftarrow j} = \sum_{j=1}^{R} |\phi_{j\leftarrow i}|$ is the absolute column-sum for ith group, and $TNP = 0.5\sum_{i=1}^{R} |NE_i|$ is the total absolute net effects. EM_i measures the relative importance and direction of HSI in determining the conditions in the ith group while EX_i measures the relative importance and direction of HSO in determining the conditions in the ith group. SI_i captures the systemic influence of the ith group.[1]

[1] EM_i, EX_i and SI_i stay within $[-1, 1]$. If $EM_i \to 1(-1)$, then the output in ith group is dominated by positive (negative) HSIs, as opposed to direct effects. If ith group receives contradictory spill-ins and/or if HSI is small in comparison to direct effects, then $EM_i \to 0$. If $0 \leq SI_i \leq 1$ $(-1 \leq SI_i \leq 0)$, then ith group is a net shock transmitter (receiver). If SI_i is close to zero, then group i is neutral with its HSOs matching HSIs.

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