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Through the Wire: Submarine Cable Dependence and the Geoeconomic Fragmentation of FDI

Federico Galletti

Bocconi University

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Abstract

Submarine telecommunications cables are increasingly recognized as critical infrastructure vulnerable to sabotage and data surveillance, particularly amid intensifying geopolitical rivalry. This thesis examines whether multinational firms have begun to reallocate foreign direct investment (FDI) in response to the geopolitical ownership of submarine cable networks. We combine a bilateral panel of FDI flows over 2009-2023 with measures of geopolitical alignment derived from UN General Assembly voting and a newly compiled dataset on the global submarine cable network. Using these sources, we construct a novel Rival-Weighted Dependence (RWD) index capturing the extent to which a destination country's digital connectivity relies on cable infrastructure owned by geopolitical rivals of the investing country. Estimates from a gravity-style model indicate that the association between RWD and bilateral FDI becomes more negative after 2017, consistent with heightened concerns over surveillance, coercion, and disruption in rival-controlled networks as geopolitical tensions deepen. These findings, robust across a series of alternative specifications, highlight ownership of critical digital infrastructure as a geoeconomic channel through which weaponized interdependence can reallocate global capital flows and contribute to the fragmentation of FDI.

Keywords: Foreign Direct Investment, Geoeconomics, Submarine Cables, Digital Infrastructure, Geopolitics.

1 Introduction

Submarine telecommunications cables constitute the physical backbone of the global internet. By linking national landing points through high-capacity fiber-optic routes, they enable the long-distance transmission of digital information that underpins contemporary commerce, finance, cloud services, and cross-border organizational activity. As a result, roughly 99 percent of intercontinental data traffic traverses these undersea networks, making them a foundational layer of the contemporary global economy.

The strategic relevance of this infrastructure has become increasingly visible in recent years, not only because of the rising economic value of cross-border data flows, but also because submarine cables are exposed to disruption and manipulation. Beyond routine accidents, subsea cable systems have long been targets of strategic interference, including sabotage and coercive disruption. Moreover, risks extend beyond physical cutting: access at landing stations and other points along a cable system can enable the interception of traffic, and the plausibility of large-scale surveillance through cable infrastructure has been underscored by past events and subsequent policy debates.

These vulnerabilities acquire a distinctly geoeconomic meaning in the context of heightened strategic competition. The submarine cable network exhibits the structural characteristics that underpin the framework of “weaponized interdependence” developed by Farrell and Newman (2019): dense global networks can generate leverage for actors positioned at central nodes, enabling both surveillance over information flows and coercive power through chokepoints. In the global submarine cable network, ownership and control are highly concentrated, and a limited number of routes and landing stations can become systemically important for international data traffic. Consequently, the prospect that a geopolitical rival could gain visibility into sensitive flows or threaten disruptions is not merely a wartime scenario; it is a latent risk that can shape expectations and behavior under strategic competition, including in contexts often described as “hybrid” conflict.

We argue that these risks are especially salient for multinational firms and cross-border investors. Foreign direct investment (FDI) is not simply a transfer of capital: it typically entails sustained operational integration between investor and recipient, which in turn relies on frequent cross-border data exchange, for example for managerial coordination, supply-chain monitoring, remote service provision, and transfers of proprietary information. When a recipient economy's international connectivity is materially dependent on submarine cable infrastructure controlled by entities associated with a rival of the investor's home country, investors may perceive heightened exposure to surveillance, disruption, or coercive pressure. Such exposure can increase expected costs and risks–through compliance and governance concerns, reputational considerations, or the need to invest in redundancy and mitigation–even in the absence of an observable crisis. The implication is that the ownership and control of digital infrastructure can operate as a geoeconomic constraint on integration: the mere perception that critical connectivity depends on rival-controlled infrastructure may be sufficient to deter, delay, or redirect investment.

Building on this logic, we develop and test the hypothesis that dependence on rival-controlled subsea cable infrastructure is associated with a relative weakening of bilateral FDI relationships in the current era of geopolitical tensions. In particular, we treat 2018 as the onset of the current phase of heightened geopolitical rivalry, commonly associated with the escalation of US-China competition beginning with the 2018 trade war and subsequently extending into wider technological and security frictions. This period also coincides with intensified debate about the national-security implications of digital interdependence, and with a growing tendency to evaluate connectivity and data infrastructure through a geopolitical lens. To examine this channel, we estimate a gravity model that combines bilateral FDI data with measures of geopolitical rivalry based on UN voting, and a novel indicator capturing the extent to which a recipient's connectivity relies on undersea cables owned by entities linked to geopolitical rivals of the investor.

The results reveal a clear timing pattern: the association between exposure to rival-controlled cable infrastructure and bilateral investment becomes meaningfully more negative in the period beginning in 2018, consistent with the hypothesis that investors increasingly price digital-infrastructure risk under heightened strategic competition. In an era of increasing FDI fragmentation, the analysis thus identifies a plausible geoeconomic channel through which the securitization of digital infrastructure may contribute to the reconfiguration of cross-border capital flows.

The remainder of the thesis proceeds as follows. Section 2 reviews the literature on geoeconomics and geoeconomic fragmentation, and situates submarine cable infrastructure within the “weaponized interdependence” framework. Section 3 serves as a primer on submarine telecommunications cables, covering their historical development, functioning, vulnerabilities, and selected incidents. Section 4 presents the data used in the empirical analysis. Section 5 describes the empirical strategy and the results, along with a range of robustness and sensitivity analyses. Finally, Section 6 concludes and discusses implications, limitations, and avenues for future research.

2 Literature Review

This section situates this thesis within the relevant strands of the literature, outlining how the present work engages with and extends each of them. We proceed in three steps. First, we review the emerging field of geoeconomics, outlining its core concepts and theoretical foundations. Building on this framework, we then turn to the literature on geoeconomic fragmentation, which examines how rising geopolitical rivalry is reshaping cross-border flows. A dedicated subsection focuses on the fragmentation of foreign direct investment (FDI). Finally, we describe the literature on the global submarine cable network and highlight the absence of a systematic integration of this critical digital infrastructure into geoeconomic analyses.

By connecting these strands, we motivate the central contribution of the thesis: to study global submarine cable dependence as a novel geoeconomic channel through which geopolitical power and rivalry may shape the fragmentation of FDI.

2.1 Geoeconomics

First and foremost, this work builds on, and seeks to contribute to, the expanding body of scholarship on geoeconomics. In what follows, we adopt the definition proposed by Mohr and Trebesch (2024), who characterize geoeconomics as "the field that examines the links between geopolitics and economics". Their formulation offers a broader and more neutral framing than many existing definitions. Notably, it does not impose a specific direction of causality between geopolitical and economic forces. Whereas several authors[1] predominantly conceptualize geoeconomics as the strategic deployment of economic instruments to attain foreign policy objectives, Mohr and Trebesch (2024) emphasize that causality can run both ways: geopolitical configurations condition economic outcomes, just as economic interdependencies can be exploited for geopolitical ends. Under this view, geoeconomics emerges as an inherently interdisciplinary field that bridges international economics and

[1] Definitions of geoeconomics include: "the interplay of international economics, geopolitics and strategy" (Schneider-Petsinger, 2020); a strategy in which "governments use their countries' economic strength from existing financial and trade relationships to achieve geopolitical and economic goals" (Clayton et al., 2023); "the study of the interaction between trade, diplomacy, and geopolitics" (Thoenig, 2024); "the use of economic means to pursue foreign policy goals" (Baldwin, 1985).

international relations, with the aim of understanding how geopolitical rivalry shapes economic policy and performance, and how economic structures feed back into geopolitical competition.

Although the term geoeconomics is commonly traced to Luttwak (1990), the intellectual foundations of the field can be dated earlier, most prominently to Hirschman's *National Power and the Structure of Foreign Trade* (1945). Hirschman is the first to formalize the idea that countries' trade patterns generate asymmetric dependencies, which in turn create potential channels of geopolitical influence. His central insight, that concentrated trade relations can render states vulnerable to coercion, captures a core mechanism that contemporary analyses continue to explore. This makes the link between geoeconomics and international power explicit. In line with this tradition, Clayton et al. (2025) define power as the ability of one actor to induce another to undertake actions it would otherwise not choose, or not to undertake actions it would otherwise choose. While any government can shape the behavior of domestic actors through regulation and taxation, only a subset of states can extend such influence beyond their borders. These states, often referred to as "hegemons" or "great powers", do so through a set of instruments commonly termed geoeconomic tools, which we examine in greater detail in a few paragraphs.

A parallel strand in the geoeconomics literature concerns the role of such hegemons in shaping the structure of the international system. Classic "hegemonic stability" theory (Kindleberger, 1973; Keohane, 1984; Gilpin, 1981) posits that a stable and open global economy requires the leadership of a dominant state capable of underwriting collective goods, such as monetary stability, crisis management, and the maintenance of open markets, while preventing protectionist policies. Recent contributions revive and formalize this logic. For instance, Broner et al. (2025) develop a theory of "hegemonic globalization" in which hegemonic powers promote cross-border economic integration by encouraging policy alignment among trading partners. In their framework, globalization flourishes in a unipolar world, whereas the transition toward multipolarity induces fragmentation.

Moreover, the resurgence of strategic rivalry between the US and China, started with the first Trump administration, has directed scholarly attention away from the stabilizing face of hegemony and toward its coercive potential. Farrell and Newman's (2019) concept of "weaponized interdependence" captures how states controlling central nodes in global production, communication, and financial networks can leverage these chokepoints to coerce others, by restricting access, monitoring flows, or imposing sanctions. Importantly, they argue that modern geoeconomic power operates precisely through the dense networks that globalization itself created: the more globally integrated economies are, the greater the potential leverage for a hegemon able to mobilize sanctions coalitions, control key technologies, or shape rules and standards.

The emergence of weaponized interdependence thus reveals a world in which economic connections can serve as conduits not only for exchange and efficiency, but also for leverage and coercion. Understanding contemporary geoeconomics therefore requires moving beyond high-level concepts of power to examine the specific instruments through which it is exercised. Clayton et al. (2025) take an important step in this direction by offering a systematic account of the tools states deploy to reshape incentives and constrain the choices of other actors. Their model stresses that all the positive inducements or negative threats imposed by a hegemonic power have in common that they either increase the inside option or lower the outside option of the participation constraint for the target entity. Crucially, the effectiveness of such threats is weakened not only by the possibility that the target may reconfigure its economic activity *ex post* but also by the target's *ex ante* anticipation of the threat, which may prompt adjustments to its economic strategies before the threat is ever implemented. As a result, the "golden question" advanced by Clayton et al. (2025) and around which empirical works in geoeconomics are converging is twofold: does effective geoeconomic coercion induce economic or geopolitical actions by the targeted entities? At the same time, does the potential threat of geoeconomic coercion, given by international power imbalances in a context of weaponized interdependence, induce preemptive actions by the possibly targeted entities?

In light of all these considerations, multiple authors have been building taxonomies of geoeconomic tools to understand in what forms geoeconomic threats can materialize. Mohr and Trebesch (2024) provide a list of geoeconomic policy tools. In particular, they review the existing literature on sanctions, blockades and embargoes, tariffs and trade agreements, export controls, foreign aid, sabotage, espionage, and cyber-attacks. McGuirk and Trebesch (2025) broaden this list further by highlighting additional instruments, including industrial espionage and foreign investment screening. The most comprehensive taxonomy to date, however, is offered by Clayton et al. (2025), who group geoeconomic tools into four macro-categories: export and import restrictions, industrial policy, financial restrictions, and macroeconomic restrictions. Export and import restrictions encompass measures such as tariffs, quotas, and export bans, as well as constraints on access to transport systems or trade infrastructure. Industrial policy tools include producer subsidies, infrastructure subsidies, and the strategic deployment of sovereign wealth funds. Financial restrictions cover instruments like foreign aid withdrawals, targeted asset freezes, and screening or limiting FDI, an area that has gained prominence following the sanctions and coordinated freezing of Russian sovereign reserves by the US and the EU after the 2022 invasion of Ukraine. Finally, macroeconomic restrictions refer to limitations on participation in international regulatory fora or on the ability to enter bilateral and multilateral treaties, thereby influencing a country's integration into the global economic order.

Against this background, digital infrastructure, and in particular the global network of submarine cables for telecommunications, emerges as a notable omission in existing literature on geoeconomics. The taxonomies discussed above do not treat the global internet backbone as a potential tool for geoeconomic leverage. Yet this set of infrastructures displays precisely the structural characteristics that underpin Farrell and Newman's (2019) notion of "weaponized interdependence." As a matter of fact, Porcellacchia et al. (2026) show that ownership and control of undersea cables are highly concentrated in a few hegemonic powers, and that a small number of routes function as chokepoints for global traffic. Similarly, Xie and Wang (2023) highlight that the spatial distribution of subsea cables is highly uneven. Hence, since connectivity underpins economic prosperity and national interests, disruptions or sanctions affecting such connectivity could be devastating both in peacetime and in conflict (APEC Policy Support Unit, 2012; Govella, 2025). Moreover, these structural features closely resemble the “panopticon” and “chokepoint” effects highlighted by Farrell and Newman (2019): ownership and control of a limited number of cable routes and landing stations create opportunities both for pervasive surveillance of data flows (the ”panopticon” effect) and for the selective interruption or degradation of connectivity (the ”chokepoint” effect), with potentially large economic costs. In the framework of Clayton et al. (2025), control over cable infrastructure can therefore be understood as a means of shifting participation constraints: ex post, through the threat or execution of cuts, rerouting, or surveillance, and ex ante, through restrictions on cable investment, landing rights, or participation in consortia. These vulnerabilities have been indeed underscored by recent episodes of suspected sabotage in the Baltic Sea and around Taiwan (Murphy and Pearl, 2025; Govella, 2025), as well as by intensifying debates over surveillance and espionage risks associated with undersea cable infrastructure (Govella, 2025).

Therefore, by foregrounding submarine cable dependence as a channel of geoeconomic power, this thesis seeks to extend the geoeconomics literature to this critical yet still underexplored dimension.

2.2 Geoeconomic Fragmentation

This work also relates to a second major line of research, namely the theoretical and empirical analyses examining geoeconomic fragmentation. Aiyar et al. (2023) describe geoeconomic fragmentation as a policy-induced unwinding of global economic integration, typically motivated by strategic considerations. Recent contributions have sought to understand what several authors–including Antràs (2020) and Goldberg and Reed (2023)–refer to as “slowbalization”, a period of diminished economic integration beginning after the 2008 global financial crisis. This stands in contrast to the preceding “liberalization era” (Aiyar et al., 2023), spanning the late twentieth century and the early 2000s, when emerging economies–most notably China–progressively lowered trade barriers, and international economic cooperation expanded substantially, including the incorporation of former Soviet economies into the global system. The shift away from integration has unfolded amid intensifying trade frictions between the United States and China, alongside a broader rise in populist sentiment and increasing public scepticism toward globalisation (Colantone et al. 2021). Hence, much of the literature on "slowbalization" and fragmentation has concentrated specifically on changes in global trade patterns (Antràs, 2020; Goldberg and Reed, 2023; Blanga-Gubbay and Rubinova, 2023; Bolhuis et al., 2023; Campos et al., 2023). However, Aiyar et al.'s (2023) conceptualisation suggests a broader perspective: geoeconomic fragmentation reflects a retreat from integration across several domains, not only trade. In particular, they highlight three core dimensions: trade, migration, and capital flows.

Under this broader definition, geoeconomic fragmentation emerges as a complex process in which various forms of cross-border flows are curtailed or reconfigured due to strategic or policy-driven choices. Building on the earlier discussion of geoeconomics, fragmentation can therefore be understood as stemming from the interaction between geopolitical dynamics and a multifaceted reversal of global economic integration, extending well beyond the realm of international trade alone.

Fernández-Villaverde et al. (2024) similarly argue that fragmentation cannot be understood solely through the lens of trade, proposing instead a framework that incorporates three additional layers: financial, mobility, and political fragmentation. They emphasise that political dynamics frequently intensify developments in the other domains, generating reinforcing feedback effects. Although they do not state this explicitly, their approach aligns closely with the multidimensional conception of geoeconomic fragmentation advanced by Aiyar et al. (2023) and adopted in this thesis. Building on this perspective, Fernández-Villaverde et al. (2024) introduce a dynamic hierarchical factor model that treats fragmentation as a latent phenomenon, allowing them to extract both a common geoeconomic fragmentation factor and the distinct trends shaping each component. Their empirical strategy relies on sixteen indicators grouped into four categories (trade, finance, mobility, and politics) from which they estimate both the shared and category-specific fragmentation factors. The results indicate that all four dimensions have become more fragmented since 2010, with political fragmentation playing a central role in driving the pronounced rise in the overall fragmentation measure. In addition, trade fragmentation exhibits a slower decline relative to the common factor, while financial fragmentation moves closely with it, suggesting that financial dynamics are also a major contributor to the broader fragmentation process.

While the empirical findings of Fernández-Villaverde et al. (2024) point to a rise in geoeconomic fragmentation, their evidence relies largely on aggregate indicators, such as the FDI-to-GDP ratio, the number of trade restrictions, and the count of sanctions imposed worldwide, that reflect a broad decline in economic integration. These measures, however, do not shed light on where fragmentation is taking place or the geopolitical dimensions along which cross-border linkages are weakening. In other words, their analysis focuses on the extensive margin of fragmentation. Yet, because geoeconomic fragmentation is intrinsically shaped by geopolitical dynamics, understanding the intensive-margin patterns–how international flows are being reallocated across geopolitical blocs–is equally important. In this respect, a growing body of research examines whether fragmentation manifests not only through an overall contraction of cross-border exchanges but also through their reorientation according to geopolitical alignments.

Gopinath et al. (2025) provide one of the first systematic analyses of this intensive margin, using granular bilateral data on trade, FDI and portfolio flows to show that, since Russia's invasion of Ukraine, trade and investment between countries in geopolitically distant blocs have fallen relative to flows within blocs, although a group of non aligned "connector" economies has absorbed part of the adjustment. Complementing this evidence for trade, Qiu et al. (2024) find that recent trade growth has been systematically stronger among politically aligned partners and weaker between more distant country pairs, indicating a reconfiguration of trade networks along geopolitical lines.

An additional strand of evidence comes from Catalán et al. (2024), who analyse the geopolitical determinants of cross-border portfolio allocation and show that rising geopolitical distance significantly reduces both equity and bond exposures. Moreover, they identify an "investment diversion" mechanism: when source countries become geopolitically more distant from third countries, investment is redirected toward relatively aligned recipients.

Finally, Raggl and Ramskogler (2025) extend this line of research to cross-border mobility, showing on the basis of global bilateral migration data and UN-voting-based geopolitical distance that an increase in geopolitical distance between two countries is associated with a sizable reduction in migration between them, effectively uncovering a migration analogue to friendshoring[2].

A complementary strand of research provides theoretical foundations for the observed reorientation of cross-border flows along geopolitical lines. Camboni and Porcellacchia (2024) develop a formal framework in which countries choose whether to align with one of two great powers or remain non-aligned, trading off their own policy preferences against the risk of coercion. Their model shows that rising geopolitical risk or a shift toward a less unipolar balance of power–such as China's rise–induces countries to deepen alignment with a preferred power, thereby creating endogenous spheres of influence. These spheres, in turn, generate systematically divergent economic and political behaviours across blocs and amplify geoeconomic fragmentation at the intensive margin. Importantly, the model rationalises several empirical patterns documented in recent work: greater reorientation of trade, financial, and investment flows within aligned blocs; non-monotonic realignments when the distribution of influence shifts; and widening cross-bloc differentials as great-power rivalry intensifies. In this sense, their analysis provides a unifying theoretical mechanism that underpins the empirical evidence on fragmentation along geopolitical lines and offers a conceptual bridge to studies examining how specific types of cross-border flows are being reshaped by geopolitical alignment.

[2]Throughout this thesis, the term "friendshoring" follows Grover and Vézina (2025) and denotes the relocation of production to countries that are geopolitically aligned or otherwise considered "friendly".

2.3 Geoeconomic Fragmentation of FDI

This thesis connects especially with the empirical literature examining the fragmentation of FDI. Interest in this topic has grown firstly because the global decline in FDI has been particularly pronounced, with worldwide FDI flows falling from 3.3 percent of GDP in the 2000s to 1.3 percent between 2018 and 2022 (International Monetary Fund, 2023). Given that FDI inflows play a critical role in fostering economic growth, mobilizing private capital, and generating employment, especially in EMDEs, understanding the drivers of this marked contraction has become increasingly important (World Bank, 2025).

Beyond this macroeconomic slowdown, a second factor underpinning the rise of FDI-fragmentation research is the proliferation of government policies aimed at tightening control over foreign investment on national security grounds. Numerous advanced economies have strengthened their investment-screening regimes, expanding the ability of domestic authorities to restrict foreign acquisitions in strategically sensitive sectors (Bencivelli et al., 2023). Recent industrial-policy initiatives–such as the US Inflation Reduction Act (IRA) and the CHIPS Acts enacted in both the US and the EU–similarly seek to reconfigure supply chains and bolster domestic production capacity, thereby reducing incentives for outward FDI from these economies.[3] This evolving policy landscape has signaled a broader rethinking of the costs and benefits of openness to foreign ownership and has heightened concerns that FDI may become increasingly segmented along geopolitical lines (Tan, 2024).

A third catalyst comes from firms themselves. Corporate surveys and textual analysis reveal that multinational enterprises are increasingly attentive to geopolitical risks, with notions such as reshoring, friendshoring, and de-risking appearing far more frequently in strategic communications (International Monetary Fund, 2023). Survey evidence shows that a substantial share of firms– particularly in advanced economies–plan to relocate or redirect investments toward politically aligned or otherwise trusted jurisdictions (Attinasi et al., 2023; International Monetary Fund, 2023; Grover and Vézina, 2025).

[3] Tan (2024) provides a detailed overview of the surge in FDI-related restrictions introduced since 2010.

As a result, a growing empirical literature has begun to document whether and how multinational firms reallocate their foreign investments toward geopolitically aligned countries, and conversely retrench from economies perceived as politically distant or exposed to rival great powers. This emerging body of work investigates whether the global reconfiguration of FDI mirrors the intensive-margin fragmentation observed in trade and portfolio flows, thereby offering key evidence for understanding the channels through which geoeconomic fragmentation occurs. The remainder of this section reviews the key contributions in this area, with particular attention to papers that quantify the effects of geopolitical distance, alignment, and strategic rivalry on bilateral FDI patterns.

Aiyar et al. (2024) investigate whether geopolitical alignment influences the global allocation of FDI, against the backdrop of rising geopolitical tensions and the increasing policy and corporate emphasis on friendshoring. Using a rich dataset of greenfield FDI projects, the authors test whether politically aligned countries invest more in each other than geopolitically distant ones. Their gravity model suggests that greater geopolitical distance between two countries is associated with significantly lower FDI flows. Moreover, the influence of geopolitical alignment has strengthened after 2018, coinciding with rising US-China tensions. Finally, they find that fragmentation along geopolitical lines is particularly pronounced in strategic sectors and when the destination country is an EMDE.

Grover and Vézina (2025) obtain only partly the results advanced by Aiyar et al. (2024). They indeed show that geopolitical differences increasingly depress FDI flows, with the negative impact roughly doubling over the past decade. However, they find no strong evidence that geopolitical alignment matters more for strategic, GVC-intensive, or contract-intensive sectors than for others. Across sector groups, the magnitude of friendshoring effects is broadly similar, implying that fragmentation is not solely driven by national-security considerations but reflects a general shift in the broader investment environment. More specifically, they suggest that the friendshoring phenomenon does not occur everywhere: while outwards FDI from countries like the US, the UK, and Canada has been redirected towards geopolitically aligned partners, such pattern is not visible when it comes to outwards FDI from countries like China, Singapore, or the United Arab Emirates.

Similarly, Tan's (2024) analysis indicates that geopolitical alignment has become a significant driver of bilateral FDI flows, especially after 2018. In line with Aiyar et al. (2024), she finds that this trend is particularly pronounced in strategic sectors. Moreover, she advances that fragmentation is more pronounced for outward FDI from the US, notably in a shift of US FDI from China to advanced Europe and the rest of Asia. Interestingly, she finds that much of the apparent fragmentation may be confined to immediate rather than ultimate FDI positions, implying that multinational firms may still preserve deeper ownership structures that span geopolitical divides.

A slightly different approach is taken by Gopinath et al. (2025). While the analyses above focused on bilateral geopolitical distance between countries, they split countries into three geopolitical blocs–US bloc, China bloc, and the "connector countries"–and investigate FDI dynamics across these. They show that, since Russia's invasion of Ukraine, FDI flows between countries in opposing geopolitical blocs have fallen by roughly 12 and 20 percent, respectively, relative to flows within blocs. Furthermore, they highlight the prominent role of "connector" countries, i.e., non-aligned economies that absorb declining bilateral flows between rival blocs and reroute them through alternative investment channels. Therefore, although direct links between geopolitically distant partners may decrease, indirect dependencies can persist.

Finally, Kallen (2025) provides a comprehensive, multi-dimensional assessment of FDI fragmentation, documenting not only ideological realignment but also the growing relevance of derisking, nearshoring, and reshoring in global investment patterns. By analysing blocs like Gopinath et al. (2025), geopolitical alignment through UNGA voting like Aiyar et al. (2024) and Grover and Vézina (2025), and geographical distance, they suggest that friendshoring is present but comparatively modest, whereas derisking and nearshoring emerge as more pervasive forces.

We therefore aim to contribute to the literature on geoeconomic fragmentation (and, more specifically, on geoeconomic fragmentation of FDI) by advancing a novel analytical perspective. Rather than explaining FDI fragmentation solely through geopolitical alignment, we incorporate the role of global digital infrastructure to uncover an additional dimension of international investment dynamics. Building on recent evidence that FDI flows are increasingly redirected along geopolitical lines, we examine whether economic actors invest less in countries that exhibit a high degree of dependence on subsea cables controlled by a geopolitical rival. In doing so, we offer the first systematic investigation of FDI fragmentation operating through this geoeconomic channel, thereby expanding the conceptual and empirical scope of the existing literature.

To achieve this goal, we position our analysis within the established empirical literature that examines the determinants of bilateral FDI flows using gravity models. Indeed, while gravity originates in trade, early work in international finance demonstrate that even "weightless" assets obey gravity patterns. Portes and Rey (2005) show that cross-border equity transactions rise with market size and fall sharply with proxies for information frictions such as distance, motivating analogous mechanisms for FDI where informational and contracting costs are central. Okawa and van Wincoop (2012) then provide a clear theoretical foundation for gravity in cross-border asset holdings and emphasize the importance of relative, multilateral resistance, thus reinforcing the modern practice of using high-dimensional fixed effects when estimating gravity equations for cross-border investment. Building on this structural foundation, several contributions mentioned in this subsection (e.g., Aiyar et al., 2024; Gopinath et al., 2025) demonstrate how gravity models can incorporate emerging determinants of international investment (and in particular FDI) including forces related to geopolitical fragmentation.

2.4 Global Submarine Cable Network

Lastly, this thesis connects with the empirical studies that exploit the global submarine cable network. Such studies remain relatively scarce, partly due to the limited public availability of detailed information on this infrastructure and partly because fiber-optic submarine cables have only become widespread in recent decades. Several contributions examine the economy-wide effects of subsea cable roll-out, typically treating submarine cables as a proxy or an instrument for access to high-speed internet, most often in developing countries. Hjort and Poulsen (2019), for example, use a difference-in-differences approach to study the impact of submarine cable arrivals in Africa on local employment. Along similar lines, D'Andrea and Limodio (2019) exploit the staggered roll-out of cables across African countries to analyze how high-speed connectivity affects credit markets, while Houngbonon et al. (2022) examine its effects on firm innovation and entrepreneurship. Cariolle and da Piedade (2023) study the impact of digital connectivity via undersea cables on export performance and find positive effects, and Simione and Li (2021) document increases in GDP per capita, labor productivity, and employment in areas connected to fiber-optic cables.

A smaller and more recent literature examines the subsea cable market itself, focusing on entry, competition, and welfare (Jeon and Rysman, 2024; Caoui and Steck, 2025). Finally, a few papers (Malecki, 2002; Zhang et al., 2022; Xie and Wang, 2023) examine empirically the structure of the global submarine cable network itself.

We aim to build on this strand of the literature by bringing the global submarine cable network into the analysis of geoeconomic dynamics. This thesis is closest in spirit to Porcellacchia et al. (2026), the only empirical work to date that explicitly adopts a geoeconomic perspective on submarine cables; however, that study provides a long-run analysis of ownership, spatial configuration, and market entry across both the telegraph era and the modern cable network, without examining macroeconomic outcomes. By contrast, the novelty of our analysis lies in leveraging the spatial and ownership structure of the submarine cable network over time to study its implications for global FDI patterns. While the development economics literature focuses on the macroeconomic effects of cable roll-out and the industrial organization literature examines investment and entry incentives within the cable market, this study takes the existing market and ownership structure as given and asks whether ownership of this critical infrastructure might have triggered a reallocation of FDI in recent years. In this sense, the thesis offers a distinct and previously unexplored contribution.

3 Context: Submarine Telecommunications Cables

The aim of this section is to provide the conceptual background on submarine telecommunications cables that underpins our hypothesis. It first outlines the historical evolution of subsea cable systems, explaining their basic functioning and economic role as the backbone of cross-border data transmission. It then examines the vulnerabilities of cable infrastructure and their geoeconomic implications within a context of "weaponized interdependence".

3.1 Brief History of Submarine Telecommunications Cables

Modern fiber-optic submarine cable systems constitute the most recent stage in the historical development of undersea telecommunications infrastructures. During the nineteenth century, the British Empire deployed a far-reaching network of submarine telegraph cables to link it to colonial territories, thereby facilitating imperial commerce and administrative control; subsequent cable building programs by other powers, including the United States and Japan, extended this model (Govella, 2025). The first transatlantic telegraph cable entered service on 27 July 1866. Thereafter, investment in telegraphy expanded rapidly, and within roughly four decades the major industrial and imperial powers had been incorporated into an increasingly dense global cable system, enabling near-immediate intercontinental communication and reshaping the temporalities of diplomacy, trade, and information exchange.

Successive technological transitions altered cable design and performance while preserving the strategic function of submarine routes as long-distance carriers. Beginning in the 1950s, analog copper coaxial systems progressively displaced earlier telegraph configurations, before long-haul fiber-optic technologies became the dominant platform from the late 1980s onward (Porcellacchia et al., 2026). The first transatlantic fiber-optic system, TAT-8, was deployed in 1988, connecting the US, the UK, and France, and it was followed by a rapid proliferation of fiber links across the world's oceans as states and firms deepened their reliance on high-capacity international communications (Frascà and Galantini, 2023). Indeed, contemporary fiber systems encode information in optical signals, thereby enabling orders-of-magnitude increases in throughput and supporting massive concurrency at very low latency. Illustratively, late-nineteenth-century transatlantic cables transmitted on the order of tens of words per minute; mid-twentieth-century coaxial systems supported approximately dozens of simultaneous voice circuits; by the 1990s, typical capacities had risen to on the order of tens of thousands of concurrent calls (Porcellacchia et al., 2026). Current fiber-optic networks, by contrast, can sustain millions of simultaneous, high-quality video communications sessions.

Despite these transformations in transmission media and capacity, the fundamental architecture of submarine connectivity has remained stable for over 150 years. Subsea cables link discrete landing points across countries and constitute the long-distance portion of the global internet backbone. Once traffic reaches shore, it is routed through terrestrial backhaul, internet exchange points, and regional distribution networks to reach end users and local access systems. As a result, submarine cables carry over 99 percent of global internet traffic, providing high-bandwidth, low-latency, and generally reliable long-distance transmission. Their systemic significance has intensified with the diffusion of cloud computing, streaming platforms, e-commerce, and AI-enabled services, which collectively increase demand for cross-border data transmission and resilient connectivity. Moreover, the dependence on submarine cable infrastructures is no longer confined to the information and communications technology sector: established industries such as manufacturing, finance, and logistics increasingly rely on these networks as operational processes become more digitized, data-driven, and integrated across geographically distributed supply chains and markets.

Despite their technical superiority and cost advantages at scale, fiber-optic submarine cables have followed an uneven development trajectory, typically divided into three phases. The first major expansion occurred in the 1990s and early 2000s, contemporaneous with the dot-com boom and a surge in expectations of, and demand for, international transmission capacity. Growth then slowed after the bubble burst and was further hampered by the global financial crisis. A third phase emerged with the consolidation and rapid growth of over-the-top (OTT) service providers–particularly, cloud computing and digital media platforms– whose data-intensive business models generated renewed, exponential growth in traffic and catalyzed their entry into direct submarine cable investment and control (Jeon and Rysman, 2024).

These demand-side transformations have coincided with an institutional reconfiguration of ownership in the subsea cable sector. Ownership is in fact typically organized into three stylized typologies: consortia, multilateral development bank (MDB)-supported projects, and single-owner systems. The consortium model has historically been predominant, reflecting both the high fixed costs and the risk profile of cable construction. In this arrangement, multiple firms jointly finance and procure a system along a specified route, pool risk, and apportion capacity and governance rights among participants in accordance with contractual allocations. A second model involves multilateral development banks (e.g., the World Bank), which can lower financing costs, offer longer and more flexible repayment terms, and are often more accommodating when states or firms face repayment difficulties. The most recent configuration is single ownership, in which one firm assumes primary responsibility for financing and control. While this structure can reduce coordination costs and accelerate decision-making, it also concentrates control in a small number of actors, potentially intensifying geopolitical scrutiny and creating a clearer potential for leverage over routes and landing points. In recent years, these types of projects have grown quickly, led by Big Tech firms such as Meta, Amazon, and Google, which increasingly build and control systems alone or with only a few partners. At the same time, Chinese state-owned enterprises have expanded their presence in the subsea cable market (Frascà and Galantini, 2023). Moreover, as these actors have become more influential, cable routing has shifted from linking major population centers–typical of incumbent telecom operators–to connecting hyperscale data centers and other key nodes in cloud and content delivery networks (Burnett, 2021).

3.2 Vulnerabilities and the Geoeconomics of Submarine Cables

The global submarine cable system is deeply embedded in modern economic and social activity, yet it remains very much exposed to disruption. Current estimates suggest that approximately 150 cable faults occur worldwide each year (Govella, 2025). These failures arise from both natural and human sources. Natural hazards include abrasion and seabed movement, as well as events such as earthquakes and volcanic activity. Human-induced damage is more frequent and is often accidental, especially in heavily trafficked coastal waters where fishing gear and ship anchors can sever cables on the seabed. For these reasons, many routes are supported by multiple cable systems to ensure redundancy and maintain high-speed data transmission even if one system fails.

Yet beyond routine accidents, submarine cables have long been targets of strategic interference. Historical records document repeated episodes of sabotage, cable cutting, and espionage involving both telegraph and contemporary fiber systems. During World War I, for instance, the UK and Germany attacked each other's undersea cable links, and the US employed cable cutting as a military tactic during the Spanish–American War in the late nineteenth century. In more recent contexts, the deliberate disruption of cable infrastructure has been reported as a coercive instrument: in 2014, Russia allegedly damaged submarine cable facilities to pressure Ukraine, contributing to communications outages in affected areas (Xie and Wang, 2023). Following the escalation of Russia's war against Ukraine in 2022, concerns about cable security in Northern Europe grew alongside reported incidents. In January 2022, the Svalbard Cable, owned by Space Norway and connecting mainland Norway to the Svalbard archipelago, was severed and was reportedly linked to Russian fishing vessels. Similarly, Taiwanese authorities have repeatedly attributed damage to cables linking Taiwan to the outside world to Chinese actors.[4]

Security risks extend beyond physical disruption to include espionage and surveillance, which have deep historical precedents, too. The British Empire, for example, leveraged

[4] See Porcellacchia et al. (2026) for an extensive review of episodes of blockades, sabotage, and espionage affecting submarine cables.

its privileged position within nineteenth-century telegraph networks to monitor communications for intelligence purposes. In the fiber-optic era, surveillance can occur at multiple points in the life-cycle and geography of cable systems: vulnerabilities may be introduced through the targeting of landing stations and onshore facilities where cables interface with terrestrial networks, or through wire-tapping operations (Govella, 2025). In practical terms, access to a cable, whether at landing points or along its route, can enable the interception of traffic traversing that link. The Snowden disclosures in 2013 reinforced the plausibility of these risks by revealing that the intelligence agencies of the US and the UK accessed fiber-optic cable traffic via landing stations to collect large volumes of internet and telephony data (Porcellacchia et al., 2026). More recently, when the US Department of Justice blocked the *Pacific Light Cable Network* in 2020, it cited concerns that the project could advance the Chinese government's objective of positioning Hong Kong as a major telecommunications hub, thereby increasing the proportion of US data routed through Chinese territory and, in turn, elevating espionage risks (Runde et al., 2024). Even when traffic does not transit China's territory, analysts have raised concerns that Chinese firms involved in cable construction or operation could be compelled to cooperate with state intelligence requirements, potentially enabling surveillance (Koshino, 2024).

Taken together, these dynamics underscore that submarine connectivity can be, and historically has been, instrumentalized during periods of geopolitical competition. As the global economy has become more dependent on digitally-mediated activity, the strategic value of controlling information infrastructure has increased, aligning with Farrell and Newman's (2019) concept of "weaponized interdependence". In this view, dense international networks do not merely generate mutual dependence; they also create asymmetric leverage for actors positioned at critical nodes. Applied to submarine cables, concentration in the ownership and governance of specific routes, landing stations, and interconnection points can produce the "panopticon" effect (enhanced visibility into cross-border flows) as well as the "chokepoint" effect (the capacity to restrict, degrade, or selectively interrupt connectivity) (Farrell and Newman, 2019). Because cross-border data transmission is increasingly foundational to economic performance and national security, the deliberate targeting of key chokepoints can generate large and rapidly propagating costs. Illustratively, in 2008, the severing of two cables near Alexandria reportedly disrupted a substantial share of connectivity across Europe, the Middle East, North Africa, and parts of South Asia (Xie and Wang, 2023). Moreover, interdependence across the digital stack can amplify the systemic consequences of disruptions: as Crosignani et al. (2023) suggest, "supply-chain" attacks can cascade across interconnected infrastructure layers, turning localized breach into broader disruption.

As discussed in the previous section, these vulnerabilities and the centrality of submarine cables to economic life together make cable networks salient instruments of geoeconomic statecraft. The growing geopolitical competition over routing, suppliers, and landing points is already reshaping the physical geography of the network. China's interest in submarine connectivity, for example, has been incorporated into the *Digital Silk Road initiative*, with ambitions to expand influence in global fiber-optic markets (Runde et al., 2024). In response, countries like the United States, Australia, and Japan have increasingly deployed geoeconomic tools to steer cable investments and routes toward configurations aligned with their security preferences. Accordingly, Porcellacchia et al. (2026) find empirically that states viewed as rivals of hegemonic powers are more likely to pursue new cable routes during periods of heightened geopolitical tension, seeking to reduce exposure and dependence by reconfiguring connectivity.

While physical rerouting and new cable construction can be slow and capital intensive, this thesis advances a complementary hypothesis: firms may respond to perceived surveillance or sabotage risks by reallocating FDI away from jurisdictions whose connectivity is heavily dependent on rival states or rival-aligned cable owners. Such exposure can indeed increase firms' costs by raising data-governance and compliance concerns, increasing the probability and expected losses associated with service disruption, heightening reputational and stakeholder risks linked to sensitive-data exposure, and requiring additional spending to build operational redundancy, such as alternative routing arrangements or multi-cloud strategies, to mitigate these threats. Because such exposure can impose significant operational and strategic costs, through heightened data vulnerability or the risk of disruption, firms may try to mitigate risk by shifting investment to alternative locations with more trusted infrastructure and governance environments.

4 Data

This section describes the data sources used to obtain the variables for the empirical analysis. We compile information on FDI from the IMF and the OECD. We then introduce our measures of geopolitical alignment based on UN voting patterns, and conclude with a description of the submarine cable data drawn from the newly developed *CableHist* dataset.

4.1 Bilateral FDI

The primary source of bilateral FDI data used in this thesis is the IMF's Direct Investment Positions (DIP) by Counterpart Economy dataset (formerly the Coordinated Direct Investment Survey, CDIS). The DIP dataset reports bilateral FDI positions from source country j to destination country i in year t. Positions are constructed under the directional principle, whereby investment by a direct investment enterprise in its direct investor (reverse investment) is netted against investment by the direct investor in the direct investment enterprise. We focus in particular on net inward FDI stocks over the period 2009–2023, that is, liabilities of resident direct investment enterprises with their nonresident direct investors, net of the reverse investment into the latter. Such inward positions are either directly reported by the destination country or inferred from the corresponding outward positions reported by the source country (so-called mirror data). Finally, we consider total FDI positions without distinguishing between debt and equity components.

To enrich the analysis, we complement the IMF data with the OECD's FDI Positions by Counterpart Area dataset. The latter is also constructed under the directional principle, so it is easy to combine with the DIP dataset. Furthermore, while the OECD dataset has more limited geographical coverage than the DIP, it provides a key advantage by distinguishing between FDI positions in "regular" entities and those in Special-Purpose Entities (SPEs). SPEs are firms with little or no employment, production, or physical presence, whose primary activities consist of holding and financing. This feature allows us to decompose inward FDI stocks into "real" FDI and "phantom" FDI (i.e., FDI directed toward SPEs). However, this decomposition is available only for a subset of country pairs.

To address this limitation, we follow the methodology proposed by Damgaard et al. (2024) to estimate real FDI positions for the remaining observations.[5] Table 10 summarizes the main characteristics of the resulting dataset of real FDI stocks.

4.2 Geopolitics

To measure countries' positions in the geopolitical spectrum, we use voting patterns at the United Nations General Assembly (UNGA). In particular, we rely on Bailey et al. (2017)'s ideal point scores, which reflect, for each year, a country's latent foreign-policy alignment as revealed by its UNGA voting pattern. Hence, countries with similar scores tend to vote similarly across many resolutions, while countries with very different scores systematically vote on opposite sides. Moreover, the advantage of their measure is that it is estimated dynamically under a constant UNGA agenda. In this way, differences in alignments over time are not driven by changes in the topics discussed at the UNGA, but by genuine shifts in geopolitical preferences between country pairs[6]. Finally, we compute the Ideal Point Distance (IPD) between two countries in a given year as the absolute value of the difference between the ideal points of each country in that year.

Following Gopinath et al. (2025) and Kallen (2025), we use the IPD to assign each country to one of three geopolitical blocs. Countries in the top 20 percent in terms of political proximity (given by the IPD) to the United States are assigned to the US-leaning bloc. Similarly, countries in the top 20 percent in their political proximity to China are assigned to the China-leaning bloc. Then, we define a nonaligned bloc, which includes the remaining countries. Since the IPD is computed annually, bloc membership varies over time as well.

Figure 3 indeed illustrates some of the evolution of these blocs between 2009 and 2023. While membership is largely stable among advanced economies, most variation occurs among emerging markets and developing economies. Beyond Southeast Asia, where countries such as Indonesia, Malaysia, Vietnam, and Laos eventually move toward the

[5]See the Appendix for a detailed description of the estimation procedure.

[6]A more detailed explanation of how ideal point scores are computed is contained in Bailey et al. (2017).

China-leaning bloc, notable realignments are also observed in the Middle East, including Jordan, Iraq, Lebanon, the United Arab Emirates, Oman, and Yemen. In other regions, changes are more sporadic: several African and Latin American countries shift between nonaligned and China-leaning positions over time, while European alignment remains largely unchanged, with Belarus emerging as the sole European country assigned to the China-leaning bloc by 2023.

4.3 Global Submarine Cable Network

Finally, the data on the global submarine cable network are drawn from a section of the *CableHist* dataset by Porcellacchia et al. (2026).[7] *CableHist* is the first dataset to systematically reconstruct the history of all known international submarine cables ever laid. The subset used in this thesis covers modern submarine telecommunications cables from 1987 onward.

The dataset is manually compiled from two publicly available sources. The first is the *Submarine Cables Almanac* produced by SubTel Forum, an ongoing initiative launched in 2011 to conduct quarterly censuses of international submarine cables. The *Submarine Cables Almanac* reports active and planned cable systems and provides detailed information including routes, landing points, length, and ownership. The second source is *Atlantic Cable*, a freely accessible website documenting submarine cable projects from the earliest telegraph cables to the most recent internet systems. Although less systematic than the *Submarine Cables Almanac*, *Atlantic Cable* also offers detailed descriptions of routes, lengths, and landing points. Each source is coded independently and subsequently merged into a consensus dataset. If discrepancies arise, *Submarine Cables Almanac* is treated as the authoritative source, given its broader coverage, greater detail, and its status as a recognized industry reference.

As reported in Table 12, the resulting dataset covers 843 active and planned cable systems over 1987–2025. Each cable system is composed of multiple individual cables (i.e., segments) and connects multiple landing points. Overall, the dataset includes almost

[7] The author personally contributed to the construction of the *CableHist* dataset during a research internship at the *Kiel Institute for the World Economy*.

1,900 landing points worldwide.

Figures 4 to 11 illustrate the evolution of the global submarine cable network as captured by the dataset, corroborating and extending the anecdotal patterns discussed in Section 3. Overall, the network has expanded continuously since the early 1990s. A first wave of growth was interrupted by the bursting of the dot-com bubble in the early 2000s, when fewer systems entered service and some were even decommissioned. From 2006 onward, expansion resumed and has continued since then. This pattern is reflected both in the rising number of active systems over time (Figure 4) and in the increase in the network's total length (Figure 5). Figure 6 also depicts similar phases of booms and busts. In addition, Figure 7 indicates that the network has also expanded geographically, as shown by the sustained growth in the number of landing points worldwide. Whereas early fiber-optic cables predominantly landed along the northern Atlantic corridor and the Mediterranean area, the network has gradually extended to all other regions of the globe. Finally, cable systems' structure has become increasingly complex over time, as evidenced by the rising average number of segments per system (Figure 8).

In addition, for each segment, the dataset reports one or more owners.[8] Owners are linked to a "parent" entity (e.g., the parent company when the recorded owner is a subsidiary), which is in turn assigned a geopolitical affiliation based on the country where it is headquartered. For example, Vodafone Malta is mapped to its parent company Vodafone, and is therefore geopolitically affiliated with the United Kingdom, where Vodafone is headquartered.[9] The dataset reports a total of 722 distinct owning entities that are affiliated to a total of 137 distinct countries. Figure 9 shows that cable-owning entities originate from an increasingly large set of countries worldwide. Moreover, after an intermediate phase during which cable consortia grew in size, since the 2010s cables are now owned by smaller groups of entities. (Figure 10). Similarly, the share of cables jointly owned by entities from different countries has been steadily declining, especially for non-

[8]When ownership shares are missing, it is assumed that the unobserved portion is split equally among the observed owners.

[9]Mapping to parent entities and geopolitical affiliation is conducted using multiple online sources, to the best of our knowledge and professional judgment.

domestic systems, as illustrated in Figure 11. Taken together, these two trends seem in line with what discussed in the previous section: a shift toward fewer, larger owners and a greater salience of regulatory and geopolitical constraints, which reduce the feasibility of large, multinational consortia.

Finally, to track relevant changes affecting systems and segments, phases are defined. A phase represents a portion of a cable system's life-cycle during which its characteristics remain unchanged. A system undergoes a phase change whenever one of the following occurs: a change in geography (i.e., modifications to landing points or system connections); a change in ownership; or a change in status (for example, from planned to in service). This approach allows to systematically account for such changes and ensures that, for any given year under analysis, all segments reflect information that is accurate for that specific point in time.

Building on this dataset, Porcellacchia et al. (2026) construct a measure of a country's dependence on submarine cables owned by another country. The measure estimates the share of data flows entering a destination country that are transmitted through submarine cables owned by entities affiliated with a given foreign country.[10] In this analysis, we employ the dependence index developed by Porcellacchia et al. (2026) to measure the extent to which a country receiving FDI from a given investor country is cable-dependent to a third country. This is crucial to explore our hypothesis that if such third country is a rival of the investor country, the investor may reduce its FDI to the recipient country to limit its exposure to the cable infrastructure controlled by the rival. Table 13 summarizes this bilateral cable dependence dataset.

[10]Starting from the *CableHist* dataset, Porcellacchia et al. (2026) develop this dependence measure as follows. First, they estimate a traffic assignment model of global telecommunications flows, proxying bilateral data flows with bilateral trade flows. These flows are routed through a simplified global network of submarine and terrestrial corridors, where routing is determined by the shortest (lowest-distance) path between each country pair. This procedure yields predicted traffic volumes on each corridor. Second, the dependence measure itself is computed by combining these predicted flows with information on cable ownership, measuring for each destination country the share of its incoming data flows that traverse corridors where submarine cables are owned (at least in part) by entities affiliated with a given foreign country. This captures the extent to which a country's telecommunications rely on foreign-controlled submarine infrastructure. For a more detailed explanation, see Porcellacchia et al. (2026).

Interestingly, exploring dependence over time indicates that there is a persistent and geographically structured pattern of reliance on foreign-owned submarine cable infrastructure. Figure 12 shows that high dependence is consistently concentrated in developing regions, notably Sub-Saharan Africa, South America, South Asia, and the Middle East. By contrast, advanced economies like the US, Canada, Western European countries, Japan, and Australia tend to display low levels of dependence across all years. China and Russia exhibit a similar pattern, too. Overall, the geographic distribution of dependence changes little across 2009, 2016, and 2023, suggesting that reliance on foreign-owned submarine cables is a persistent, structural feature

Furthermore, Figures 13 and 14 crucially decompose this overall dependence by focusing on the geopolitical affiliation of cable owners, distinguishing between dependence on China-bloc owners and on US-bloc owners. Taken together, these maps reveal substantial heterogeneity in the provenance of digital infrastructure ownership. Dependence on China-bloc owners is comparatively more spatially concentrated and becomes more salient throughout the period of analysis, with higher values visible across parts of Asia and, to a lesser extent, the Middle East and Africa. By contrast, dependence on US-bloc owners is more geographically diffuse and relatively stable over time. Importantly, the two measures are not mutually exclusive: many countries exhibit non-trivial exposure to both blocs. Such overlap is a key feature of the data, as it suggests that the relevance of foreign cable dependence for bilateral investment decisions might depend not only on the recipient country's exposure, but also on the geopolitical position of the investing country.

In this regard, a direct comparison with the maps of geopolitical alignment (Figure 3) reveals only a partial correspondence between political blocs and the origin of digital infrastructure ownership. In some cases, geopolitical alignment and cable dependence coincide: countries classified as China-leaning or nonaligned, particularly in parts of Africa, Southeast Asia, and the Middle East, also tend to exhibit relatively high dependence on China-bloc-owned cables, while US-leaning advanced economies are more frequently exposed to US-bloc-owned infrastructure. However, the comparison also highlights numerous mismatches. Several countries firmly embedded in the US-leaning bloc display substantial dependence on cables owned by the China bloc, while some China-leaning or nonaligned countries rely heavily on US-bloc-owned infrastructure. These patterns indicate that geopolitical alignment does not mechanically translate into reliance on domestically or bloc-aligned digital infrastructure. Instead, exposure to foreign-owned submarine cables often cuts across geopolitical lines. This divergence between political alignment and infrastructure dependence is central to our hypothesis: it implies that investors may face situations in which investing in a politically aligned country nonetheless entails indirect exposure to digital infrastructure controlled by a geopolitical rival.

5 Empirical Analysis

This section empirically examines whether bilateral FDI declines when the recipient's subsea cable infrastructure is predominantly controlled by the rivals of the investor country. We begin by introducing the principal regressor, Rival-Weighted Dependence (RWD). Then, we set out the empirical model and baseline results, and conclude with robustness and sensitivity analyses based on alternative specifications.

5.1 Rival-Weighted Dependence

The main explanatory variable used in the empirical analysis is Rival-Weighted Dependence. The objective of this measure is to capture the extent to which a recipient country's digital connectivity relies on submarine cable infrastructure owned by geopolitical rivals of the investing country. The construction of RWD combines information on foreign ownership of submarine cables, described in Section 4.3, with measures of geopolitical alignment introduced in Section 4.2, thereby operationalizing the mechanism of weaponized interdependence in the context of global digital infrastructure.

Let $d_{i,t}^{CHN}$ and $d_{i,t}^{USA}$ denote, respectively, the exposure of destination country i in year t to submarine cables owned by entities affiliated with China-leaning bloc and the US-leaning bloc. These variables correspond to the bloc-level cable dependence ratios constructed from the index by Porcellacchia et al. (2026) and described in Section 4.3:

$$d_{i,t}^{CHN} = \frac{\sum_{o \in \text{China bloc}} dependence_{iot}}{\sum_o dependence_{iot}}, \qquad d_{i,t}^{USA} = \frac{\sum_{o \in \text{US bloc}} dependence_{iot}}{\sum_o dependence_{iot}}$$

They indeed measure the degree to which a country's digital connectivity depends on infrastructure controlled by each geopolitical bloc, independently of the identity of the investing country.

To link cable dependence to bilateral investment, we introduce rivalry weights $\rho_{j,CHN,t}$ and $\rho_{j,USA,t}$, which capture the extent to which the China bloc and the US bloc are geopolitical rivals of the investor country j in year t. These weights take values in the interval $[0, 1]$ and are derived from the bloc assignment described in Section 4.2. Intuitively, a bloc is assigned a higher weight when it is geopolitically distant from the investor country and therefore more likely to be perceived as a rival. The RWD index for investment from country j into country i in year t is then defined as:

$$RWD_{i,j,t} = \rho_{j,CHN,t} \cdot d_{i,t}^{CHN} + \rho_{j,USA,t} \cdot d_{i,t}^{USA}. \tag{1}$$

This expression aggregates the recipient country's exposure to bloc-owned cable infrastructure, weighting each bloc by its degree of rivalry vis-à-vis the investor.

In the baseline specification, rivalry weights are defined using a discrete, bloc-based approach. Each investor country j is classified annually as belonging to the US-leaning bloc, the China-leaning bloc, or the nonaligned group. When j belongs to the US-leaning bloc, dependence on China-bloc-owned infrastructure is classified as fully rival ($\rho_{j,CHN,t} = 1$), while dependence on US-bloc-owned infrastructure as non-rival ($\rho_{j,USA,t} = 0$). Symmetrically, when j belongs to the China-leaning bloc, dependence on US-bloc-owned infrastructure receives full weight, while dependence on China-bloc-owned infrastructure is treated as non-rival. For nonaligned investors, dependence on both blocs is assigned an intermediate weight of 0.5.[11] Under this definition, the index simplifies to:

$$\begin{aligned} RWD_{i,j,t} = {} & 1\{j \in \text{US bloc}\} \cdot d_{i,t}^{CHN} + 1\{j \in \text{China bloc}\} \cdot d_{i,t}^{USA} \\ & + 0.5 \cdot 1\{j \in \text{Nonaligned}\} \cdot \left(d_{i,t}^{CHN} + d_{i,t}^{USA}\right). \end{aligned} \tag{2}$$

This formulation has the following interpretation: when the investor belongs to the US-leaning bloc, the RWD index collapses to the recipient country's dependence on China-bloc-owned cable infrastructure; when the investor belongs to the China-leaning bloc, it collapses to dependence on US-bloc-owned infrastructure. For nonaligned investors, the index captures exposure to both blocs symmetrically. As a result, higher values of RWD indicate greater reliance of the recipient country on digital infrastructure controlled by

[11] An alternative RWD measure constructed with continuous weights based on IPD is presented and tested as robustness in Section 5.4.

geopolitical rivals of the investor. Finally, variation in RWD arises both across country pairs, reflecting differences in cable ownership and geopolitical alignment, and over time, due to changes in cable systems, ownership structures, and countries' geopolitical positions. This makes the index well suited to capturing the evolving interaction between global digital infrastructure and geopolitical rivalry that underpins the empirical analysis.

5.2 Empirical Specification

To quantify the extent of fragmentation of FDI flows based on exposure to rival-controlled cables, we estimate a gravity model, which has become the conventional framework for estimating the determinants of investment flows (Portes and Rey, 2005; Okawa and van Wincoop, 2012; Aiyar et al., 2024; Catalàn et al., 2024; Gopinath et al., 2025). In our bilateral panel, the outcome variable is annual inward FDI flows from investor j to destination i in year t, denoted by $FDI_{i\leftarrow j,t}$. We construct an implied FDI flow measure starting from our data on bilateral real FDI stocks. Following Kallen (2025), we define FDI flows as:

$$FDI_{i\leftarrow j,t} = \frac{FDIStock_{i\leftarrow j,t} - FDIStock_{i\leftarrow j,t-1}}{FDIStock_{i\leftarrow j,t} + FDIStock_{i\leftarrow j,t-1}}.$$

This measure is bounded between -1 and 1, which enhances robustness to outliers.[12][13]

The main explanatory variable is the RWD index defined in Section 5.1, interacted with an indicator $Post_t$ indicating the post-2017 period. We adopt 2018 as the break point marking the onset of the current phase of heightened geopolitical rivalry. This period is commonly associated with the escalation of US-China strategic competition, beginning with the 2018 trade war and subsequently expanding into broader technology and security frictions. In the following years, geopolitical risk further intensified with,

[12] As in Kallen (2025), observations in our source dataset with negative real FDI positions are excluded. Negative bilateral stocks mainly reflect accounting and reporting conventions (e.g., netting and reverse investment) rather than economically meaningful inward investment. Including them would add noise unrelated to our mechanism and blur the interpretation of the relationship between cable exposure and FDI. We therefore restrict attention to non-negative positions that more directly capture investor FDI exposure in the recipient country.

[13] We propose alternative specifications with different outcome variables in Section 5.4.

among others, Russia's full-scale invasion of Ukraine in 2022, rising tensions between China and Taiwan, and the Israeli-Palestinian conflict. Kallen (2025) also uses 2018 as the start of a period of heightened geopolitical tensions. Finally, RWD is lagged one period to mitigate simultaneity and reflect the relatively long times required for direct investments to adjust.

The baseline specification is

$$\begin{aligned} FDI_{i \leftarrow j,t} = \beta_0\, RWD_{i,j,t-1} + \beta_1 \Big(RWD_{i,j,t-1} \times Post_t\Big) + \phi\, GeoDist_{i,j,t} \\ + \mu_{i,j} + \gamma_{i,t} + \lambda_{j,t} + \varepsilon_{i,j,t}. \end{aligned} \tag{3}$$

Country-pair fixed effects $\mu_{i,j}$ absorb all time-invariant bilateral determinants of FDI (e.g., geographic distance, colonial ties, and common language). Destination-year fixed effects $\gamma_{i,t}$ capture recipient-wide conditions in year t (the "pull" factors), such as market size and growth, reforms, and country-level risk. Investor-year fixed effects $\lambda_{j,t}$ capture investor-wide determinants of outward FDI in year t (the "push" factors), including domestic financial conditions, tax and capital-account policies, outbound screening rules, geopolitical posture, and business-cycle phases. Standard errors are clustered at the country-pair level to allow for arbitrary serial correlation within pairs. Table 14 summarizes the variables included in the baseline model.

Moreover, the covariate $GeoDist_{i,j,t}$ controls for geopolitical distance between i and j in year t, measured as the logarithm of Bailey et al. (2017)'s ideal-point distance described in Section 4.2. Since $GeoDist_{i,j,t}$ varies within dyads over time, it is not absorbed by $\mu_{i,j}$ and allows the analysis to separate the digital-infrastructure channel from the broader barrier posed by deteriorating political alignment. A coefficient $\phi < 0$ would therefore be consistent with the evidence that greater geopolitical distance depresses bilateral FDI (as discussed in Section 2.3).

Given the saturated fixed-effects structure, identification of β_0 and β_1 comes from within-pair changes in $RWD_{i,j,t-1}$ over time, after netting out any investor-wide shocks common across destinations in year t (captured by $\lambda_{j,t}$) and any recipient-wide shocks common across investors in year t (captured by $\gamma_{i,t}$). In other words, the coefficient is identified by dyad-time variation in RWD that remains once time-invariant bilateral frictions and contemporaneous investor- and recipient-year factors are absorbed.

In terms of interpretation, β_0 captures the pre-2018 association between rival-weighted dependence and bilateral FDI, while β_1 measures the change in that association from 2018 onward; the 2018-onward slope is $\beta_0+\beta_1$. A negative β_0 (and/or $\beta_0+\beta_1<0$) implies that, holding fixed bilateral fundamentals and country-year shocks, FDI from j to i declines as a larger share of i's digital connectivity depends on cables controlled by rivals of j. A negative β_1 implies that this association becomes more negative in the post period.

In practice, residual variation in $RWD_{i,j,t-1}$ arises from the interaction of two time-varying components: (i) recipient-side exposure ($d^{CHN}_{i,t-1}, d^{USA}_{i,t-1}$), which changes with entry of new systems, rerouting, and ownership updates in the cable network; and (ii) investor-side rivalry weights ($\rho_{j,CHN,t-1}, \rho_{j,USA,t-1}$), which evolve with investor countries' geopolitical positions. Their interaction yields investor-specific exposure to rival-controlled infrastructure even after absorbing investor-year and destination-year shocks.

In this baseline model, a key concern is endogeneity, i.e. that $RWD_{i,j,t-1}$ may be correlated with the error term in Eq. (3). It is useful to distinguish three sources of endogeneity. First, reverse causality from bilateral FDI to cable exposure is unlikely: at annual frequency, bilateral investment within a specific dyad is implausible to affect the global ownership and routing configuration of submarine cable segments that determine ($d^{CHN}_{i,t}, d^{USA}_{i,t}$). Cable infrastructure and ownership changes are large-scale and shaped by consortium decisions and regulatory processes with long planning horizons, making them unlikely to respond mechanically to short-run fluctuations in bilateral FDI.

Second, omitted variables may operate through investor- or recipient-wide shocks in a given year that could jointly shift FDI and the objects entering RWD. These confounders are absorbed by $\lambda_{j,t}$ and $\gamma_{i,t}$, so identification does not rely on comparisons across investors or recipients within a year, but on within-dyad changes over time net of investor-year and recipient-year factors.

However, a main remaining threat is time-varying, dyad-specific confounders, such as bilateral diplomatic disputes, targeted sanctions, or security incidents that directly affect $FDI_{i\leftarrow j,t}$ and may also correlate with changes in $RWD_{i,j,t-1}$. Conditioning on the time-varying dyadic control $GeoDist_{i,j,t}$ mitigates this concern by absorbing observed shifts in investor-recipient political alignment, but *GeoDist* may not capture all relevant dyad-specific shocks. The identifying assumption therefore remains that there are no unobserved dyad-year disturbances that jointly move RWD and bilateral FDI. To further probe this assumption, Section 5.4 reports an alternative specification including leads of RWD. Nevertheless, this robustness test cannot rule out all the confounding factors, in particular shocks that move RWD and FDI contemporaneously within the same dyad-year. Accordingly, the estimates are best interpreted as isolating variation consistent with the proposed mechanism rather than as definitive causal effects.

5.3 Results

Table 1 reports estimates from the baseline specification in Eq. (3). The coefficient on $RWD_{i,j,t-1}$ is positive but small and statistically indistinguishable from zero, suggesting no significant association between rival-weighted dependence and bilateral FDI in the pre-2018 period. By contrast, the coefficient of the interaction term $RWD_{i,j,t-1} \times \{Post = 1\}$ is negative and statistically significant at the 1 percent level, indicating that the marginal relationship between RWD and FDI becomes markedly more negative after 2017. This pattern is consistent with the hypothesis that, in the current era of heightened geopolitical tensions, exposure to rival-controlled digital infrastructure has become a salient determinant of bilateral investment.

Furthermore, to interpret the post-period magnitude of this effect we have to compute the post-2017 slope of $RWD_{i,j,t-1}$, equal to the sum of the pre-period slope and the interaction term $(\hat{\beta}_0 + \hat{\beta}_1)$. The implied post-2017 slope is negative, -0.0770 and statistically different from zero at the 10 percent level. Hence, while the sharp post-2017 change in the relationship is strongly supported by the data, evidence that the post-period association is strictly negative is not as precisely estimated but still suggestive in the baseline specification. It indeed hints to the fact that, in the current era of geopolitical tensions, an investor country pours lower FDI into a recipient country if the latter is more dependent on data infrastructure (specifically, submarine cables) controlled by rivals of the former. Indeed, a one-unit increase in RWD, that is, moving from a situation in which the recipient is not dependent on the investor's rivals' cable infrastructure to one in which it is fully dependent, is associated with a 0.077 decrease in the normalized FDI outcome, ceteris paribus. Although this magnitude is not directly interpretable in levels because the dependent variable is a bounded, normalized change measure, it is sizable relative to the distribution of the outcome in the estimation sample (mean ≈ 0.044, median ≈ 0.016), implying a notable shift in investment patterns in this extreme scenario. A more moderate increase in RWD by one standard deviation (≈ 0.1208) is in turn associated with a decrease in the FDI outcome by roughly 0.0093. While smaller in absolute terms, this effect still implies a systematic shift in bilateral FDI patterns for economically plausible changes in exposure to rival-controlled cable infrastructure.

Finally, the control for geopolitical distance enters with the expected sign: it is negative and significant, in line with the view that greater political distance between countries depresses bilateral FDI, independently of the cable-exposure channel captured by RWD.

Table 1: Baseline Specification

	$FDI_{i\leftarrow j,t}$
$RWD_{i,j,t-1}$	0.0506
	(0.0444)
$RWD_{i,j,t-1} \times \{Post = 1\}$	-0.128***
	(0.0425)
$GeoDist_{i,j,t}$	-0.00777***
	(0.00273)
Constant	0.0425***
	(0.00987)
Post-2017 slope of $RWD_{i,j,t-1}$ ($\hat{\beta}_0+\hat{\beta}_1$)	-0.0770^{*}
	(0.0467)
Observations	61,658
No. of Recipient Countries (i)	127
No. of Investor Countries (j)	181
No. of Country Pairs (i, j)	6,915
R-squared	0.219
Adj. R-squared	0.049
Method	OLS
Country-pair FEs	✓
Recipient-Year FEs	✓
Investor-Year FEs	✓
Clustered SEs	✓

Note: Standard errors clustered by country-pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample period: 2009-2023. The "Post-2017 slope of $RWD_{i\leftarrow j,t-1}$" is computed as $\hat{\beta}_0 + \hat{\beta}_1$ and tested using a linear combination (Wald) test of $H_0 : \beta_0 + \beta_1 = 0$.

5.4 Robustness and Sensitivity Analysis

5.4.1 Testing for Pre-Trends

To probe the endogeneity concern that changes in geopolitics might jointly drive both cable exposure and bilateral investment, Table 2 reports a lead-augmented version of our baseline specification that includes K leads of rival-weighted dependence, $RWD_{i,j,t+k}$ for $k = 1, 2, 3$, while retaining the baseline regressor $RWD_{i,j,t-1}$ interacted with $Post_t$. Under the maintained timing assumption that RWD does not respond to contemporaneous bilateral investment within the same dyad-year, future values of RWD should not predict current FDI. Statistically significant lead coefficients would indicate pre-trends consistent with anticipation or with unobserved shocks that reduce FDI before they materialize in the measured exposure variables. The estimates show no such predictive power: the lead coefficients are small and jointly insignificant, while the baseline coefficients remain qualitatively similar. This diagnostic cannot fully rule out contemporaneous dyad-year confounding, but it reduces concerns that the baseline results are driven by systematic anticipation effects.

5.4.2 Alternative RWD Measures

In the baseline RWD measure, rivalry is implemented through discrete bloc membership of the investor (US/China/nonaligned), which implies step-function weights that take values $\{0, 0.5, 1\}$. While this approach provides a transparent and intuitive mapping from geopolitical blocs to rivalry intensity, it relies on a discrete classification and on a cutoff rule in IPD space. This raises concerns about arbitrariness and measurement coarseness. Moreover, the discrete construction assigns an intermediate rivalry intensity to investors classified as nonaligned by imposing weights equal to 0.5. Although this can be interpreted as capturing attenuated (but nonzero) sensitivity to US-China rivalry, one could alternatively argue that genuinely nonaligned investors should be comparatively indifferent to the bloc composition of cable ownership. To reduce reliance on hard thresholds and to let "nonalignment" emerge as an intermediate position rather than a separate dis-

Table 2: Alternative Specification with Lead Values of RWD

	(1) $FDI_{i \leftarrow j,t}$	(2) $FDI_{i \leftarrow j,t}$
$RWD_{i,j,t+3}$	0.0775	0.0799
	(0.0501)	(0.0644)
$RWD_{i,j,t+2}$	-0.000917	-0.0162
	(0.0501)	(0.0573)
$RWD_{i,j,t+1}$	0.0781	0.0855
	(0.0520)	(0.0596)
$RWD_{i,j,t+3} \times \{Post = 1\}$		-0.0124
		(0.101)
$RWD_{i,j,t+2} \times \{Post = 1\}$		0.0585
		(0.101)
$RWD_{i,j,t+1} \times \{Post = 1\}$		-0.0371
		(0.113)
$RWD_{i,j,t-1}$	0.0163	0.0153
	(0.0510)	(0.0556)
$RWD_{i,j,t-1} \times \{Post = 1\}$	-0.212***	-0.215**
	(0.0557)	(0.0985)
$GeoDist_{i,j,t}$	-0.00630*	-0.00630*
	(0.00347)	(0.00347)
Constant	0.0190	0.0202
	(0.0217)	(0.0224)
Post-2017 slope of $RWD_{i,j,t-1}$ ($\hat{\beta}_0$+$\hat{\beta}_1$)	-0.1961^{***}	-0.1999^{***}
	(0.0651)	(0.0893)
Observations	46,068	46,068
R-squared	0.240	0.240
Adj. R-squared	0.042	0.042
Method	OLS	
Country-pair FEs	✓	✓
Recipient-Year FEs	✓	✓
Investor-Year FEs	✓	✓
Clustered SEs	✓	✓
F-test: Leads jointly = 0 (p-value)	0.1337	0.1979
F-test: Lead×Post jointly = 0 (p-value)		0.9475

Note: Standard errors clustered by country-pair in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample period: 2009-2023. The "Post-2017 slope of $RWD_{i,j,t-1}$" is computed as $\hat{\beta}_0 + \hat{\beta}_1$ and tested using a linear combination (Wald) test of $H_0 : \beta_0 + \beta_1 = 0$.

crete category, we construct two continuous robustness versions of RWD based directly on IPD. This also improves internal consistency with the IPD-based geopolitical distance used as a control variable in the analysis.

Let $dist_{USA,j,t}$ and $dist_{CHN,j,t}$ denote investor j's geopolitical distance from the US and from China, respectively. For the first variant RWD^{cont1}, we define continuous alignment weights toward the US (and China) as a softmax transformation of these distances:

$$w_{j,t}^{USA} = \frac{\exp(-\kappa\, dist_{USA,j,t})}{\exp(-\kappa\, dist_{USA,j,t}) + \exp(-\kappa\, dist_{CHN,j,t})}, \qquad w_{j,t}^{CHN} = 1 - w_{j,t}^{USA}. \tag{4}$$

The parameter $\kappa > 0$ governs the "sharpness" of the mapping from distances to weights. For low values of κ, the weights are diffuse and remain close to 0.5 even when one distance is moderately smaller than the other; for higher values of κ, the mapping becomes more polarized and weights concentrate closer to 0 or 1, approximating a discrete bloc assignment in the limit.[14] In this sense, κ controls how strongly the continuous measure treats geopolitical proximity as a binary alignment versus a gradual continuum.

To preserve the interpretation of the baseline rivalry component (namely that exposure to the opposing bloc is salient for investors aligned with the other bloc), we define continuous rivalry weights as

$$\tilde{\rho}_{j,CHN,t} = w_{j,t}^{USA}, \qquad \tilde{\rho}_{j,USA,t} = w_{j,t}^{CHN}. \tag{5}$$

Using these weights, the first continuous variant of RWD is then

$$RWD_{i,j,t}^{cont1} = \tilde{\rho}_{j,CHN,t} \cdot d_{i,t}^{CHN} + \tilde{\rho}_{j,USA,t} \cdot d_{i,t}^{USA}, \tag{6}$$

where $d_{i,t}^{CHN}$ and $d_{i,t}^{USA}$ are the recipient-side dependence measures on China- and US-bloc owned cable infrastructure as in the baseline construction.

[14] To better understand the role of κ, we can rewrite $w_{j,t}^{USA} = \frac{\exp(-\kappa\, dist_{USA,j,t})}{\exp(-\kappa\, dist_{USA,j,t}) + \exp(-\kappa\, dist_{CHN,j,t})}$ as $w_{j,t}^{USA} = \left[1 + \exp\big(\kappa(dist_{USA,j,t} - dist_{CHN,j,t})\big)\right]^{-1}$. Hence, κ scales the distance gap: as $\kappa \to 0$, $w_{j,t}^{USA} \to 1/2$ (diffuse weights), while larger κ makes the mapping increasingly sharp, pushing $w_{j,t}^{USA}$ toward 1 when $dist_{USA,j,t} < dist_{CHN,j,t}$ and toward 0 otherwise.

For the second variant ($RWD^{cont2}_{i\leftarrow j,t}$), the only difference relies in the construction of the alignment weights. First, we define a relative distance index

$$s_{j,t} \;=\; \frac{dist_{CHN,j,t} - dist_{USA,j,t}}{dist_{CHN,j,t} + dist_{USA,j,t}} \;\in\; [-1, 1], \tag{7}$$

so that $s_{j,t} > 0$ indicates that j is closer to the US than to China (i.e., $dist_{USA,j,t} < dist_{CHN,j,t}$), while $s_{j,t} < 0$ indicates greater proximity to China. We then map this signed index to $[0, 1]$ weights via

$$w^{USA}_{j,t} \;=\; \frac{1 + s_{j,t}}{2}, \qquad w^{CHN}_{j,t} \;=\; 1 - w^{USA}_{j,t}, \tag{8}$$

and define the corresponding continuous rivalry weights analogously to the previous logic, $\tilde{\rho}_{j,CHN,t} = w^{USA}_{j,t}$ and $\tilde{\rho}_{j,USA,t} = w^{CHN}_{j,t}$. Compared to the softmax-based construction in Eq. (4), this version is mechanically simpler and eliminates the choice of the parameter κ: weights vary linearly with the normalized distance gap rather than being generated by an exponential mapping. The trade-off is that, unlike the softmax, this index cannot flexibly "sharpen" alignment when desired; instead, it imposes a gradual, symmetric adjustment that treats changes in relative proximity as having constant marginal effects across the support. In this sense, the relative-distance weights provide a transparent, parameter-free benchmark, whereas the softmax weights allow for a more polarized mapping that may better approximate discrete strategic alignment when κ is large.

Table 3 reports the regression results when replacing the baseline RWD measure with continuous IPD-based variants. Columns (1)–(3) use the softmax construction of alignment weights in Eq. (4) for increasing values of the sharpness parameter κ, while column (4) uses the parameter-free relative-distance index described in Eq. (7). Across all specifications, the post-2017 association between rival-weighted dependence and bilateral FDI ranges from -0.160 to -0.205 and is statistically significant at the 1 percent level in every column. Overall, the negative post-period relationship is robust to the choice of κ and also to the parameter-free continuous mapping in column (4). However, it is statistically different from zero at the 10 percent level only in specification (3).

Table 3: Alternative Continuous RWD Measures

	(1) $\kappa = 1$	(2) $\kappa = 2$	(3) $\kappa = 3$	(4) *Rel. Distance*
$RWD^{cont}_{i,j,t-1}$	0.127	0.0785	0.0667	0.168^{**}
	(0.0774)	(0.0593)	(0.0529)	(0.0815)
$RWD^{cont}_{i,j,t-1} \times \{Post = 1\}$	-0.205^{***}	-0.172^{***}	-0.160^{***}	-0.208^{***}
	(0.0514)	(0.0417)	(0.0388)	(0.0547)
Post-2017 slope of $RWD^{cont}_{i,j,t-1}$ ($\hat{\beta}_0$+$\hat{\beta}_1$)	-0.0775	-0.0932	-0.0930^{*}	-0.0402
	(0.0822)	(0.0608)	(0.0529)	(0.0883)
Observations	61,658	61,658	61,658	61,658
R-squared	0.219	0.219	0.219	0.219
Adj. R-squared	0.049	0.049	0.049	0.049
Method	OLS	OLS	OLS	OLS
Country-pair FEs	✓	✓	✓	✓
Recipient-Year FEs	✓	✓	✓	✓
Investor-Year FEs	✓	✓	✓	✓
Controls	*GeoDist*	*GeoDist*	*GeoDist*	*GeoDist*
Clustered SEs	✓	✓	✓	✓

Note: Standard errors clustered by country-pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. All columns include the same fixed effects and controls as the baseline specification. Columns (1)–(3) use the softmax-based continuous weights with parameter κ. Column (4) uses the parameter-free relative-distance index. Sample period: 2009-2023. The "Post-2017 slope of $RWD_{i,j,t-1}$" is computed as $\hat{\beta}_0 + \hat{\beta}_1$ and tested using a linear combination (Wald) test of $H_0 : \beta_0 + \beta_1 = 0$.

Although the coefficient of interest remains negative and statistically significant across values of κ, the choice of κ still affects how the investor-side rivalry component is distributed across countries and, in turn, the precision with which the post-period slope is estimated. For low κ, the alignment weights are more diffuse and compress toward 0.5 for a sizable set of investors, implying relatively limited cross-investor variation in rivalry intensity. As κ increases, the mapping becomes more polarized and the weights move closer to 0 or 1, approximating the discrete bloc logic in the limit. Consistent with this sharpening, standard errors on the interaction term decline across columns (1)–(3), and the implied post-2017 slope $\hat{\beta}_0 + \hat{\beta}_1$ becomes statistically distinguishable from zero only when $\kappa = 3$ (column (3)), where the continuous weights most closely resemble the baseline discrete assignment. The relative-distance index in column (4) yields a similarly negative post-period interaction effect without requiring a tuning parameter, reinforcing that the main finding, a significantly more negative RWD-FDI relationship after 2017, does not hinge on a particular functional form used to translate IPD distances into rivalry weights; however, its implied post-2017 slope is estimated less precisely in this specification.

Figure 15 helps interpret the role of κ in practice. It plots the distribution of alignment weights within baseline investor blocs, comparing the softmax mapping for $\kappa \in \{1, 2, 3\}$ with the parameter-free relative-distance index. Panel (a) shows the kernel density of the US-alignment weight $w_{j,t}^{USA}$ among baseline US-bloc investors. For $\kappa = 1$, the distribution is centered around intermediate values, whereas larger κ shifts mass toward one and produces a more polarized mapping, consistent with a sharper notion of strategic alignment. The additional relative-distance panel provides a benchmark without a tuning parameter: relative-distance weights remain more concentrated around intermediate values and therefore resemble a low-κ mapping rather than the highly polarized $\kappa = 3$ case. Panel (b) reports the analogous densities for China-bloc investors using $w_{j,t}^{CHN}$. Here, the softmax weights are already tightly concentrated near one even at $\kappa = 1$ and change little as κ increases; the relative-distance index likewise assigns weights close to one for most baseline China-bloc investors. Overall, the figure indicates that sensitivity to the mapping choice is driven primarily by how the weighting reallocates alignment intensity within the baseline US-bloc, whereas the mapping for China-bloc investors is comparatively stable.

These patterns are consistent with the fact that UNGA-based ideal points often place many countries relatively close to China. Since ideal points are inferred from UNGA voting behavior, which reflects a broad set of issues and strategic bargaining rather than purely security-related alignment, even some countries commonly viewed as Western-aligned may not appear extremely distant from China in IPD space. As a result, gradual mappings from distances to weights (such as the relative-distance index or the softmax specification with low κ) tend to yield diffuse "intermediate" alignment weights, which weakens the sharpness of the rivalry component for some baseline US-bloc investors. By contrast, increasing κ provides a systematic way to translate these UNGA-based proximity measures into a sharper notion of strategic alignment, generating weights closer to 0 or 1 and thereby approximating the discrete bloc logic that is most directly relevant for our mechanism.

Finally, we modify the baseline RWD measure by setting the rivalry weights for nonaligned investors to zero, rather than 0.5. By doing so, we impose that nonaligned investors do not perceive either bloc as a geopolitical rival (or, at least, do not condition their investment decisions on which bloc controls the recipient's cable infrastructure). Under this assumption, the recipient's dependence on US- or China-bloc cables affects investment only for investors that are clearly aligned with the opposing bloc, while nonaligned investors contribute no variation through the rivalry channel. This robustness check therefore assesses whether the baseline results are driven by the intermediate 0.5 assignment for nonaligned countries, or whether the main findings persist when nonalignment is treated as indifference to bloc-specific cable ownership. Table 4 shows a downward shift in the RWD–FDI relationship after 2017, but the implied post-period slope is negative yet no longer statistically different from zero. This pattern is consistent with the baseline results being partly driven by intermediate (nonaligned) investors, while still pointing to a post-period increase in the salience of rival-controlled infrastructure for investment decisions.

Table 4: Alternative Discrete RWD Measure: Null Weights for Nonaligned Investors

	$FDI_{i\leftarrow j,t}$
$RWD_{i,j,t-1}$	0.0253
	(0.0394)
$RWD_{i,j,t-1} \times \{Post = 1\}$	-0.0778*
	(0.0450)
Post-2017 slope of $RWD_{i,j,t-1}$ ($\hat{\beta}_0+\hat{\beta}_1$)	-0.0525
	(0.0398)
Observations	61,658
R-squared	0.219
Adj. R-squared	0.049
Method	OLS
Country-pair FEs	✓
Recipient-Year FEs	✓
Investor-Year FEs	✓
Controls	*GeoDist*
Clustered SEs	✓

Note: Standard errors clustered by country-pair in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Sample period: 2009-2023. The "Post-2017 slope of $RWD_{i,j,t-1}$" is computed as $\hat{\beta}_0 + \hat{\beta}_1$ and tested using a linear combination (Wald) test of $H_0 : \beta_0 + \beta_1 = 0$.

5.4.3 Alternative Outcome Variables

Our baseline dependent variable is a symmetric, scale-free measure of changes in bilateral FDI positions constructed from stocks, which is bounded in $[-1, 1]$ and mitigates the strong skewness of raw FDI data. While this normalization is useful for comparability across country pairs, it imposes a specific functional form. Because bilateral FDI data are characterized by a large mass of zeros and highly skewed changes in positions, it is important to verify that the baseline findings are not an artifact of this particular transformation. We therefore re-estimate the baseline specification using alternative dependent variables that (i) apply a log-like transformation to the level change in stocks, and (ii) focus on the extensive margin.

First, starting from the unnormalized change in bilateral FDI positions,

$$\Delta FDIStock_{i \leftarrow j,t} = FDIStock_{i \leftarrow j,t} - FDIStock_{i \leftarrow j,t-1},$$

we define an alternative outcome using the inverse hyperbolic sine transformation[15],

$$y^{(1)}_{i \leftarrow j,t} = \text{asinh}(\Delta FDIStock_{i \leftarrow j,t}) \, .$$

This robustness specification therefore tests whether the post-2017 relationship between rival-weighted dependence and bilateral investment is present when the dependent variable is measured in log-like units of changes in positions rather than in bounded normalized form.

Second, to capture the extensive margin, we define an indicator for whether the bilateral position increases:

$$y^{(2)}_{i \leftarrow j,t} = 1\{\Delta FDIStock_{i \leftarrow j,t} > 0\} \, .$$

[15] $\text{asinh}(x) = ln(x + \sqrt{x^2 + 1})$. This transformation is well suited to bilateral investment data because it is defined at zero and for negative values (disinvestment), while behaving similarly to the logarithm for large magnitudes (Bellemare and Wichman, 2020).

This specification isolates the probability of a positive expansion in bilateral positions. It is particularly informative in the presence of many zero changes, and directly speaks to whether rival-weighted dependence affects the likelihood that an investor increases its exposure to a given recipient.

Table 5 reports the results for these two specifications. The qualitative pattern remains consistent with the baseline: the RWD-FDI relationship becomes more negative after 2017. In column (1), the interaction term is negative and highly significant, and the implied post-2017 slope equals -0.6508, significant at the 1 percent level. Hence, holding fixed dyad effects and investor- and recipient-year shocks, a one-unit increase in RWD is associated with a 0.651 lower value of asinh($\Delta FDIStock$) in the post period. For sufficiently large FDI changes, this corresponds approximately to a 65 percent reduction in the growth of bilateral FDI positions, indicating substantially smaller expansions (or larger contractions) when recipients are more exposed to rival-controlled cable infrastructure.[16]

Column (2) turns to the extensive margin by estimating a linear probability model for $1(\Delta FDIStock_{i\leftarrow j,t} > 0)$. The interaction term is again negative and statistically significant, indicating that the marginal association between RWD and the probability of a positive stock change becomes more negative after 2017. However, the implied post-2017 slope is small and not statistically different from zero. Thus, while the data support a significant downward shift in the extensive-margin relationship after 2017, they do not provide precise evidence that the post-period probability of observing a positive expansion is decreasing in RWD once the fixed effects are absorbed.

A difference relative to the baseline is that the pre-2018 slope is positive and statistically significant in both columns. One interpretation is that, before the recent intensification of geopolitical competition, greater dependence on large-bloc cable infrastructure may have been correlated with broader integration into global digital connectivity and commercial networks, which in turn supported investment growth. Alternatively, this positive pre-period association may reflect that the level-based stock-change outcomes

[16] As in the baseline, a one-unit increase corresponds to moving from zero exposure to full exposure; more economically plausible changes can be obtained by scaling this coefficient by the standard deviation of RWD in the estimation sample.

capture long-run expansions in positions that are mechanically larger for country pairs involving more globally connected destinations. The key finding for our analysis, however, concerns the structural break: the interaction term is strongly negative, and the post-2017 slopes are consistently negative and significant, reinforcing that the adverse association between exposure to rival-controlled digital infrastructure and bilateral FDI emerges in the post-2017 period across both intensive- and extensive-margin outcome definitions.

Table 5: Alternative Outcome Variables (Aggregate FDI Data)

	(1) $asinh(\Delta FDIStock_{i\leftarrow j,t})$	(2) $1(\Delta FDIStock_{i\leftarrow j,t} > 0)$
$RWD_{i,j,t-1}$	0.775***	0.0463*
	(0.179)	(0.0274)
$RWD_{i,j,t-1} \times \{Post = 1\}$	-1.425***	-0.0664**
	(0.231)	(0.0333)
$GeoDist$	-0.0380***	-0.00303*
	(0.0125)	(0.00179)
Constant	0.207***	0.266***
	(0.0388)	(0.00608)
Post-2017 slope of $RWD_{i,j,t-1}$ (β_0+β_1)	-0.6508^{***}	-0.020
	(0.1955)	(0.0299)
Observations	129,697	129,697
No. of Recipient Countries (i)	127	127
No. of Investor Countries (j)	181	181
No. of Country Pairs (i, j)	13,575	13,575
R-squared	0.192	0.492
Adj. R-squared	0.064	0.411
Method	OLS	OLS
Country-pair FEs	✓	✓
Recipient-Year FEs	✓	✓
Investor-Year FEs	✓	✓
Clustered SEs	✓	✓

Note: Standard errors clustered by country-pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample period: 2009-2023. The "Post-2017 slope of $RWD_{i,j,t-1}$" is computed as $\hat{\beta}_0 + \hat{\beta}_1$ and tested using a linear combination (Wald) test of $H_0 : \beta_0 + \beta_1 = 0$.

Lastly, we propose an additional specification where we replace the aggregate bilateral FDI data with micro-level information on cross-border M&A deals from Orbis. Thus, we study the relationship between RWD and investment by using, as the dependent variable, the total number of completed M&A deals from investor country j into recipient country

i in year t[17]. This approach serves several purposes. First, it provides a robustness check based on an alternative data source and a conceptually similar measure of cross-border investment activity. Second, it helps mitigate the well-known investment-hub misattribution problem in aggregate FDI statistics: multinational firms often route investments through intermediary jurisdictions, so that flows recorded by immediate counterpart country can obscure the identity of the ultimate investor and destination (Coppola et al., 2021; Damgaard et al., 2024). By contrast, Orbis data identify both the ultimate acquiring firm and the ultimate target company, enabling a more accurate assignment of investment origins and destinations. Third, the deal-count outcome is well suited to Poisson Pseudo-Maximum Likelihood (PPML) estimation, which accommodates zero-inflated outcomes and is robust to heteroskedasticity. Finally, the micro-data allow us to exclude transactions in which either party operates in telecommunications-related industries. This restriction helps ensure that the analysis captures whether dependence on rival-controlled digital infrastructure is associated with broader investment fragmentation, rather than reflecting investment dynamics within the sector that directly produces or manages digital connectivity.

Table 6 shows that, also in this case, the RWD-FDI relationship becomes more negative after 2017. Beside the coefficient on the interaction term being negative and significant at the 1 percent level, the post-2017 slope is estimated at -0.9360, also significant at the 1 percent level. This indicates that a one-unit increase in RWD is associated, on average, with a decrease in bilateral deals of roughly 61 percent between year $t-1$ and year t, ceteris paribus. The coefficient associated to geopolitical distance is also negative and significant, as expected. Column (2) shows that the results are robust to excluding the top 1 percent of dyad-year observations by deal counts: the coefficients of interest are smaller but still negative and significant.

[17]For a detailed description of the Orbis data and the construction of the deal-based outcome variable, see the Appendix.

Table 6: Alternative Outcome Variable (Orbis Data)

	(1) $Deals_{i \leftarrow j,t}$	(2) $Deals^{(\text{winsorized})}_{i \leftarrow j,t}$
$RWD_{i,j,t-1}$	0.347*	0.365
	(0.195)	(0.252)
$RWD_{i,j,t-1} \times \{Post = 1\}$	-1.283***	-1.122***
	(0.231)	(0.280)
$GeoDist_{i,j,t}$	-0.0222**	-0.0259
	(0.0106)	(0.0165)
Constant	2.636***	0.0474
	(0.0365)	(0.0533)
Post-2017 slope of $RWD_{i,j,t-1}$ ($\hat{\beta}_0+\hat{\beta}_1$)	-0.9360***	-0.7567***
	(0.2613)	(0.3203)
Observations	35,566	32,234
No. of Recipient Countries (i)	115	115
No. of Investor Countries (j)	111	111
No. of Country Pairs (i, j)	2,909	2,784
Pseudo R-squared	0.810	0.343
Method	PPML	PPML
Country-pair FEs	✓	✓
Recipient-Year FEs	✓	✓
Investor-Year FEs	✓	✓
Clustered SEs	✓	✓

Note: Standard errors clustered by country-pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample period: 2010-2023. The "Post-2017 slope of $RWD_{i,j,t-1}$" is computed as $\hat{\beta}_0 + \hat{\beta}_1$ and tested using a linear combination (Wald) test of $H_0 : \beta_0 + \beta_1 = 0$. $Deals^{(\text{winsorized})}_{i \leftarrow j,t}$ is obtained by trimming the distribution of deal counts, excluding the top 1 percent of country-pair–year observations.

5.4.4 Alternative Break Point

As an additional sensitivity check, we redefine the post indicator to start in 2022 (i.e., *Post*=1 for 2022-2023) to proxy the onset of heightened geopolitical tensions with Russia's invasion of Ukraine. The resulting estimates provide no clear evidence of a distinct post-2022 break in the RWD-FDI relationship. The pre-2022 slope is close to zero and not statistically significant, and while the coefficient of the interaction term is negative, it is not statistically different from zero. Two considerations likely account for this. First, the post-2022 period in the sample contains only two years, which limits the time variation available to identify a slope change once the specification absorbs country-pair fixed effects as well as investor-year and recipient-year shocks; with such a short post window, standard errors are expected to be large. Second, the relevant "geoeconomic tension" period for the proposed mechanism is not confined to the Ukraine shock: the escalation of US-China strategic rivalry and the associated securitization of digital infrastructure arguably intensified earlier than 2022, so a post-2017 break is conceptually closer to the hypothesized channel. Therefore, this exercise suggests that the main results are better interpreted as capturing a broader post-2017 shift in the salience of rival-controlled digital infrastructure for investment decisions, rather than a discrete discontinuity tied to the 2022 invasion.

5.4.5 Excluding the US and China

We also re-estimate the baseline specification after excluding observations in which either the investor or the recipient is one of the two great powers at the center of the contemporary geoeconomic rivalry, namely the US and China. This restriction serves two purposes. First, given their outsized role in global investment networks and their centrality in the construction of geopolitical blocs, the baseline estimates could in principle be disproportionately influenced by dyads involving the US or China. Second, because the mechanism studied in this thesis concerns indirect exposure to rival-controlled digital infrastructure, it is useful to verify that the results are not driven mechanically by the direct decoupling of US-China bilateral investment links or by idiosyncratic shocks affecting either country.

Table 7: Alternative Break Point: Russian Invasion of Ukraine (2022)

	$FDI_{i \leftarrow j,t}$
$RWD_{i,j,t-1}$	0.0098
	(0.0415)
$RWD_{i,j,t-1} \times \{Post = 1\}$	-0.0447
	(0.0558)
$GeoDist_{i,j,t}$	-0.0077***
	(0.0027)
Constant	0.0393***
	(0.0099)
Post-2021 slope of $RWD_{i,j,t-1}$ ($\hat{\beta}_0+\hat{\beta}_1$)	-0.0348
	(0.0607)
Observations	61,658
R-squared	0.219
Adj. R-squared	0.049
Method	OLS
Country-pair FEs	✓
Recipient-Year FEs	✓
Investor-Year FEs	✓
Clustered SEs	✓

Note: Standard errors clustered by country-pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample period: 2009-2023. The "Post-2021 slope of $RWD_{i,j,t-1}$" is computed as $\hat{\beta}_0 + \hat{\beta}_1$ and tested using a linear combination (Wald) test of $H_0 : \beta_0 + \beta_1 = 0$.

As illustrated by Table 8, the results continue to point to a clear change in the relationship after 2017: the association between rival-weighted dependence and bilateral FDI becomes more negative in the post period even when dyads involving the two great powers are removed. At the same time, once the sample is restricted in this way, the estimated post-2017 slope of $RWD_{i \leftarrow j,t-1}$ is less precisely estimated and no longer statistically distinguishable from zero. Taken together, this test suggests that the evidence is robust with respect to the presence of a post-2017 shift in the relationship, while the magnitude of the post-period effect is harder to pin down when excluding the most geopolitically central and systemically important countries. The bottom line is that the core finding of a post-2017 strengthening of the negative association survives, but inference on the post-period slope becomes weaker in the restricted sample.

Table 8: Alternative Specification Excluding the US and China

	$FDI_{i \leftarrow j,t}$
$RWD_{i,j,t-1}$	0.0541
	(0.0470)
$RWD_{i,j,t-1} \times \{Post = 1\}$	-0.125***
	(0.0463)
$GeoDist_{i,j,t}$	-0.00769***
	(0.00292)
Constant	0.0430***
	(0.0103)
Post-2017 slope of $RWD_{i,j,t-1}$ ($\hat{\beta}_0 + \hat{\beta}_1$)	-0.0709
	(0.0492)
Observations	56,217
No. of Recipient Countries (i)	125
No. of Investor Countries (j)	178
No. of Country Pairs (i, j)	6,395
R-squared	0.225
Adj. R-squared	0.049
Method	OLS
Country-pair FEs	✓
Recipient-Year FEs	✓
Investor-Year FEs	✓
Clustered SEs	✓

Note: Standard errors clustered by country-pair in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample period: 2009-2023. The "Post-2017 slope of $RWD_{i \leftarrow j,t-1}$" is computed as $\hat{\beta}_0 + \hat{\beta}_1$ and tested using a linear combination (Wald) test of $H_0 : \beta_0 + \beta_1 = 0$.

6 Conclusion

This thesis investigates whether global digital infrastructure (specifically, dependence on submarine telecommunications cables owned by geopolitical rivals) acts as a geoeconomic channel through which great-power rivalry contributes to the fragmentation of FDI. Building on Farrell and Newman's (2019) idea of weaponized interdependence, the core hypothesis is that investors may reduce exposure to destinations whose cross-border data connectivity relies heavily on infrastructure controlled by states perceived as strategic rivals, because this reliance raises perceived risks and costs linked to surveillance, coercion, disruption, compliance, and reputational concerns. To operationalize this mechanism, the empirical analysis combines bilateral FDI data, time-varying measures of geopolitical alignment, and a novel index of countries' dependence on foreign-owned submarine cables: Rival-Weighted Dependence. We thus estimate a gravity-style bilateral panel model featuring RWD as the key regressor, interacted with a post-2017 indicator to test whether the relevance of rival-controlled digital infrastructure for investment changed in the recent period of heightened geopolitical tensions.

The results deliver a clear and robust finding regarding the timing dimension: across baseline specifications and a broad set of robustness checks, there is strong evidence of a structural break after 2017 in the relationship between RWD and bilateral investment outcomes. In other words, the data consistently indicate that the RWD–FDI relationship shifts downward in the post-2017 period, in line with the mechanism that rival-controlled digital infrastructure becomes a more salient consideration for investors once geopolitical tensions rise and connectivity is increasingly viewed through a security lens. This break remains visible across a variety of alternative specifications.

At the same time, evidence about the level of the post-2017 relationship (i.e., whether the post-2017 slope is consistently and significantly negative in every specification) is less robust: while the post-period slope is often negative and in several specifications statistically distinguishable from zero, it is not uniformly so across all designs and sample restrictions, and it becomes less precisely estimated in some sensitivity checks. Taken together, the thesis therefore provides strong support for the claim that the importance of rival-controlled cable exposure for investment decisions increased meaningfully after 2017, while being more cautious about pinning down a single, fully stable estimate of the post-2017 marginal effect across all variants.

These findings matter for two reasons. Substantively, they suggest that geoeconomic fragmentation in capital flows cannot be fully understood through bilateral political alignment alone: countries may be politically aligned yet still "import" exposure to rival influence through the ownership and topology of global connectivity networks. This adds a network-based, third-country dimension to the study of FDI fragmentation and offers a concrete way to connect the geoeconomics literature to the material governance of the digital backbone. Conceptually, the results highlight an underappreciated mechanism through which global infrastructure ownership can shape economic integration: the perception that critical connectivity depends on rival-controlled infrastructure may induce firms to reallocate investment toward jurisdictions that are not merely politically friendly, but also embedded in more trusted infrastructure configurations. This perspective is particularly relevant for developing regions, where dependence on foreign-owned cable infrastructure is structurally higher and more persistent, implying that the geoeconomics of digital infrastructure may have distributional consequences for investment and development.

The analysis also has important limitations. First, the estimates remain vulnerable to time-varying dyad-specific confounders that could simultaneously affect investment decisions and correlate with changes in measured dependence, especially around periods of heightened geopolitical tension. Hence, results are best interpreted as evidence consistent with the mechanism rather than definitive causal parameters. Second, measurement constraints remain. Cable dependence is constructed using modeled traffic assignments and ownership attribution that necessarily abstracts from operational details, such as firm-specific routing redundancy, encryption and data-localization practices, the distinction between minority ownership and effective control, and the fact that not all data flows are equally sensitive. Moreover, the *CableHist* dataset is still under construction, so measures of dependence could get slightly different as the dataset is updated. Similarly, UNGA-based ideal points are a well-established proxy for alignment but may not perfectly map into the security-relevant notion of rivalry that drives private investment decisions. Third, the post-2017 period is still relatively short compared to the long-run evolution of both investment and infrastructure networks; this limits the precision with which post-period marginal effects can be estimated once the specification absorbs extensive fixed effects, and it helps explain why the structural break is more robust than any single estimate of the post-2017 slope.

In light of all of this, future research can build on this work in several directions. A first priority is to strengthen causal identification by exploiting plausibly exogenous shocks that create sharp changes in dependence not driven by bilateral investment dynamics. Examples could include well-identified disruption and sabotage episodes or sudden cancellations of cable projects. A second direction is to explore heterogeneity: the mechanism should be stronger in sectors and firms that are more data-intensive, more exposed to cross-border digital operations, or more constrained by compliance and data-governance regulation, and weaker where operations are less digitally sensitive. Linking the framework to sectoral FDI, firm-level investment, or project-level greenfield data could therefore sharpen interpretation. A third direction is to generalize the approach beyond submarine cables to other layers of the global digital backbone, such as cloud regions, data centers, and internet exchange points, where ownership and governance may similarly shape cross-border economic integration. Finally, it would be valuable to revisit this analysis in coming years using more recent data, given the growing awareness of the strategic and security risks surrounding subsea cable infrastructure and the continued intensification of geopolitical tensions. Since our sample ends in 2023, extending the dataset through 2026 could yield further insights, either by revealing a strengthening of the estimated effects as cable securitization deepens, or by uncovering new patterns of adaptation as firms and states invest in redundancy and risk mitigation.

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A Appendix

A.1 Construction of the Bilateral FDI Dataset

To combine the data from the IMF's DIP and the OECD, we follow the procedure outlined by Damgaard et al. (2024). The dataset compiled by the authors is publicly available but ends in 2017. We therefore reconstruct the dataset from scratch, following their procedure to expand it until 2023.

We have the following variables contained in the two sources:

- $FDI^{own}_{i,j,t}$: inward FDI stock in economy i vis-à-vis immediate investors in economy j in year t, as reported by i (DIP).
- $FDI^{mirror}_{i,j,t}$: inward FDI stock in economy i vis-à-vs immediate investors in economy j in year t, as reported by j (DIP).
- $RealFDI^{OECD}_{i,t}$: inward FDI stock in economy i in non-SPEs in year t across all investor economies (OECD).
- $RealFDI^{OECD}_{i,j,t}$: inward FDI stock in economy i in non-SPEs in year t vis-à-vis immediate investors in economy j (OECD).

In the DIP database, 130 recipient economies i report inward positions $FDI^{own}_{i,j,t}$ from 243 counterpart economies j, while mirror (outward) positions $FDI^{mirror}_{i,j,t}$ are available for 242 reporters covering 97 recipient economies. Because mirror positions are available only for counterpart economies that participate in the Coordinated Direct Investment Survey (CDIS), relying exclusively on mirror data would systematically underestimate inward FDI for recipient economies that do not report their own positions. To mitigate this bias, we apply an adjustment factor to the aggregate mirror-based estimates when constructing economy-level inward FDI for recipients that lack reported values of $FDI^{own}_{i,j,t}$. The adjustment factor is the ratio of the total reported inward positions to the total sum of mirror positions calculated over the set of reporting recipients:

$$\gamma_t^{mirror} = \frac{\sum_{i \in \mathbb{R}} FDI_{i,j,t}^{own}}{\sum_{j \in \mathbb{R}} FDI_{i,j,t}^{mirror}},$$

where $\mathbb{R}$ is the set of countries reporting bilateral FDI positions to DIP. We apply the same year-specific adjustment ratio γ_t^{mirror} to all the economies not reporting $FDI_{i,j,t}^{own}$ and assign the adjustment value to a "Not Specified" category, since we are unable to allocate it to any specific investor economy. As a result, roughly 85 percent of total FDI in our dataset is directly reported to the DIP, roughly 11 percent is indirectly reported to the DIP as mirror data, and the remaining around 4 percent is estimated. We then make the data a balanced panel including also country-pair-year observations not originally included in the DIP database and set them to missing. The criterion described above is summarized as follows:

$$\mathrm{FDI}_{i,j,t} = \begin{cases} \mathrm{FDI}_{i,j,t}^{\mathrm{own}}, & \text{if } i \in \mathcal{R}, \\ \\ \gamma_t \cdot \mathrm{FDI}_{i,j,t}^{\mathrm{mirror}}, & \text{if } j \notin \mathcal{R} \text{ and } i \in \mathcal{R}. \end{cases}$$

The next step consists in decomposing bilateral FDI into investment into SEPs and non-SPEs, that is, "real" and "phantom" investment. For the sample of OECD countries reporting by counterpart economy how much inward FDI is into SPEs and non-SPEs respectively, we use this information directly. For the sample of OECD countries specifying the decomposition on SPEs and non-SPEs only in the aggregate, we impose the same decomposition across all counterpart countries. For instance, in 2018 Ireland reports a total of 32 billion USD in aggregate inward FDI into SPEs and of 1,049 billion USD into non-SPEs, that is, around 2.9 percent of total FDI into SPEs and around 97.1 into non-SPEs. Then, if Ireland reports around 413 million USD of inward FDI from Australia in 2018, this figure gets decomposed into 410 ($\approx 0.971 \times 413$) million USD of real inward FDI and the remainder as phantom FDI.

Based on the information from the 32 economies reporting an actual breakdown of total FDI into real and phantom FDI, we estimate a similar decomposition for the remaining economies in the world. To do so, we exploit a correlation within the sample of reporting economies between the ratio of real to total FDI and the ratio of total FDI to GDP. This relationship is documented by Damgaard et al. (2024) and present in our data as well. The intuition is that an economy's capacity to absorb genuine investment into firms with employees and productive assets is limited, whereas there are effectively no economic constraints on "phantom" investment routed through empty corporate shells that have no ties to the domestic economy. Consequently, when an economy's total FDI position is very large relative to its GDP, we should expect the share of FDI that is truly real to be smaller. We therefore estimate (and extrapolate) the relationship between the unobserved ratio of real FDI to total FDI, which can be computed for nearly all countries.

We thus estimate the following model for the 32 reporting economies and the period 2013-2023:

$$\ln\left(\frac{\text{Real FDI}_{i,t}^{\text{OECD}}}{\text{FDI}_{i,t}}\right) = \alpha + \beta \ln\left(\frac{\text{FDI}_{i,t}}{\text{GDP}_{i,t}}\right) + \varepsilon_{i,t}, \tag{9}$$

where $GDP_{i,t}$ is the Gross Domestic Product in economy i in year t from the World Bank Database.

Table 9 shows the regression results, which highlight that, on average, increasing the ratio of total FDI to GDP by 1 percent reduces the predicted ratio of real FDI to total FDI by around 0.2 percent[18]. We use the estimated coefficients to predict the ratio of real to total FDI for all non-reporting economies. The decomposition of total FDI into its real and phantom components therefore proceeds according to the following scheme:

$$\text{Real FDI}_{i,j,t} = \begin{cases} \text{Real FDI}_{i,j,t}^{\text{OECD}} & \text{if } i \in \mathcal{Q}^{bil}, \\ \omega_{i,t} \cdot \text{FDI}_{i,j,t} & \text{if } i \in \mathcal{Q}^{agg}, \\ \omega_{i,t} \cdot \text{FDI}_{i,j,t} & \text{if } i \notin \mathcal{Q}^{agg},\ \mathcal{Q}^{bil}, \end{cases} \tag{10}$$

$$\text{Phantom FDI}_{hi,t} = \text{FDI}_{i,j,t} - \text{Real FDI}_{i,j,t},$$

[18]Damgaard et al. (2024) perform a range of robustness checks to assess the validity of this estimation approach. We do not replicate these exercises here and instead rely on their results, treating the methodology as reliable.

where

$$\omega_{i,t} = \begin{cases} \dfrac{\text{Real FDI}^{\text{OECD}}_{i,t}}{\text{FDI}_{i,t}} & \text{if } i \in \mathcal{Q}^{agg}, \\ \exp\left[\hat{\alpha} + \hat{\beta}\ln\left(\dfrac{\text{FDI}_{i,t}}{\text{GDP}_{i,t}}\right)\right] & \text{if } i \notin \mathcal{Q}^{agg},\ \mathcal{Q}^{bil}, \end{cases} \tag{11}$$

where $\hat{\alpha}$ and $\hat{\beta}$ are obtained from estimating:

$$\log\left(\frac{\text{Real FDI}^{\text{OECD}}_{h,t}}{\text{FDI}_{h,t}}\right) = \alpha + \beta \log\left(\frac{\text{FDI}_{h,t}}{\text{GDP}_{h,t}}\right) + \varepsilon_{h,t}, \tag{12}$$

and where

- $\mathcal{Q}^{bil}$: Set of economies reporting bilateral FDI into SPEs and non-SPEs to the OECD.
- $\mathcal{Q}^{agg}$: Set of economies reporting aggregate FDI into SPEs and non-SPEs to the OECD.

Table 9: Estimating Real FDI Adjustment Factors

	$\ln\left(\frac{\text{Real FDI}^{\text{OECD}}_{i,t}}{\text{FDI}_{i,t}}\right)$
$\ln\left(\frac{\text{FDI}_{i,t}}{\text{GDP}_{i,t}}\right)$	-0.2279***
	(0.0306)
Constant	5.4141***
	(0.1184)
Observations	342
R-squared	0.504
Method	OLS
Robust SEs	Yes

Note: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Sample period: 2013-2023.

The resulting real FDI stock dataset is summarized in Table 10. Our measure of real FDI stock is highly consistent with Damgaard et al. (2024)'s, with a correlation of 94 percent, suggesting we closely replicated their approach.

A.2 Construction of the Bilateral M&A Deals Dataset

To obtain the number of M&A deals completed annually between country j and country i, we collect investment data from Orbis M&A. This database provides micro-data on such deals, identifying relevant information on each deal. We aggregate these into deal counts between pairs of countries in each year, creating a structure resembling our baseline bilateral FDI dataset.

Specifically, we collect worldwide information on completed FDI deals between 2009 and 2024. We restrict the sample to cross-border transactions, i.e., deals in which the country of the ultimate investor differs from the country of the target, and we retain four deal types: (1) acquisitions, (2) joint ventures, (3) mergers, and (4) minority stake increases. Regardless of deal type, a transaction is included only if the investing party's final stake in the recipient firm exceeds 10 percent, the same threshold used in the IMF's DIP dataset to identify significant direct investments. Finally, we exclude deals in which either party operates in a telecommunications-related industry.[19]

As a result, we obtain a dataset of approximately 140,000 deals, involving ultimate recipients from 212 distinct countries and ultimate investors from 168 distinct countries. We then collapse the transaction-level data to construct a bilateral panel that records, for each year t, the number of deals from investor country j to recipient country i. Table 11 summarizes the main features of both the transaction-level source data and the resulting bilateral dataset.

[19] We exclude deals where either the investor or the recipient are in the following NACE-2 industries: wired telecommunications activities (6110); wireless telecommunications activities (6120); satellite telecommunications activities (6130); other telecommunications activities (6190).

A.3 Additional Tables and Figures

Table 10: Summary: Bilateral Real FDI Dataset (Source Data)

	Real FDI Stocks
Number of observations (country-pair–year)	878,460
Number of destination countries	242
Number of investor countries	243
Distinct country pairs	58,564
Coverage period	2009-2023
Non-missing observations (%)	39.2
Non-zero observations (% of non-missing)	38.9

Note: The table reports descriptive statistics for the bilateral real FDI source dataset prior to the application of sample restrictions.

Table 11: Summary: Orbis Cross-Border M&A Dataset (Source Data)

Panel A: Transaction-Level Deals	
Number of deals	140,524
Destination countries	212
Investor countries	212
Coverage period	2009–2024
Average acquired stake (%)	81.6
Average final stake (%)	88.1
Deal type distribution	
Acquisitions (%)	80.4
Mergers (%)	0.2
Joint ventures (%)	7.6
Minority stake increases (%)	11.8
Panel B: Bilateral Deal Counts	
Number of observations (country-pair–year)	715,712
Destination countries	212
Investor countries	212
Distinct country pairs	44,732
Coverage period	2009-2024
Non-missing observations (%)	100
Non-zero observations (% of observations)	4.0

Note: Panel A reports summary statistics for the transaction-level Orbis M&A data. Panel B reports summary statistics for the bilateral panel constructed from these transactions. To obtain a symmetric, balanced country-pair panel, the set of countries is expanded to include pairs with no observed transactions; for these investor–recipient pairs, the number of deals is recorded as zero.

Table 12: Summary: Global Submarine Cable Network Dataset (Source Data)

Total number of cable systems	843
Ever-active systems	698
Ever-active systems (% of total)	82.8
Total cable length (km)	34,506,641
Total number of landing points	1,889
Average number of phases per system	2.076
Coverage period	1987-2024
Number of owning entities	722
Number of parent entities	525
Countries of origin of parent entities	137

Note: The table reports descriptive statistics for the *CableHist* source dataset and does not reflect the restricted sample used in the empirical analysis.

Table 13: Summary: Bilateral Cable Dependence Dataset (Source Data)

Number of observations (country-pair–year)	202,642
Number of destination countries	137
Number of owning countries	129
Coverage period	2009–2023

Note: The table reports descriptive statistics for the full bilateral cable dependence dataset prior to sample restrictions applied in the empirical analysis.

Table 14: Summary Statistics of Variables Used in the Baseline Regression

Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Median**	**Max**
FDI	61,658	0.0442688	0.3910536	-1	0.0158008	1
$GeoDist$	61,658	-0.5700791	1.336832	-10.91933	-0.068189	1.494684
RWD	61,658	0.2445112	0.1208028	0.0115495	0.2397648	0.8312249
$Post = 0$ (2009-2017)	31,512	0.2391512	0.1239964	0.0115495	0.2376112	0.8312249
$Post = 1$ (2018-2023)	30,146	0.2501142	0.1171118	0.0166492	0.2410306	0.7456182

Note: The statistics are computed on the estimation sample. Unit of observation is the directed dyad-year for $FDIFlows$ and RWD, and undirected dyad-year for $GeoDist$. Sample period: 2009-2023

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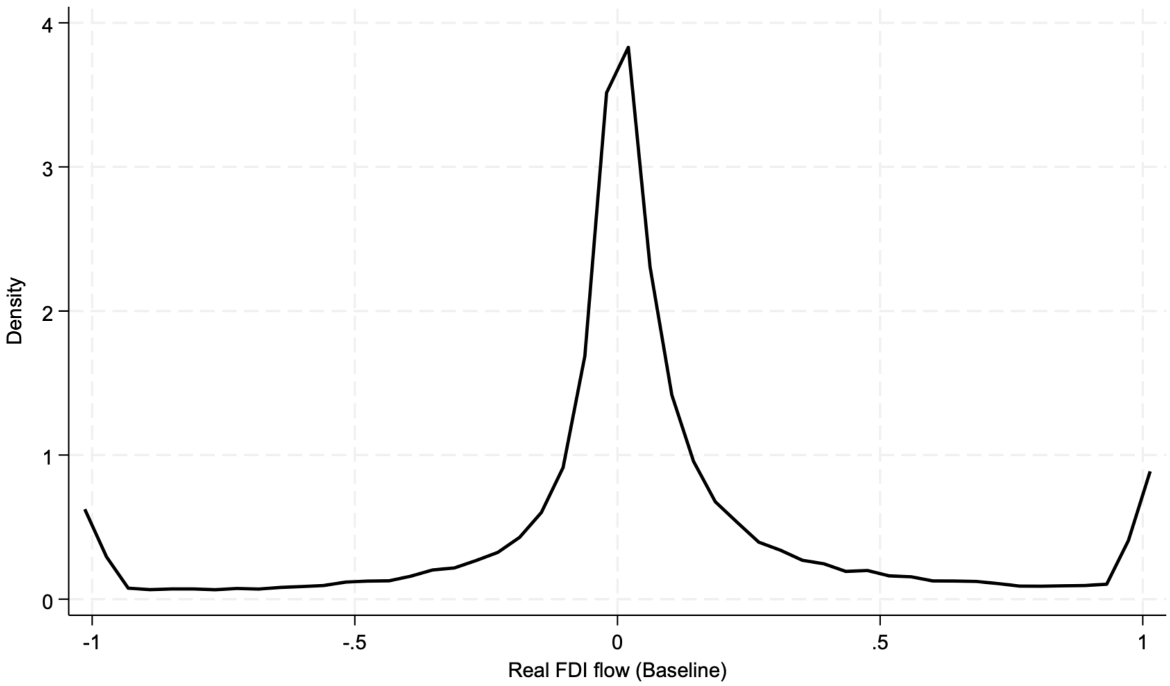
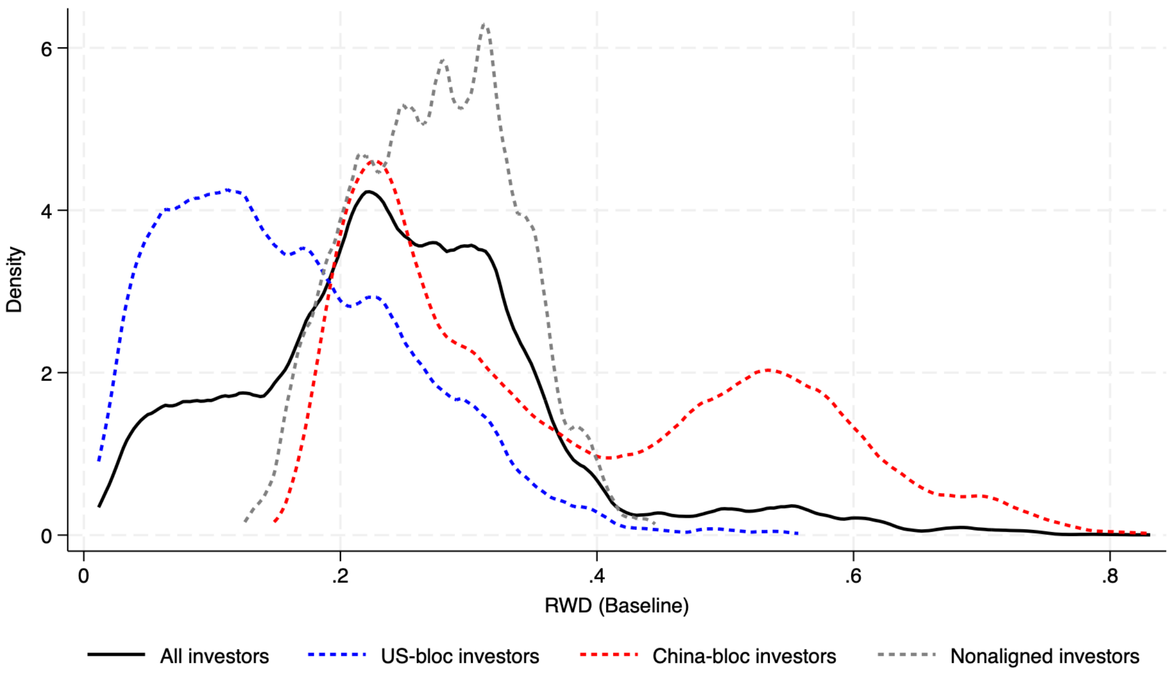
Figure 1: Distribution of Real FDI Flows



Note: The figure plots the kernel density of the baseline real FDI flow measure, estimated using the estimation sample.

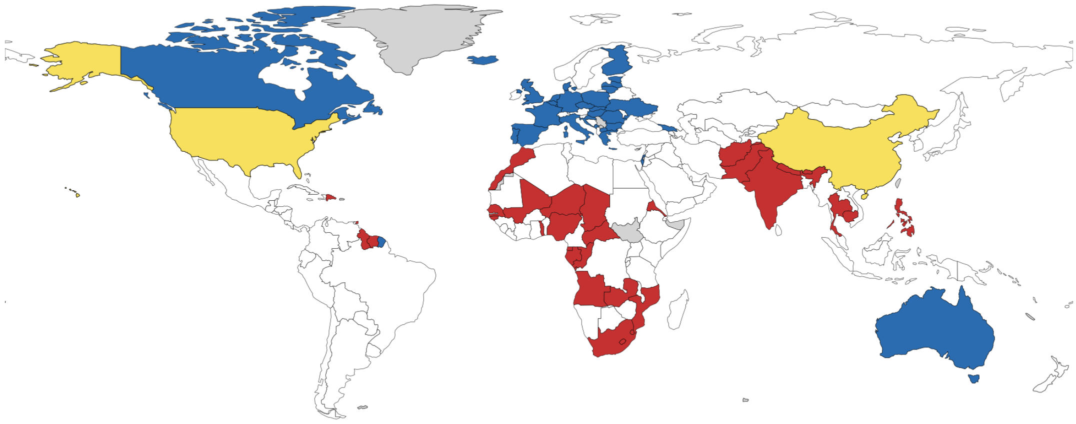
Figure 2: Distribution of RWD, by Investor Bloc



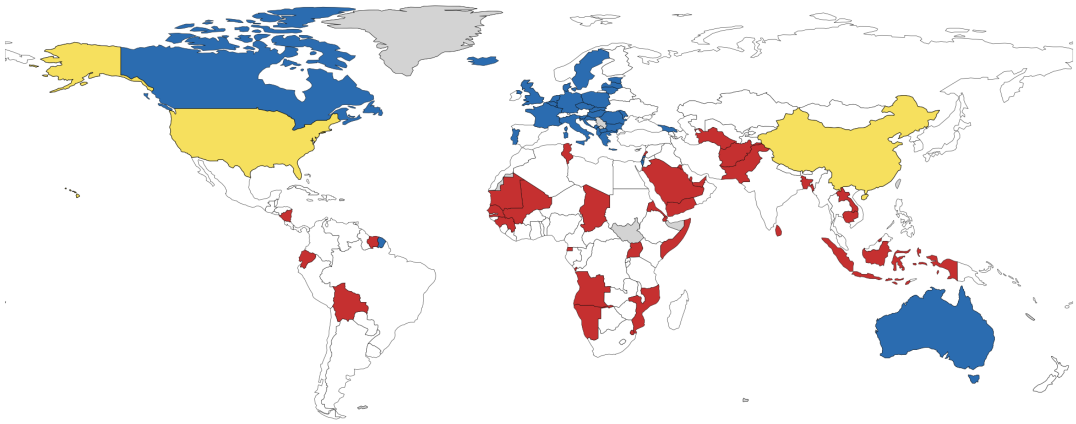
Note: The figure plots the kernel densities of the baseline RWD measure, estimated on the estimation sample.

Figure 3: Geopolitical Blocs over Time

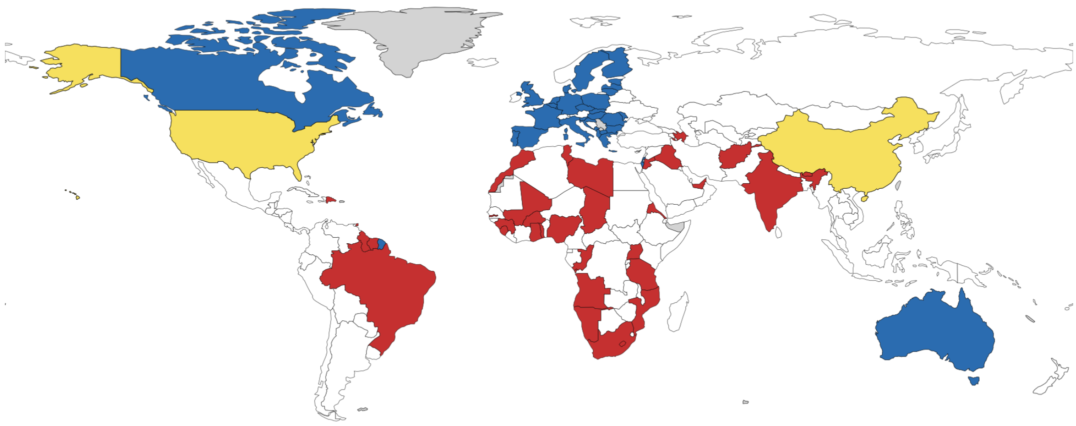
(a) 2009



(b) 2010



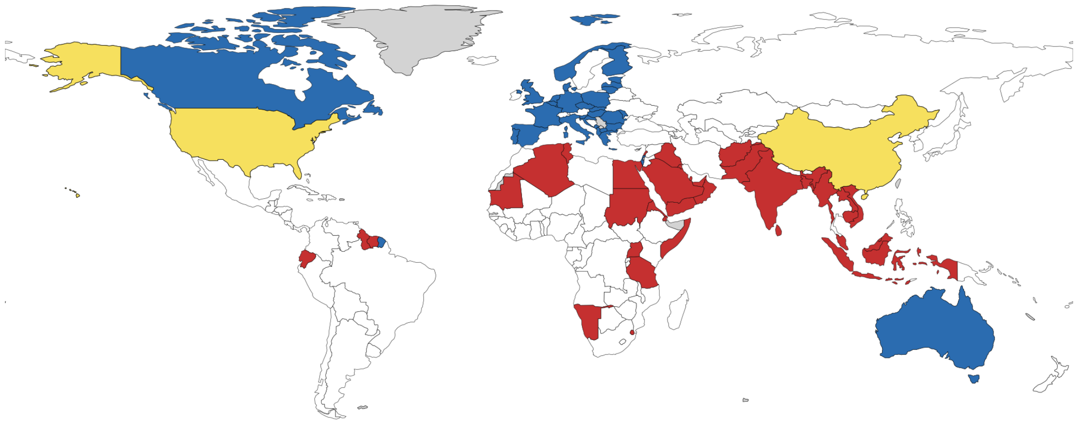
(c) 2011



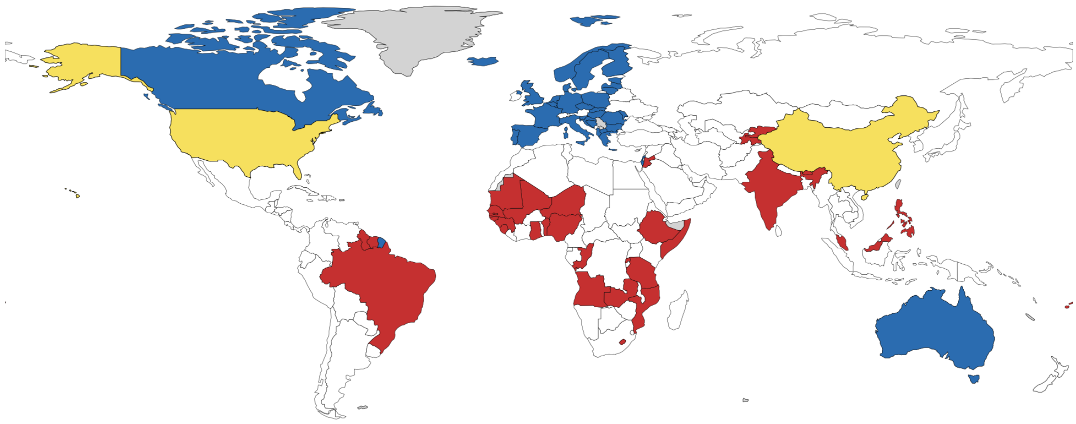
Note: Geopolitical blocs are constructed using annual bilateral ideal point distances (IPD). Countries in the US-leaning bloc are shown in blue, those in the China-leaning bloc in red, and nonaligned countries in white. The United States and China are highlighted in yellow, and countries for which no data are available are reported in gray.

Figure 3: Geopolitical Blocs over Time (continued)

(d) 2012



(e) 2013



(f) 2014

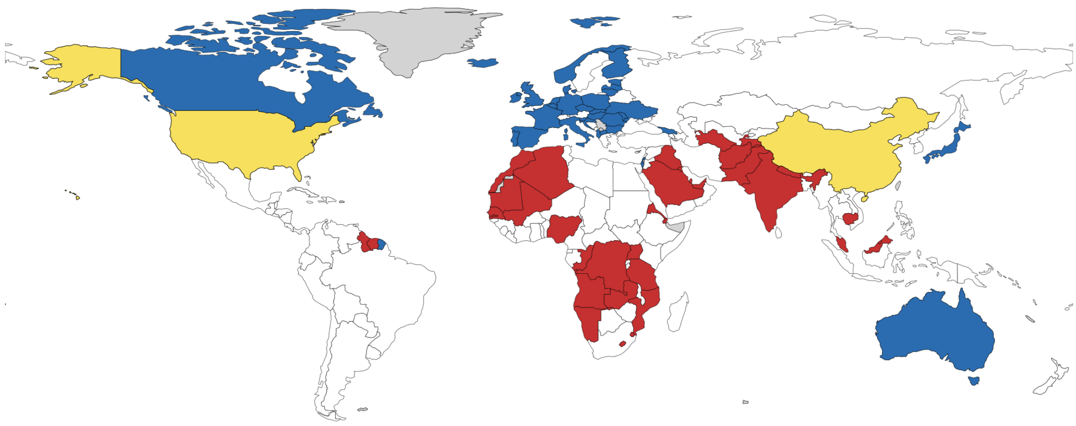
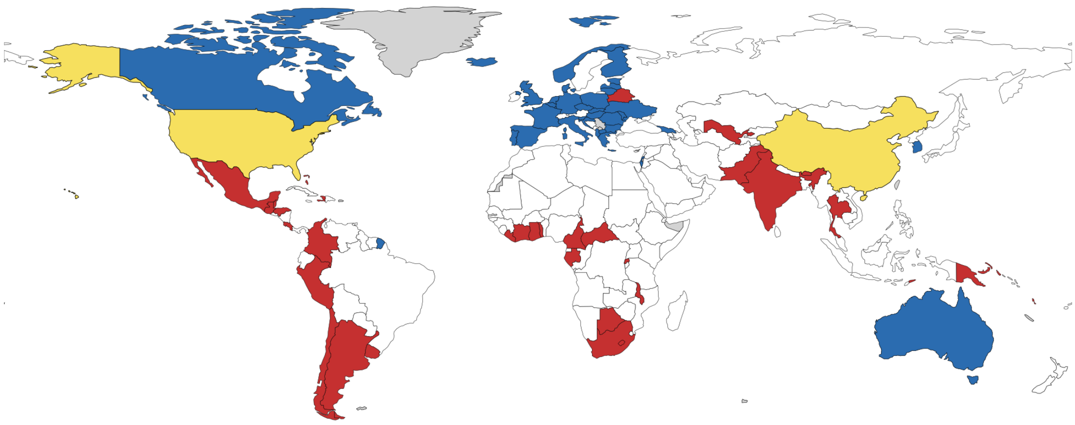
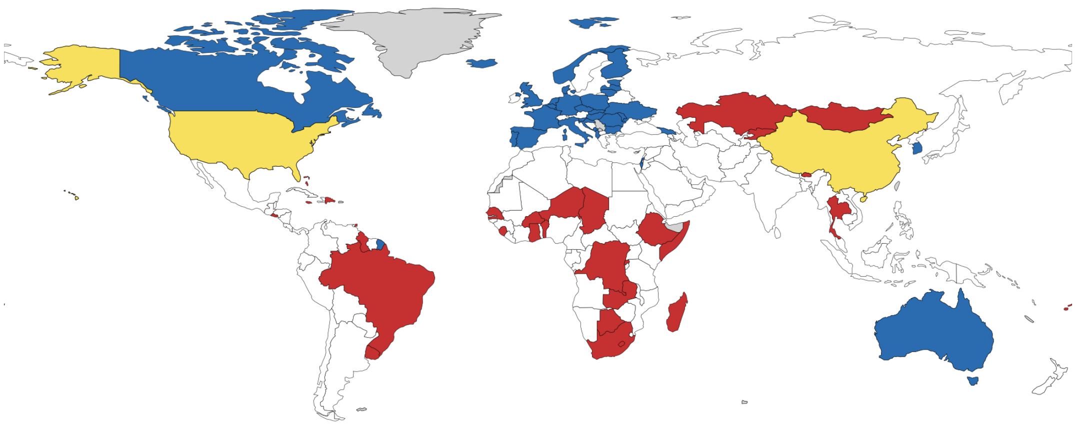


Figure 3: Geopolitical Blocs over Time (continued)

(g) 2015



(h) 2016



(i) 2017

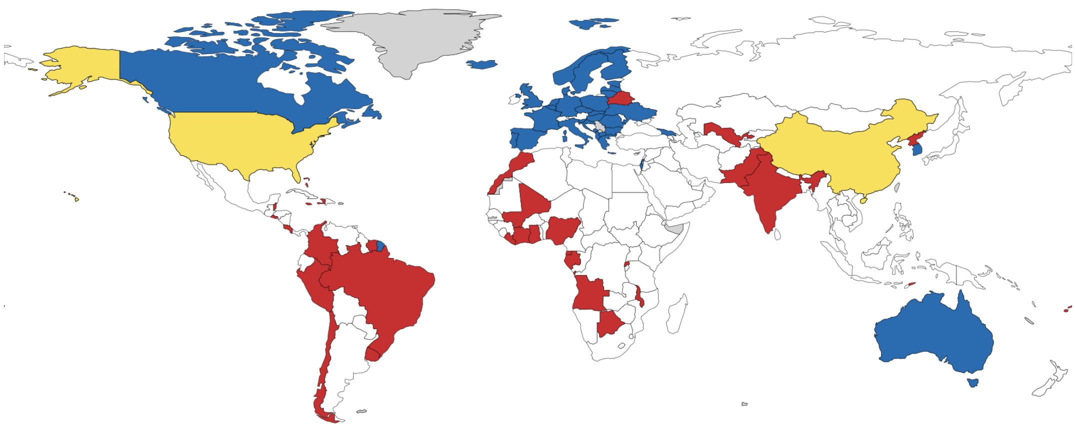
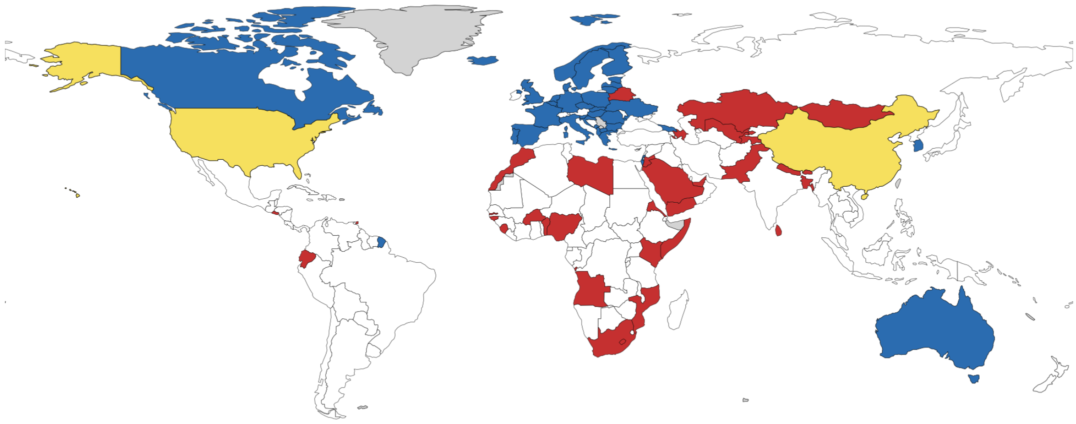
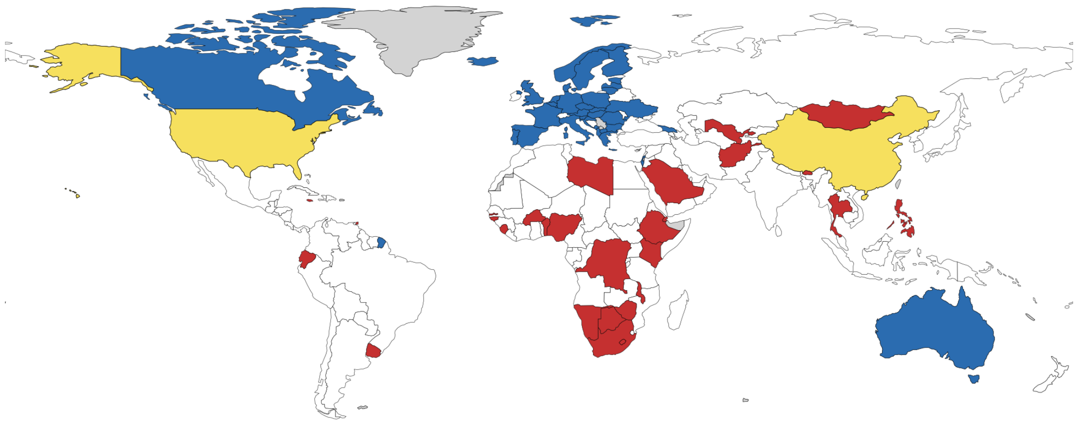


Figure 3: Geopolitical Blocs over Time (continued)

(j) 2018



(k) 2019



(l) 2020

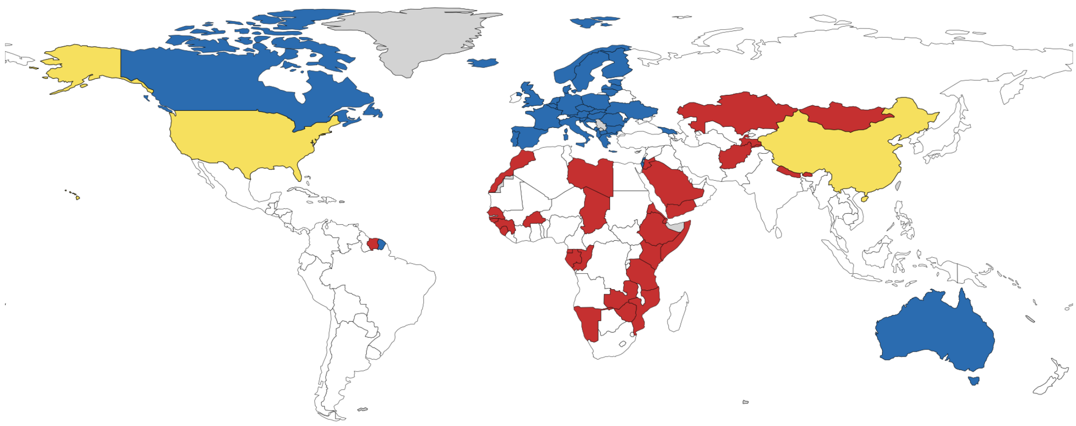
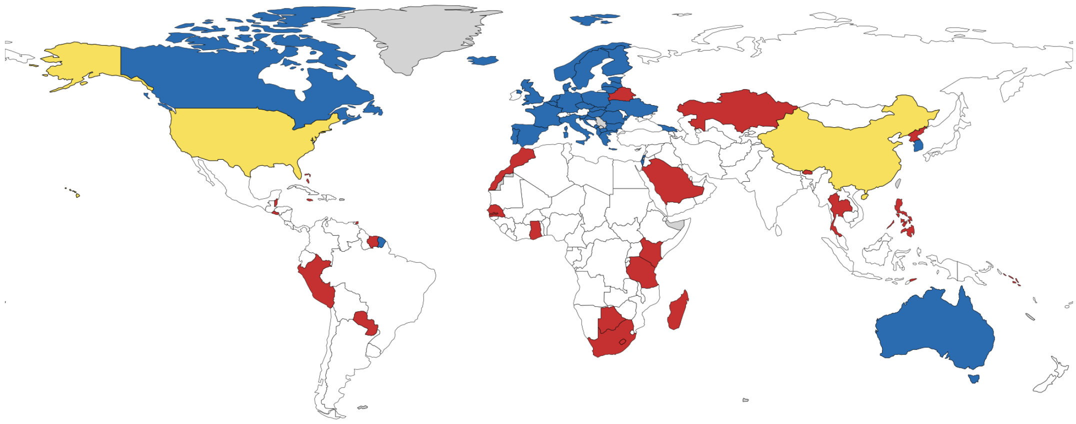
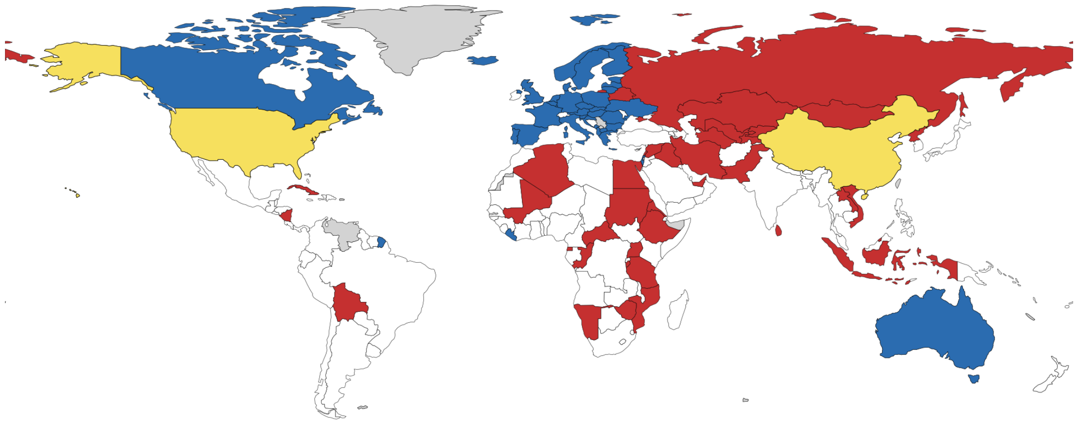


Figure 3: Geopolitical Blocs over Time (continued)

(m) 2021



(n) 2022



(o) 2023

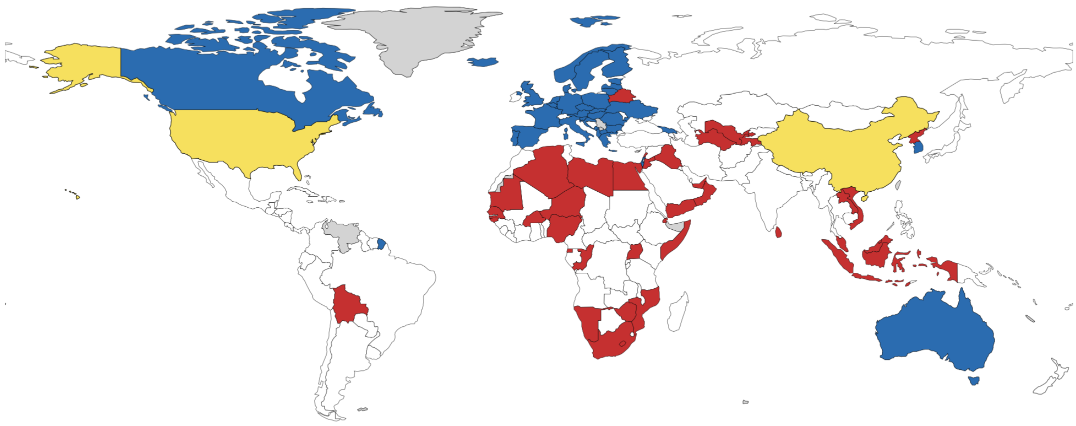


Figure 4: Total Number of Active Systems Over Time

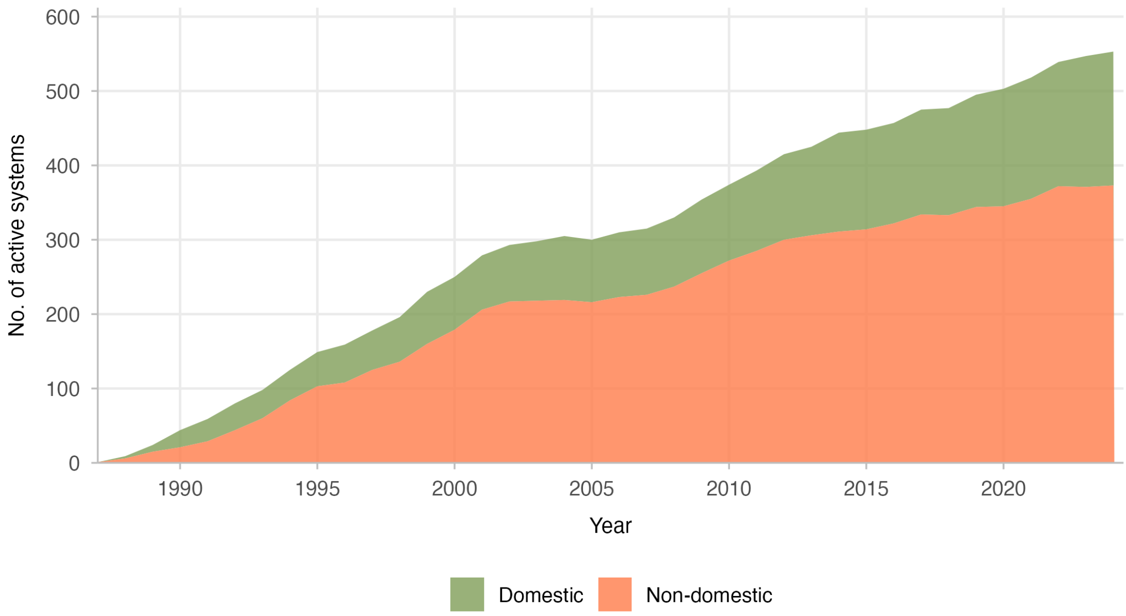


Figure 5: Total Length of Active Systems Over Time

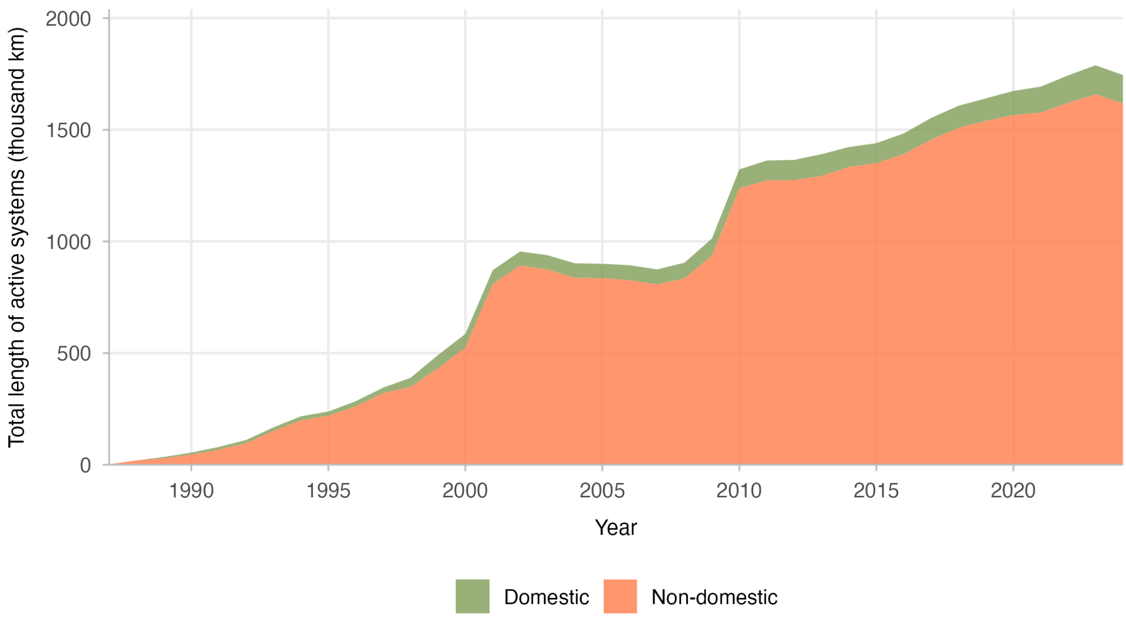


Figure 6: New Systems Entering Service Over Time

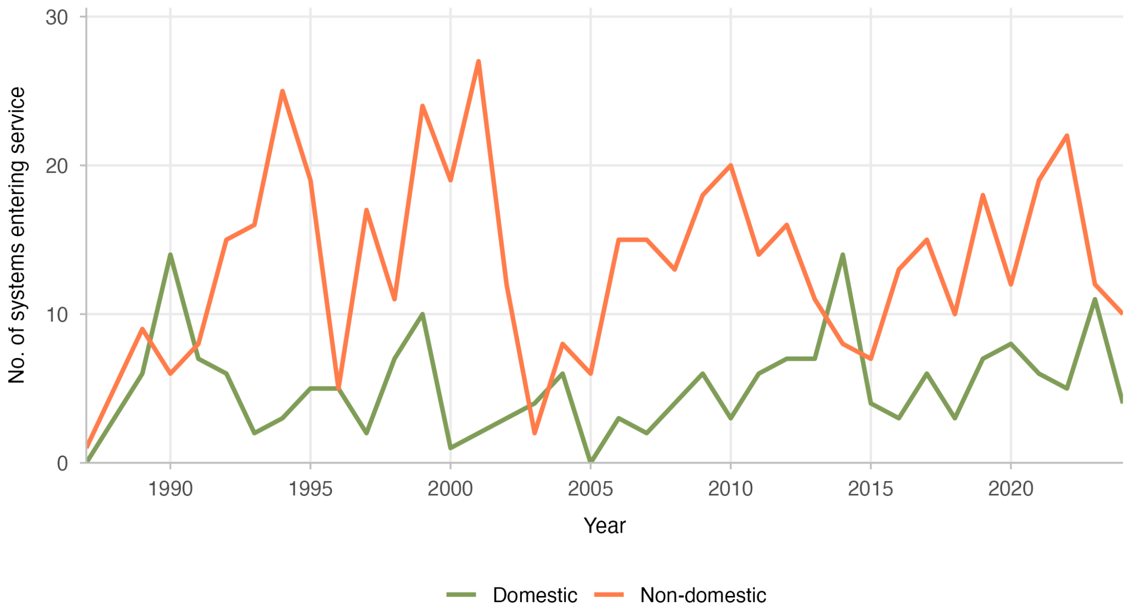
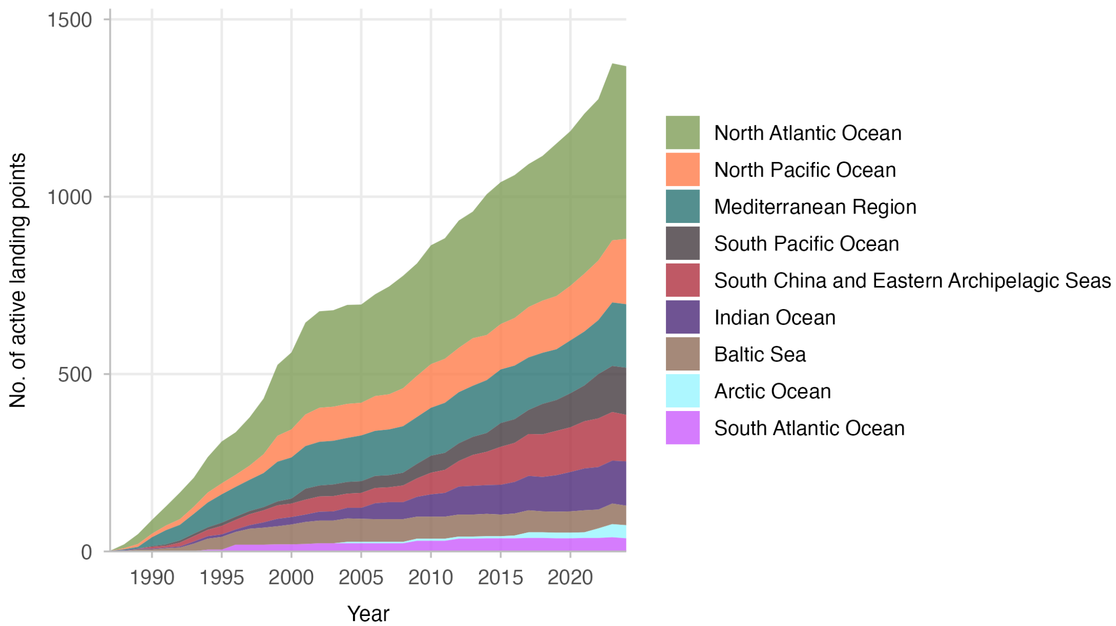


Figure 7: Total Number of Active Landing Points Over Time, by Region



Note: Each landing points is assigned to one of the nine marine region defined in the *Marine Regions* database by the *Flanders Marine Institute*. Since landing points are located on land while marine regions correspond to areas of oceans and seas, each landing point is assigned to a marine region by mapping it to the nearest sea point based on geographic coordinates, and then attributing it to the corresponding marine region.

Figure 8: Average Number of Segments per System Over Time

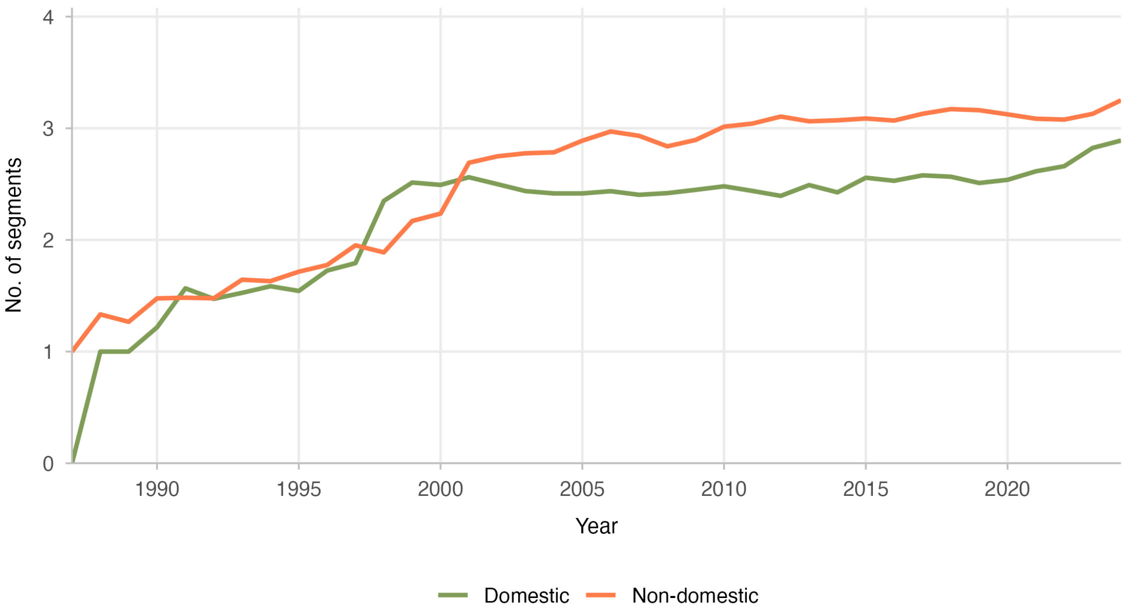


Figure 9: Total Number of Countries of Origin of Owning Entities Over Time

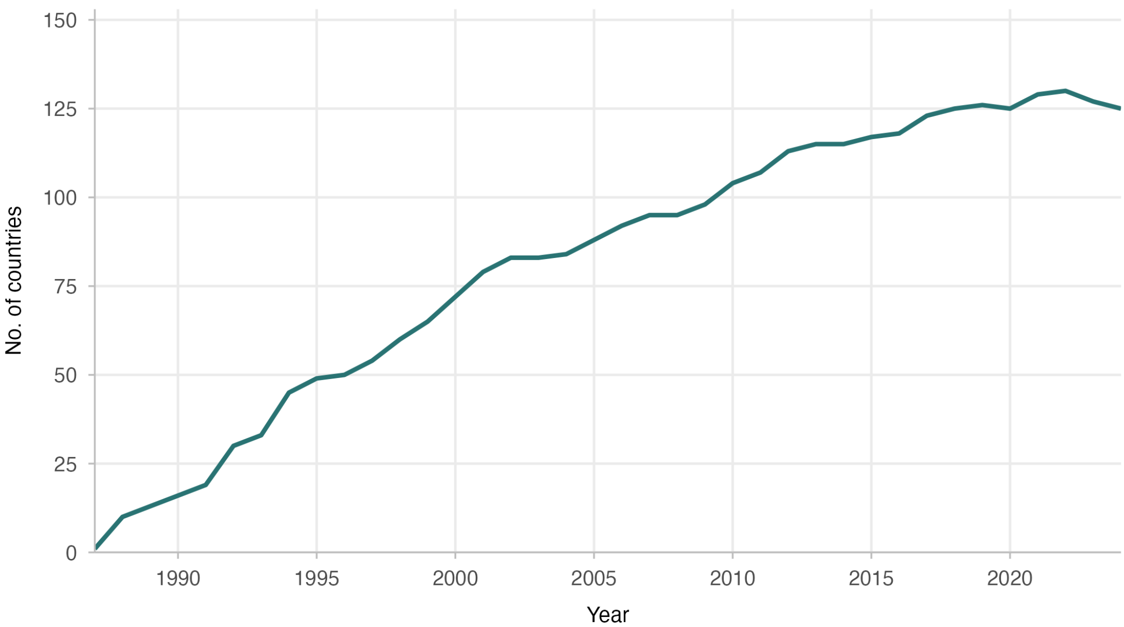


Figure 10: Average Number of Owners per Segment Over Time

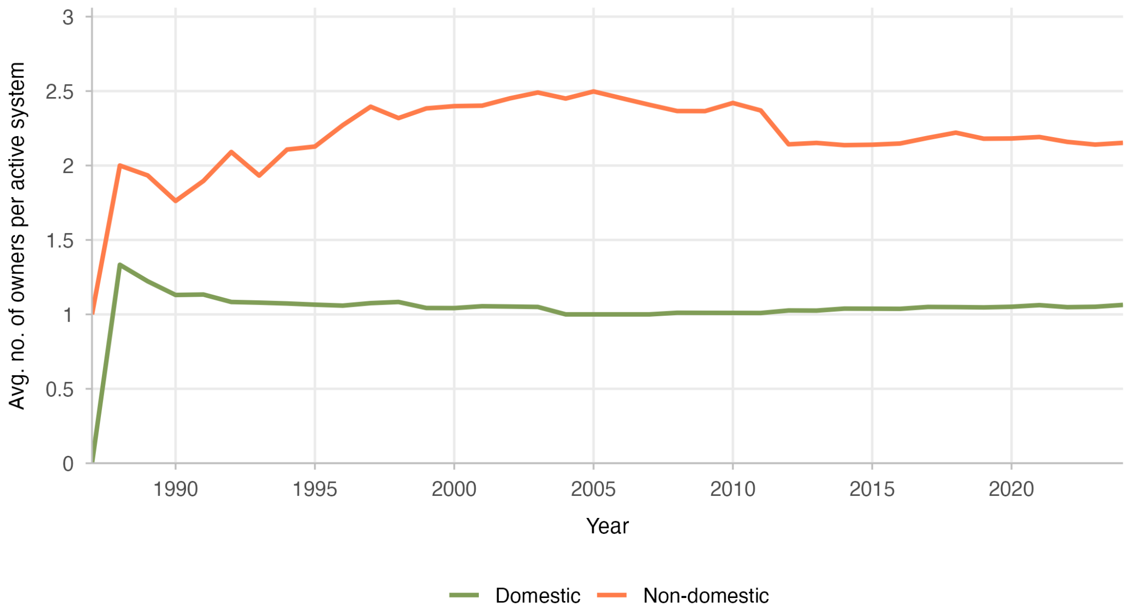


Figure 11: Share of Segments Owned by Entities from Different Countries

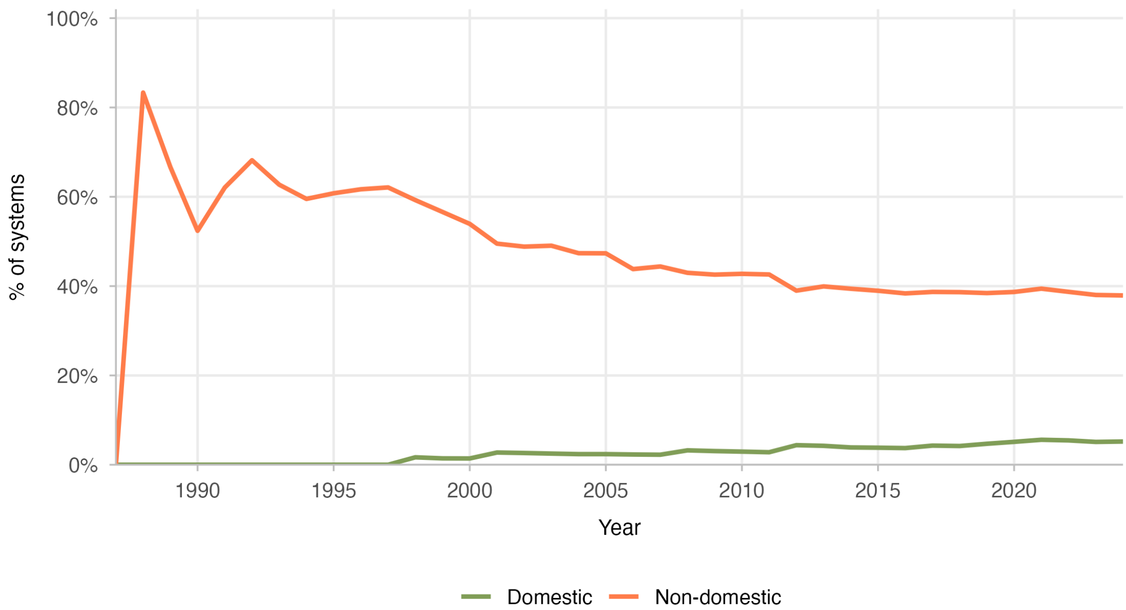
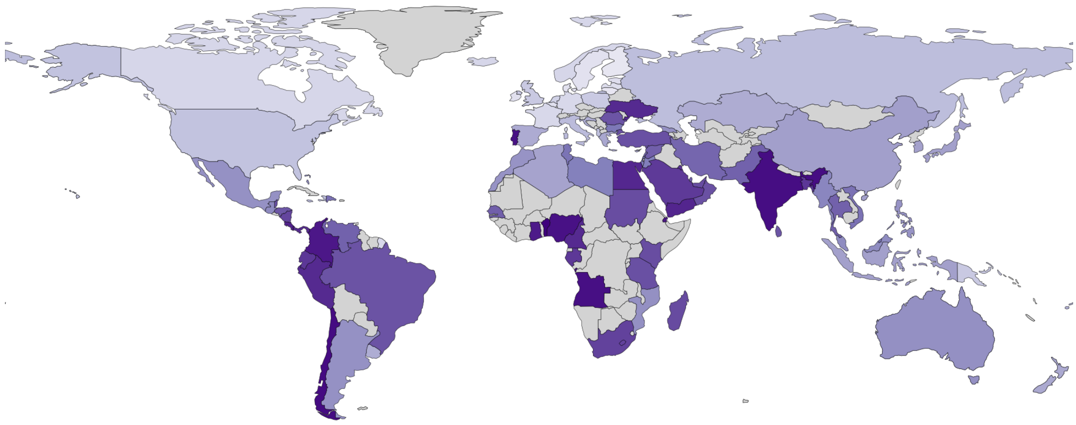
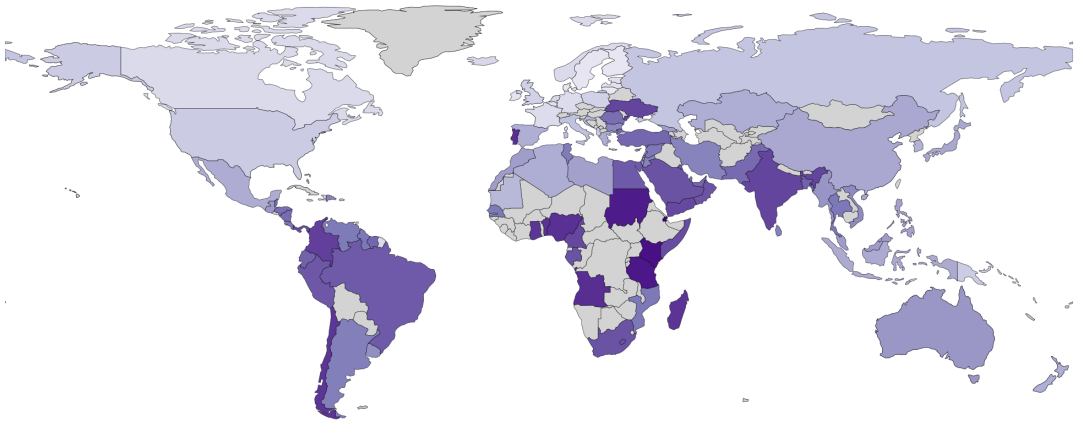


Figure 12: Dependence on Foreign-Owned Cables over Time

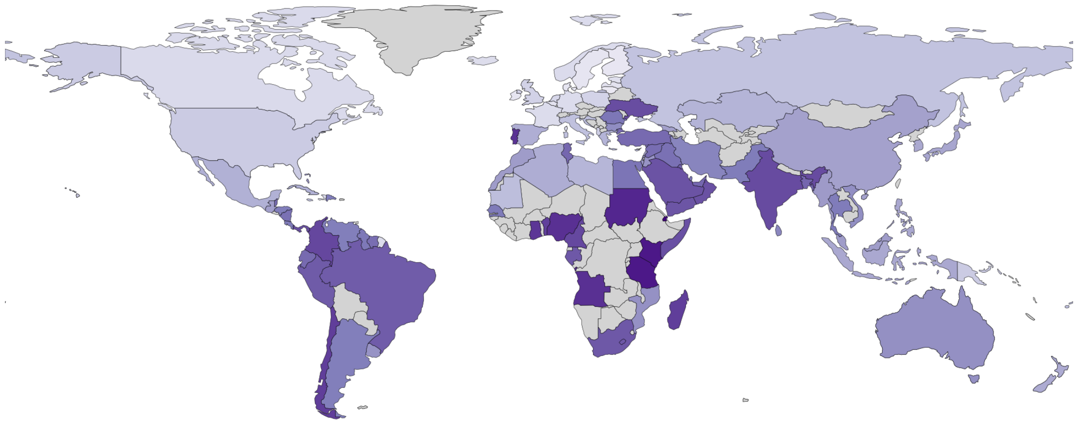
(a) 2009



(b) 2010



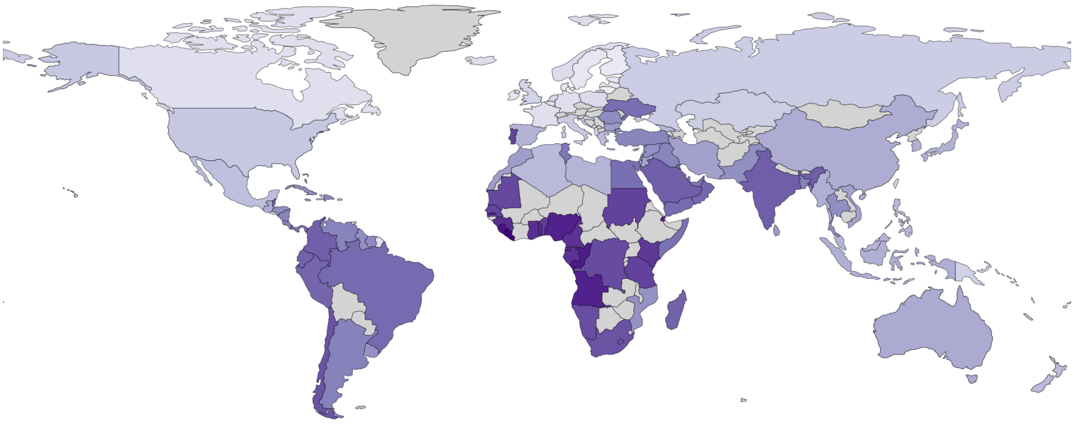
(c) 2011



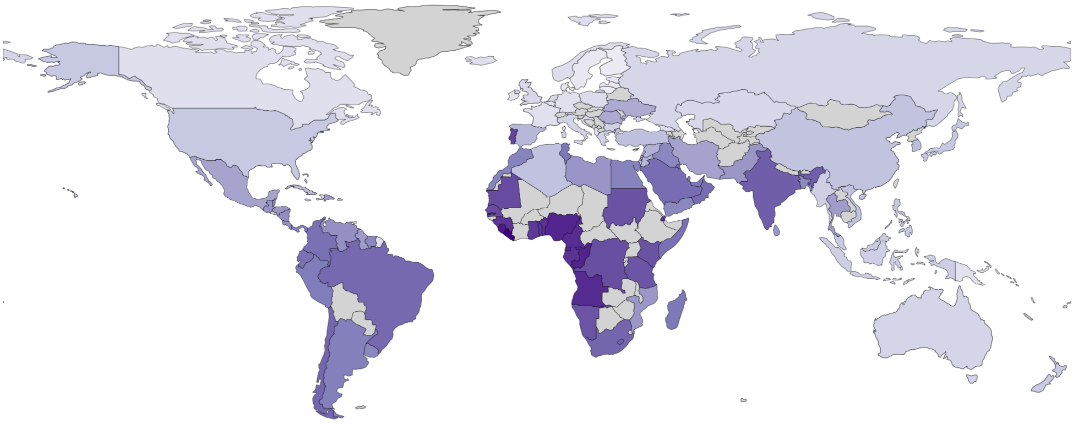
Note: For each country, total dependence is computed as the sum of bilateral exposure shares across all foreign owners. Values are then rescaled within each year to a 0–100 index, where 100 corresponds to the most dependent country in that year and 0 indicates no measured foreign dependence. Countries for which no data are available are reported in gray.

Figure 12: Dependence on Foreign-Owned Cables over Time (continued)

(d) 2012



(e) 2013



(f) 2014

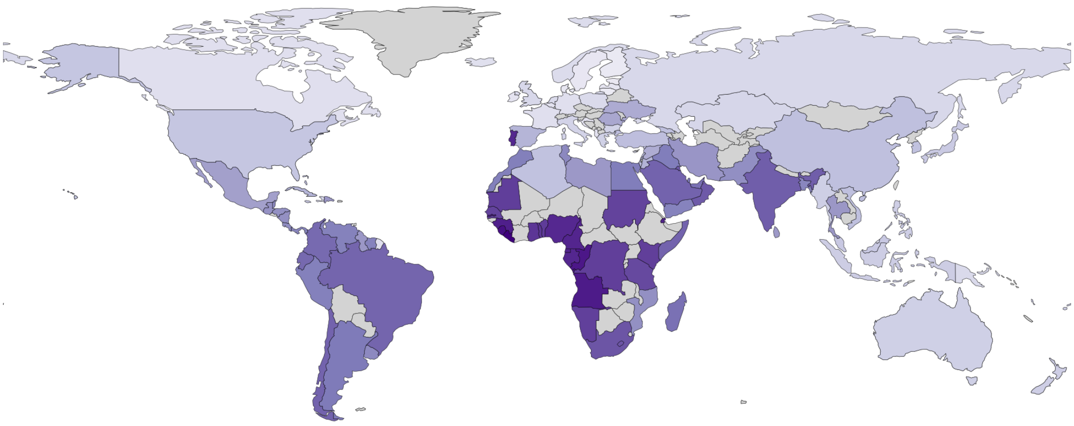
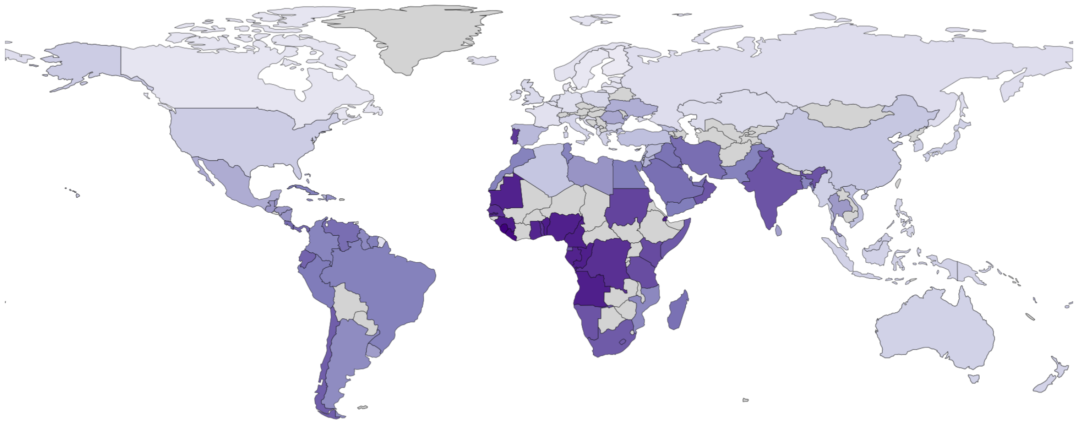
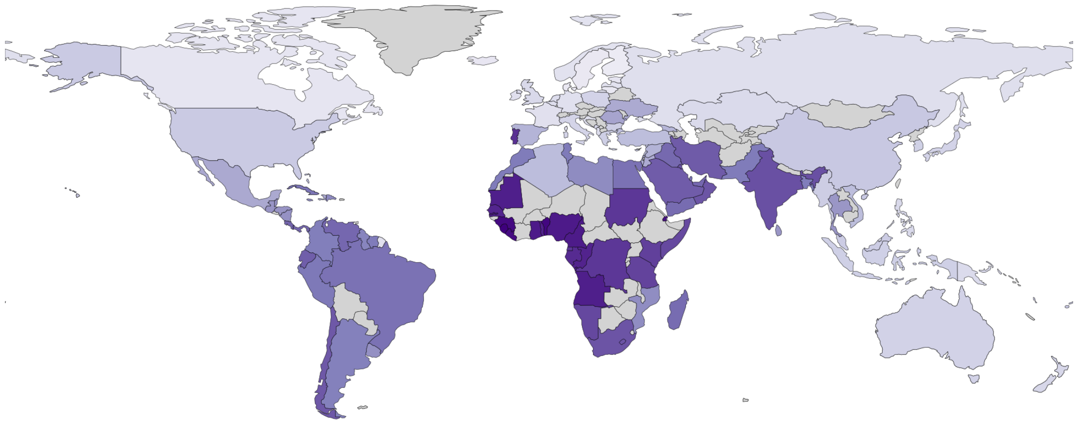


Figure 12: Dependence on Foreign-Owned Cables over Time (continued)

(g) 2015



(h) 2016



(i) 2017

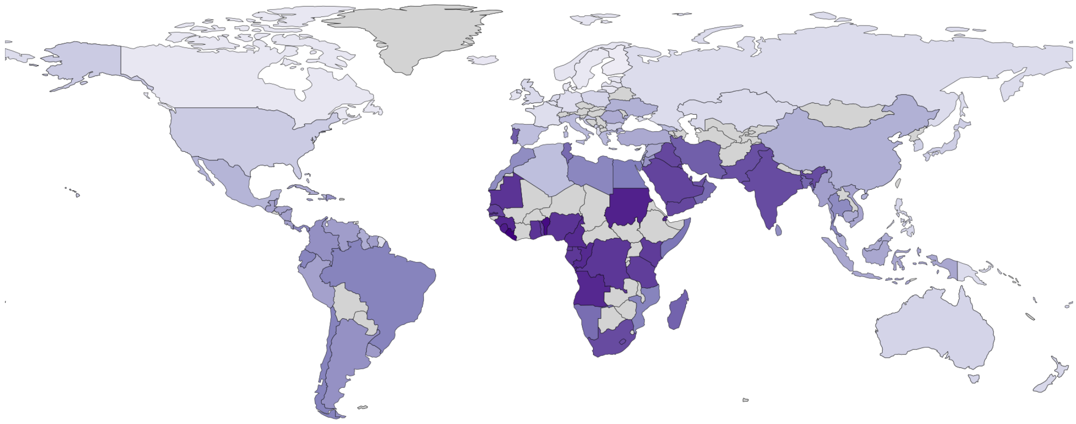
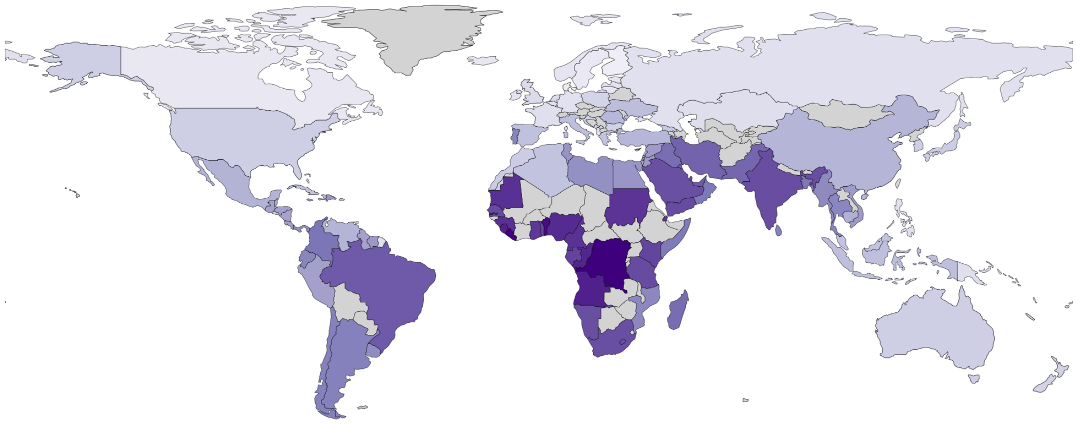
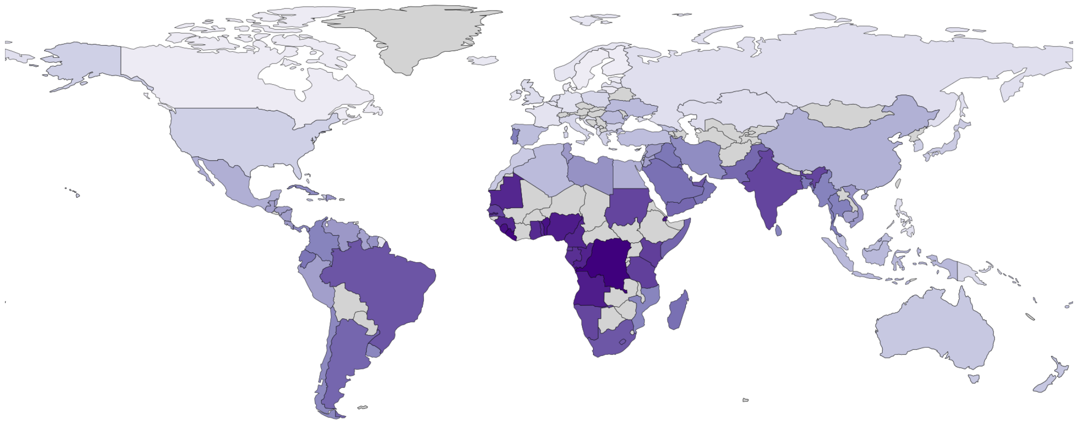


Figure 12: Dependence on Foreign-Owned Cables over Time (continued)

(j) 2018



(k) 2019



(l) 2020

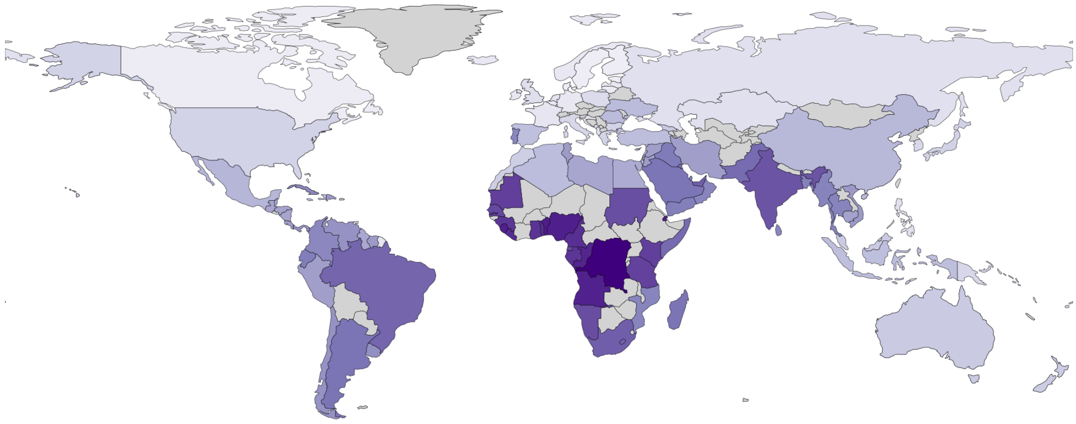
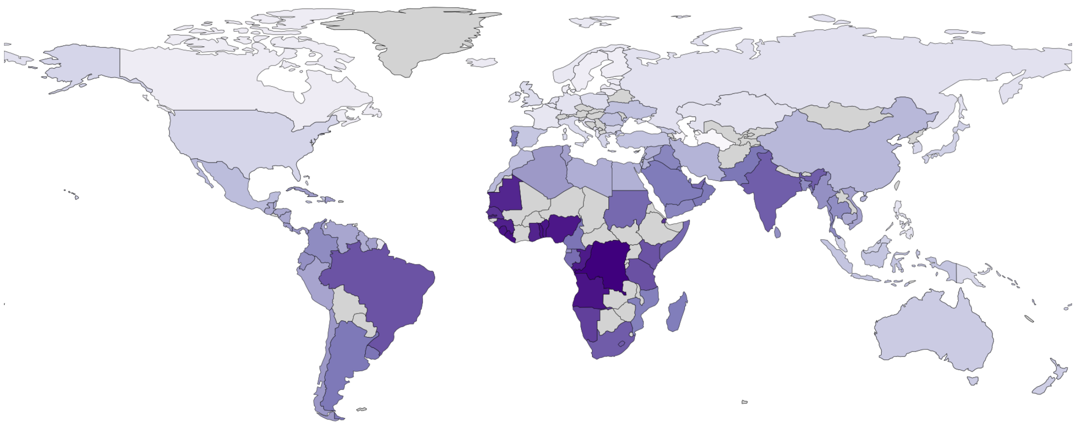
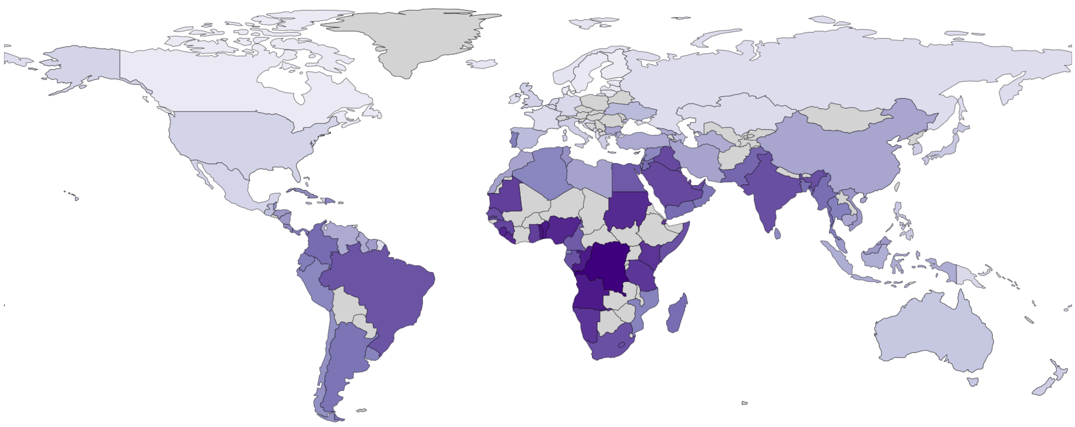


Figure 12: Dependence on Foreign-Owned Cables over Time (continued)

(m) 2021



(n) 2022



(o) 2023

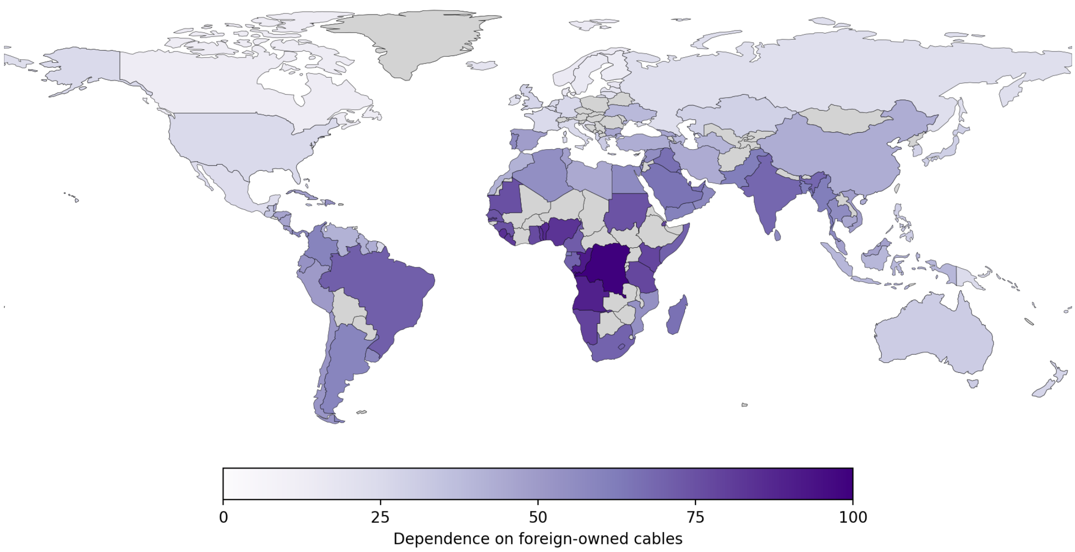
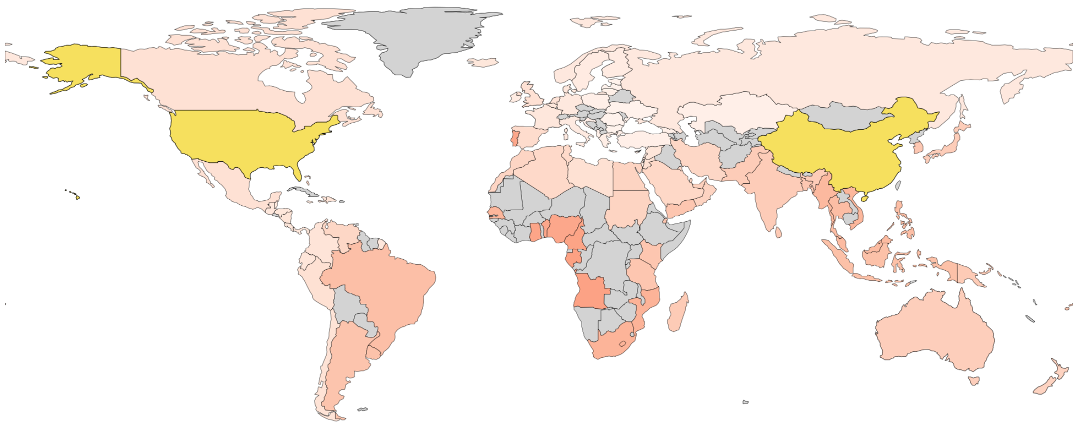
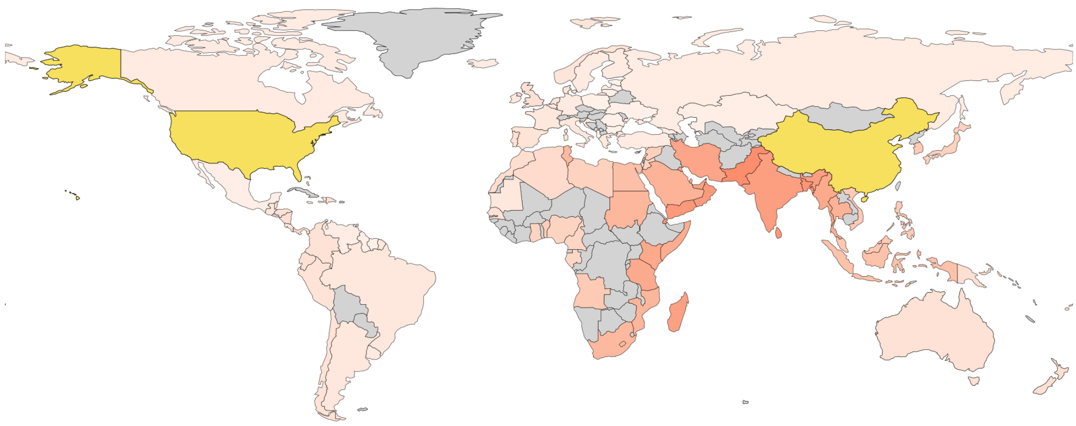


Figure 13: Dependence on the China Bloc over Time

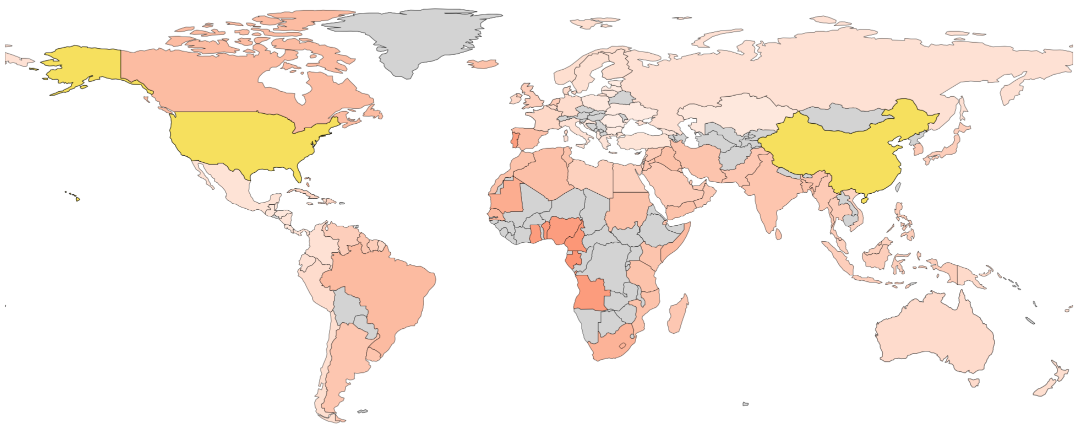
(a) 2009



(b) 2010



(c) 2011



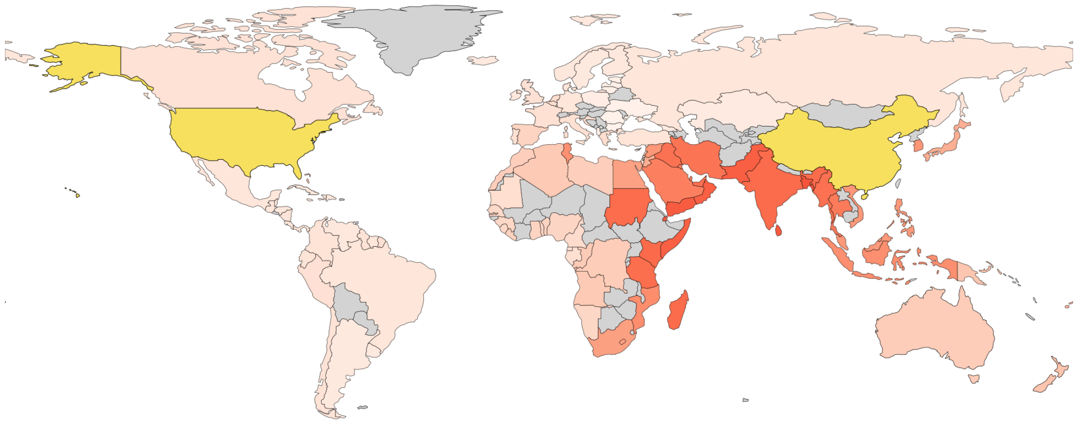
Note: The map reports, for each destination country i and year t, the share of overall cable exposure accounted for by owners belonging to the China-aligned bloc:

$$\text{ChinaBlocShare}_{it} = \frac{\sum_{o \in \text{China bloc}} exposure_{iot}}{\sum_{o} exposure_{iot}}.$$

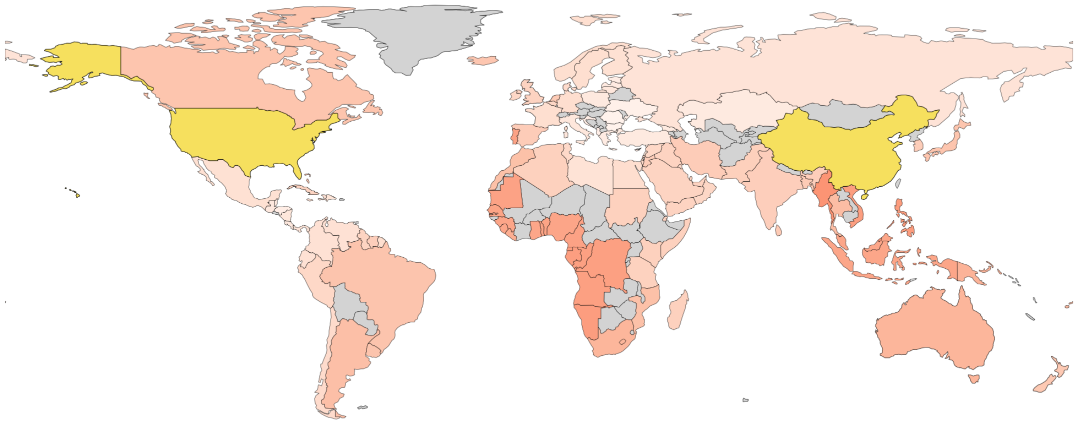
The denominator sums exposure to all owners (including domestic owners). Color intensity varies continuously from 0 to 1, with darker shades indicating a larger China-bloc share. The United States and China are shown in yellow as reference countries; countries for which no data are available are shown in grey.

Figure 13: Dependence on the China Bloc over Time (continued)

(d) 2012



(e) 2013



(f) 2014

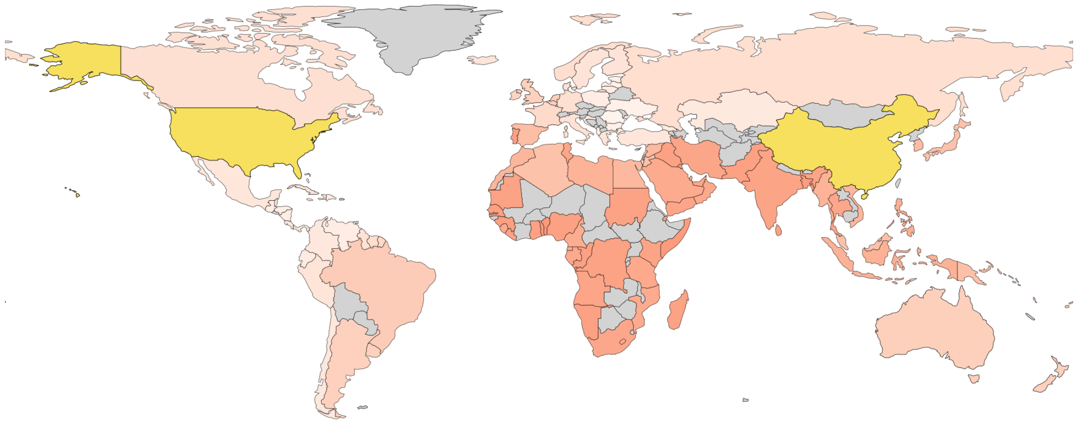
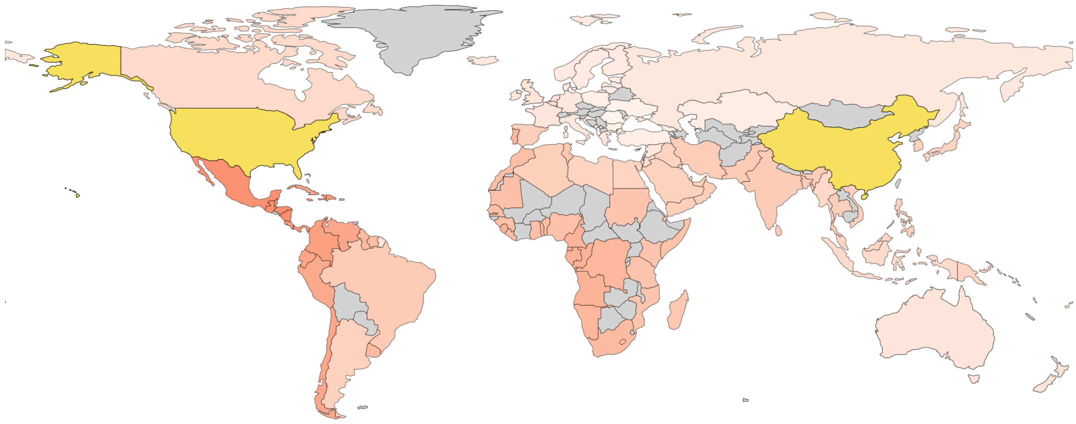
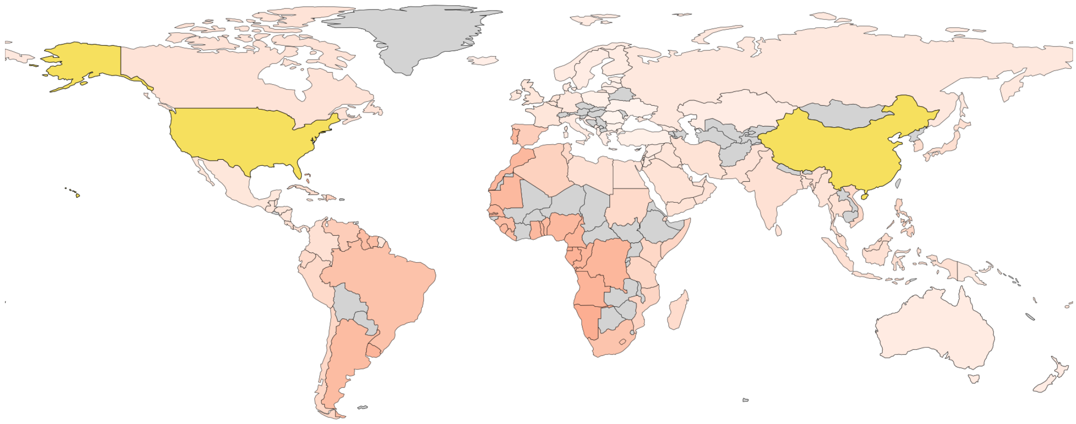


Figure 13: Dependence on the China Bloc over Time (continued)

(g) 2015



(h) 2016



(i) 2017

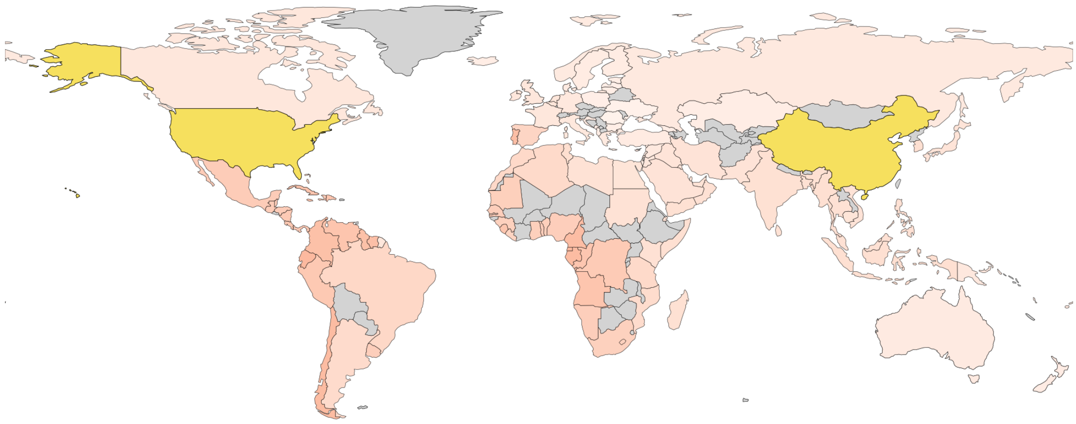
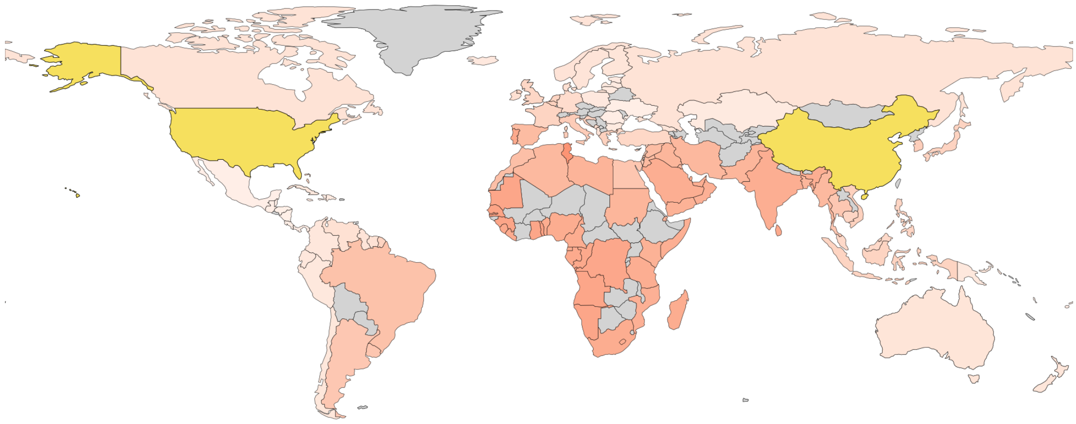
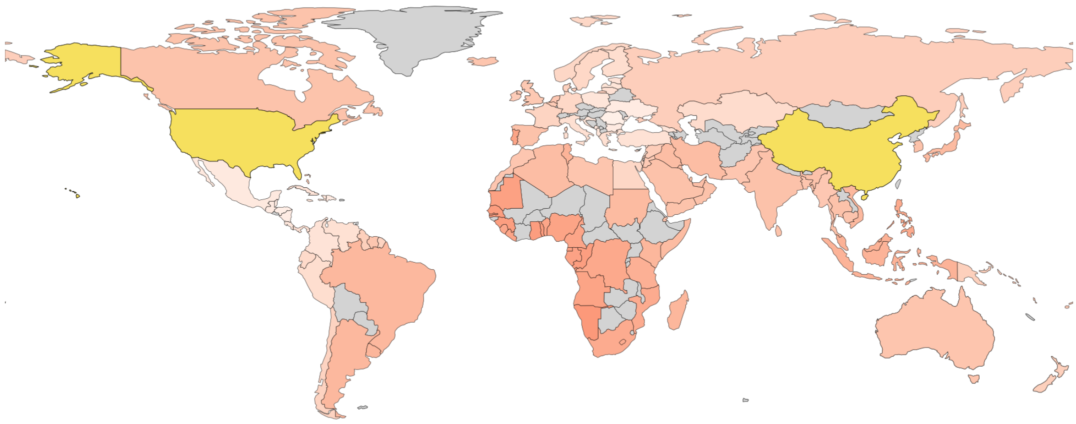


Figure 13: Dependence on the China Bloc over Time (continued)

(j) 2018



(k) 2019



(l) 2020

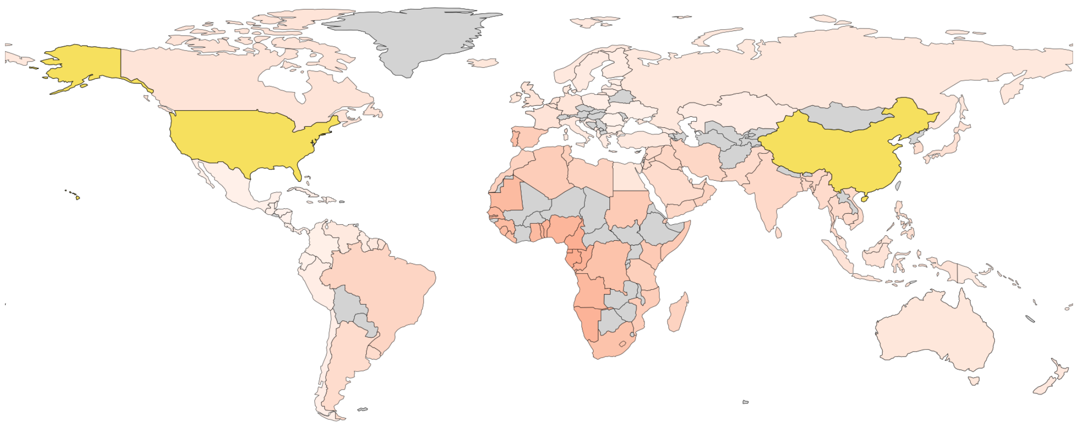
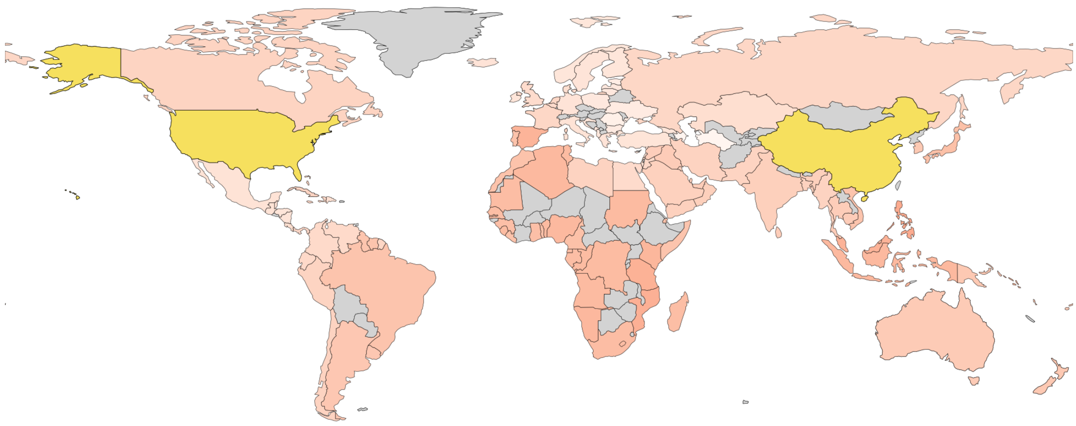
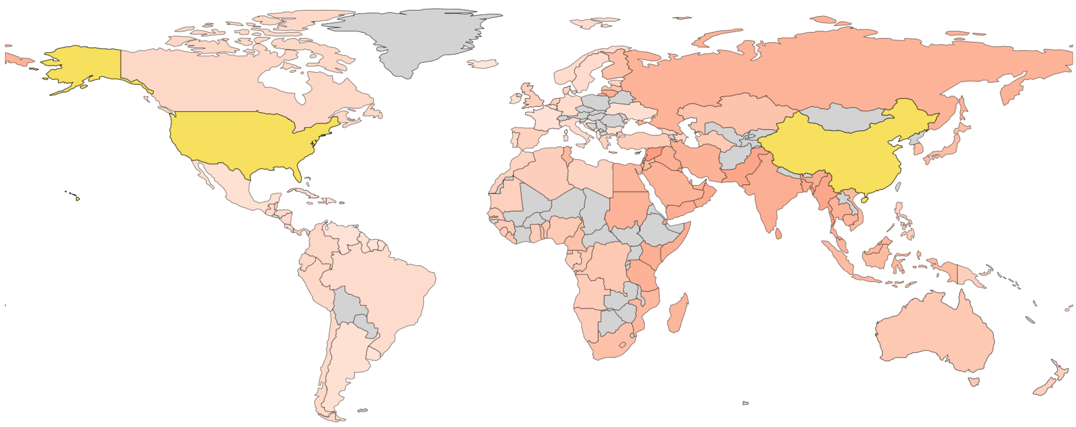


Figure 13: Dependence on the China Bloc over Time (continued)

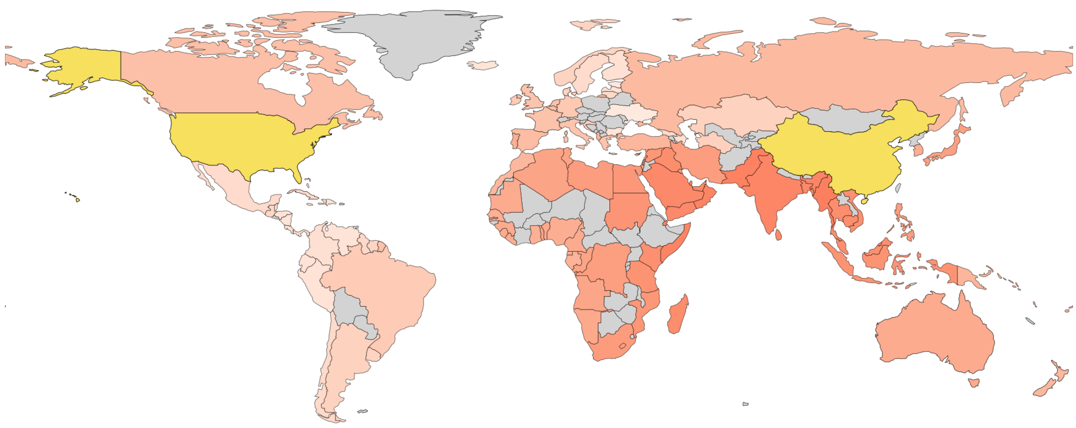
(m) 2021



(n) 2022



(o) 2023



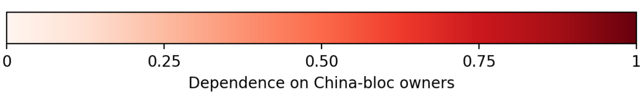
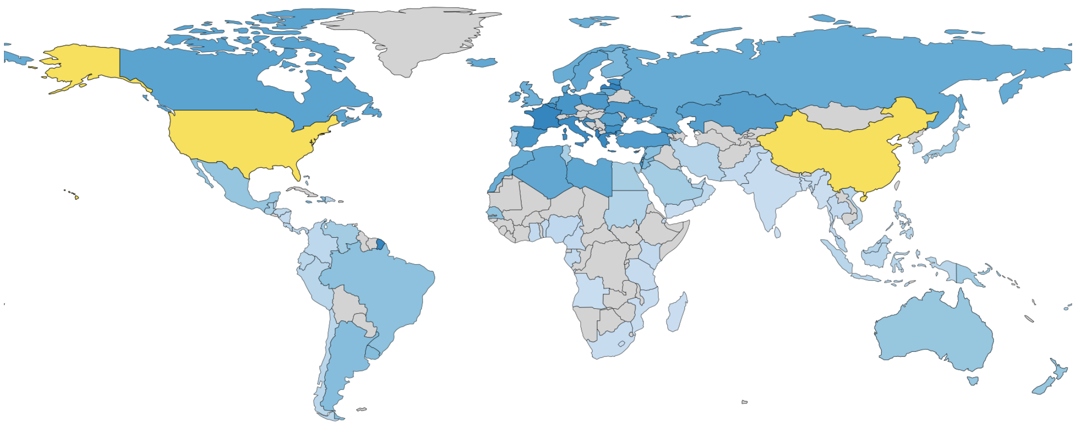
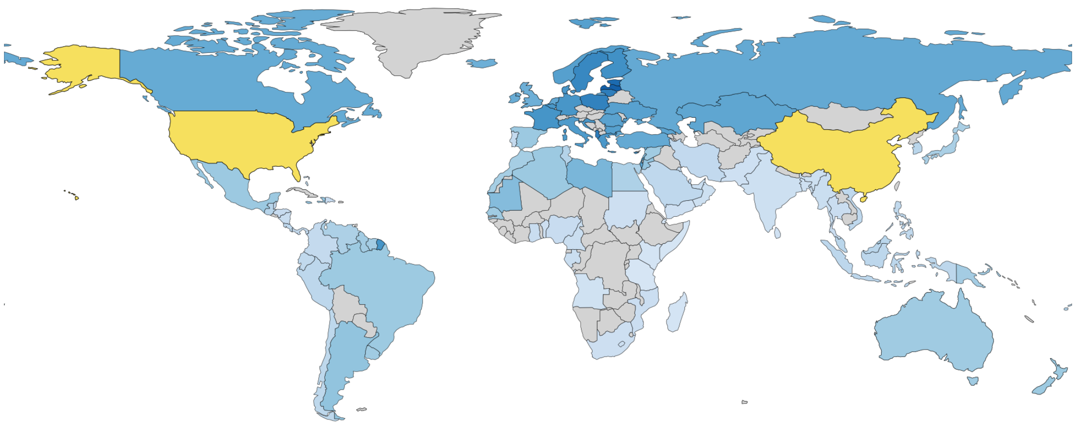


Figure 14: Dependence on the US Bloc over Time

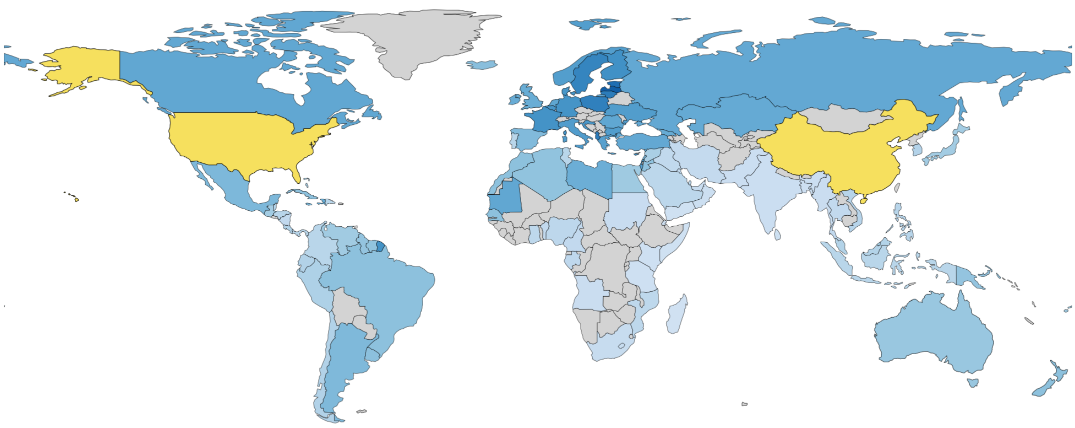
(a) 2009



(b) 2010



(c) 2011



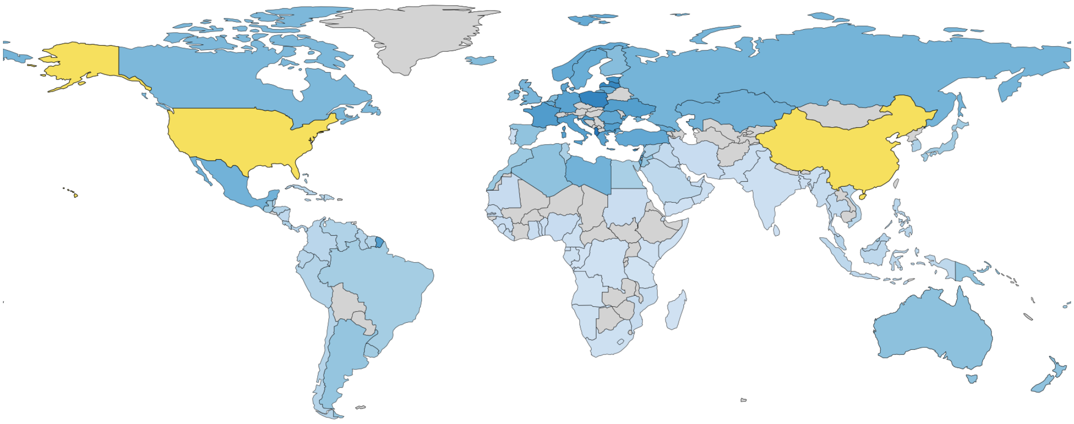
Note: The map reports, for each destination country i and year t, the share of overall cable exposure accounted for by owners belonging to the US-leaning bloc:

$$\text{USBlocShare}_{it} = \frac{\sum_{o \in \text{US bloc}} exposure_{iot}}{\sum_{o} exposure_{iot}}$$

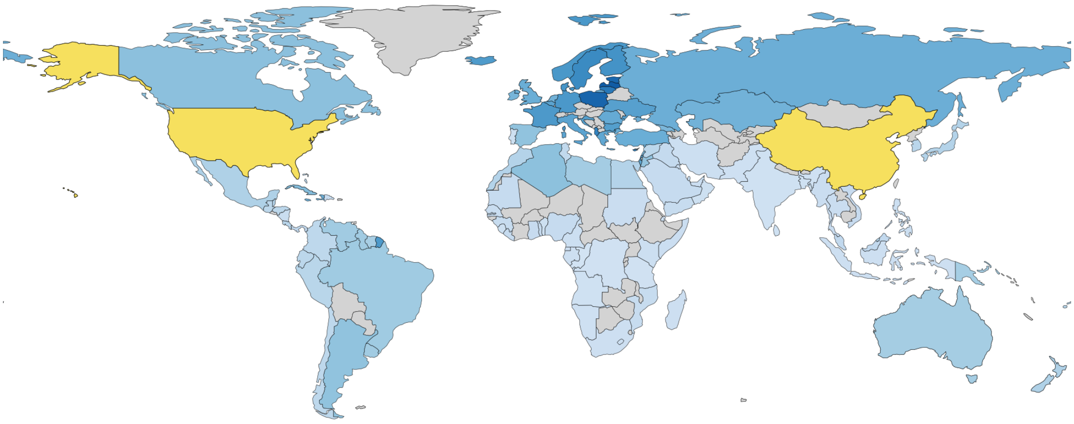
The denominator sums exposure to all owners (including domestic owners). Color intensity varies continuously from 0 to 1, with darker shades indicating a larger US-bloc share. The United States and China are shown in yellow as reference countries; countries for which no data are available are shown in grey.

Figure 14: Dependence on the US Bloc over Time (continued)

(d) 2012



(e) 2013



(f) 2014

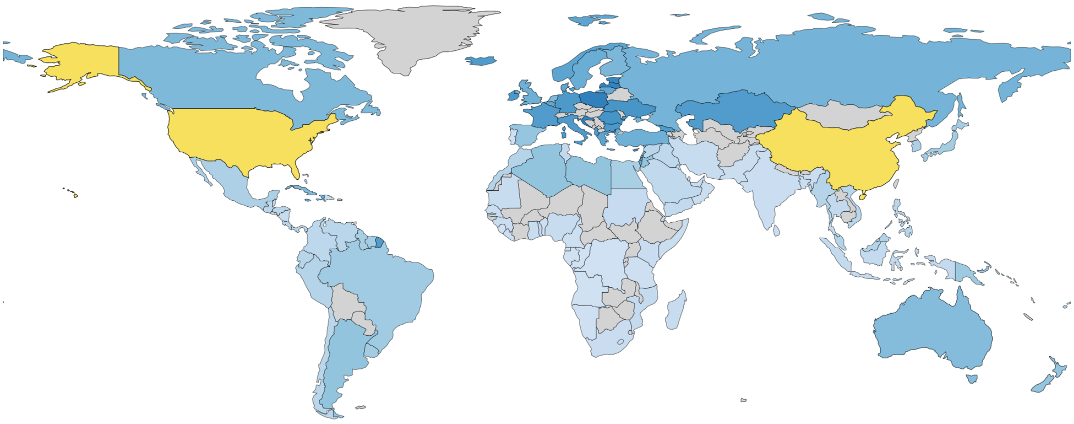
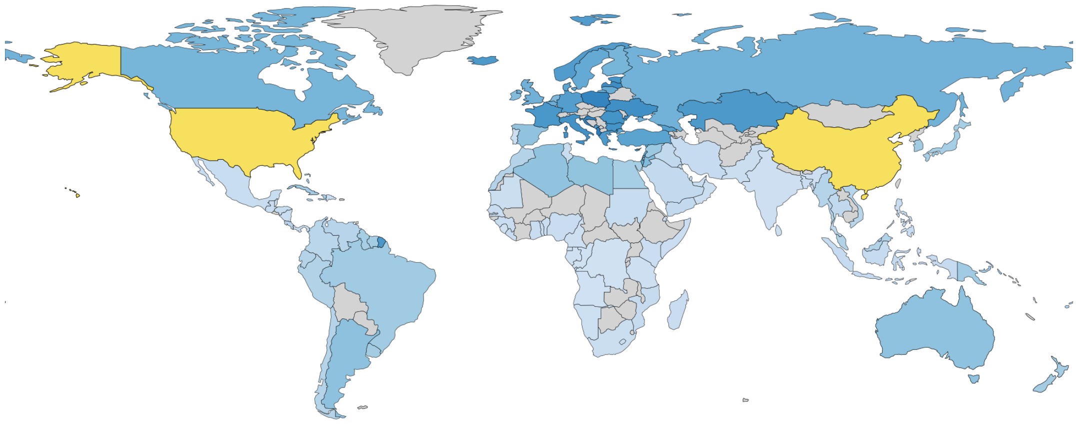
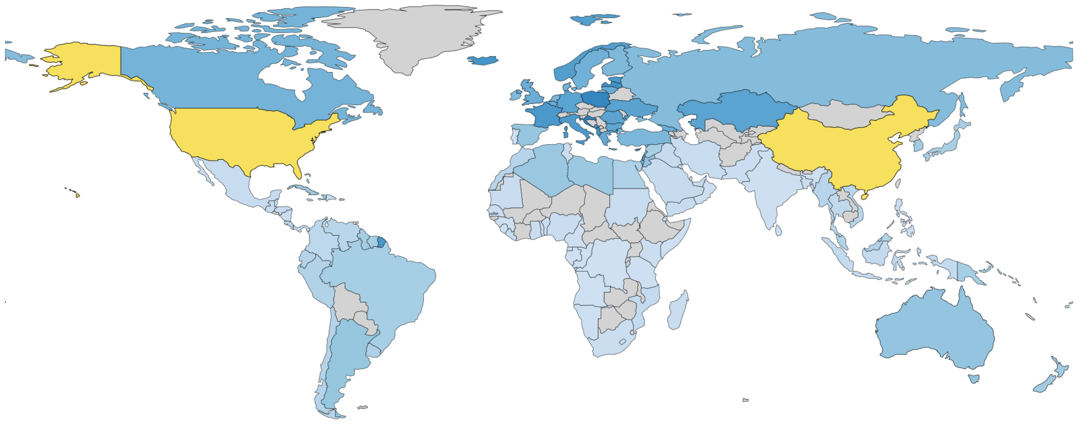


Figure 14: Dependence on the US Bloc over Time (continued)

(g) 2015



(h) 2016



(i) 2017

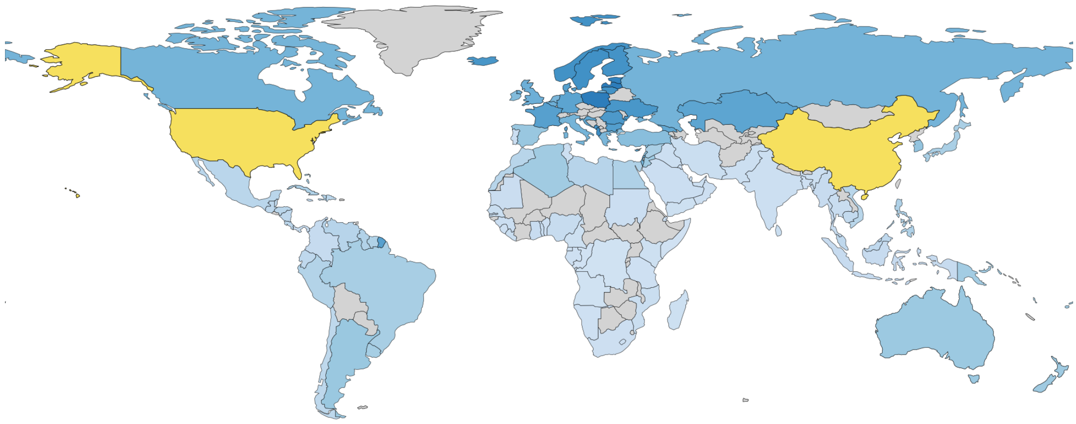
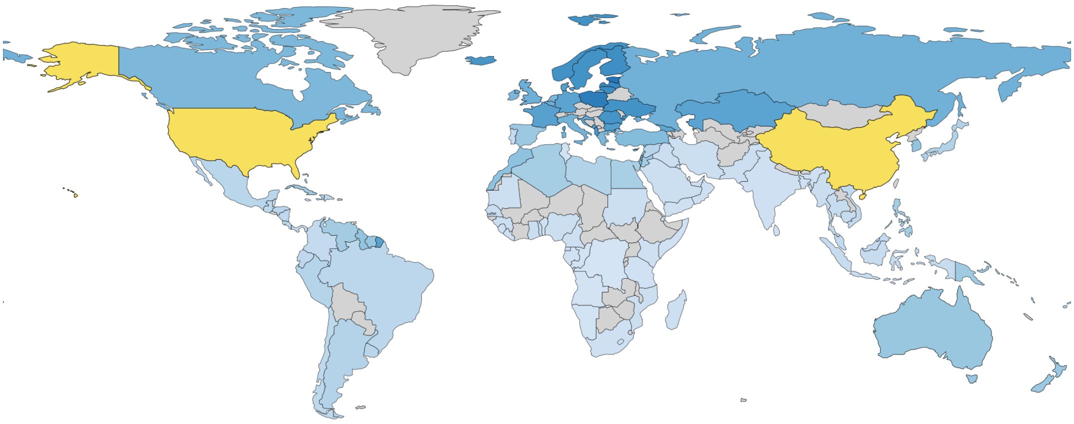
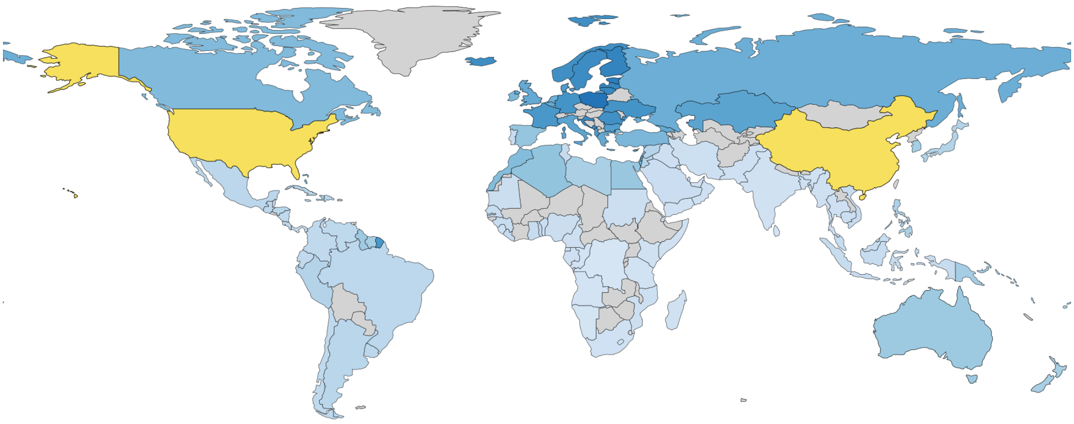


Figure 14: Dependence on the US Bloc over Time (continued)

(j) 2018



(k) 2019



(l) 2020

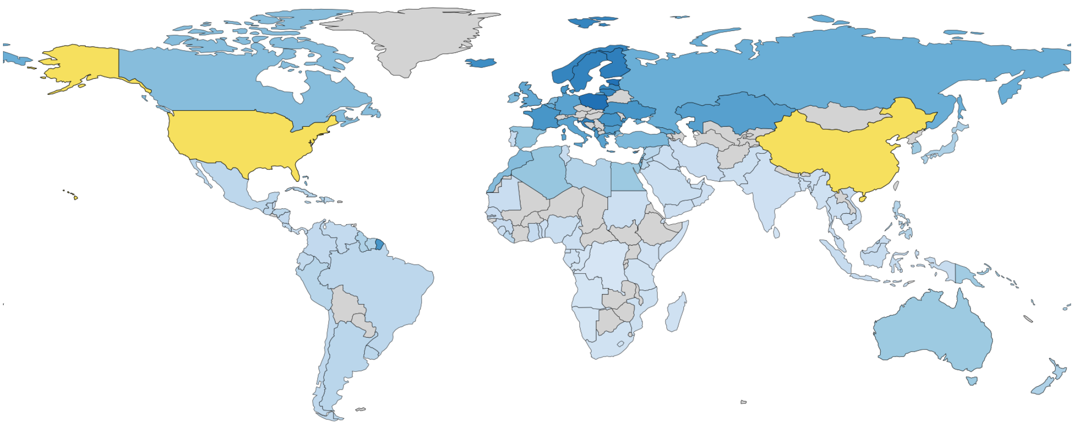
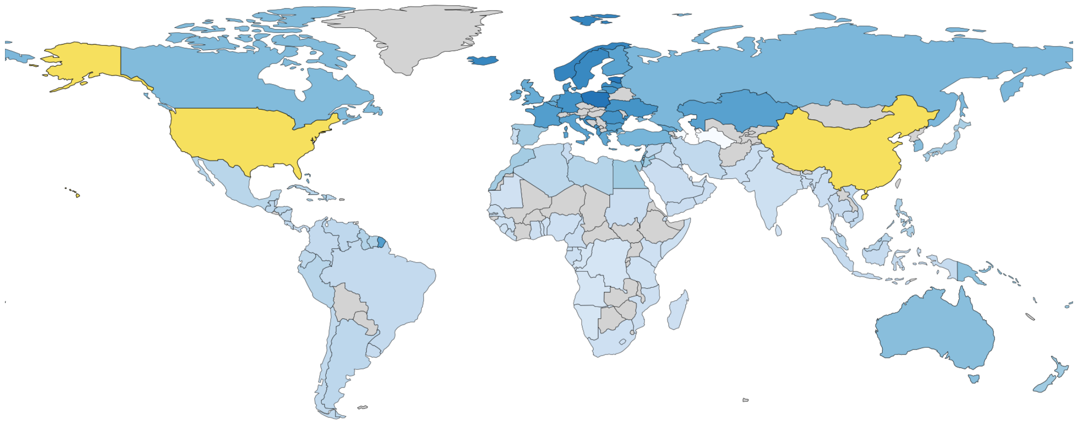
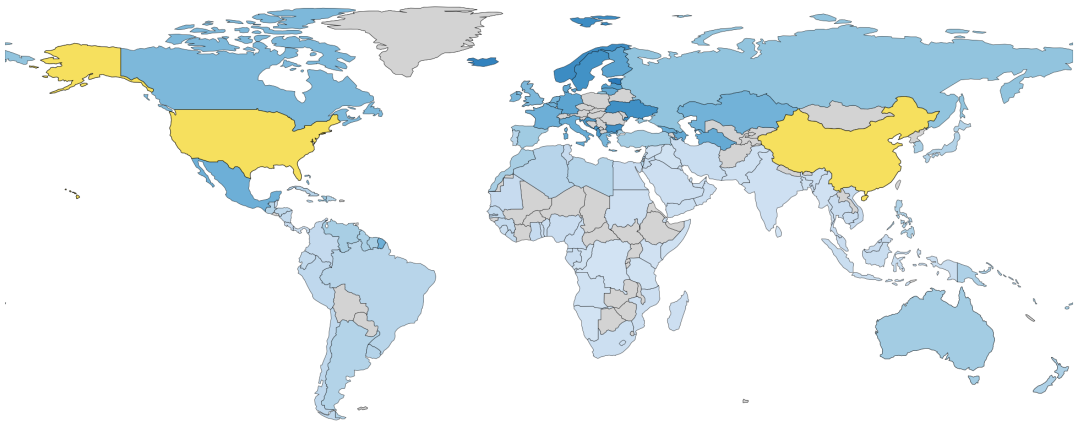


Figure 14: Dependence on the US Bloc over Time (continued)

(m) 2021



(n) 2022



(o) 2023

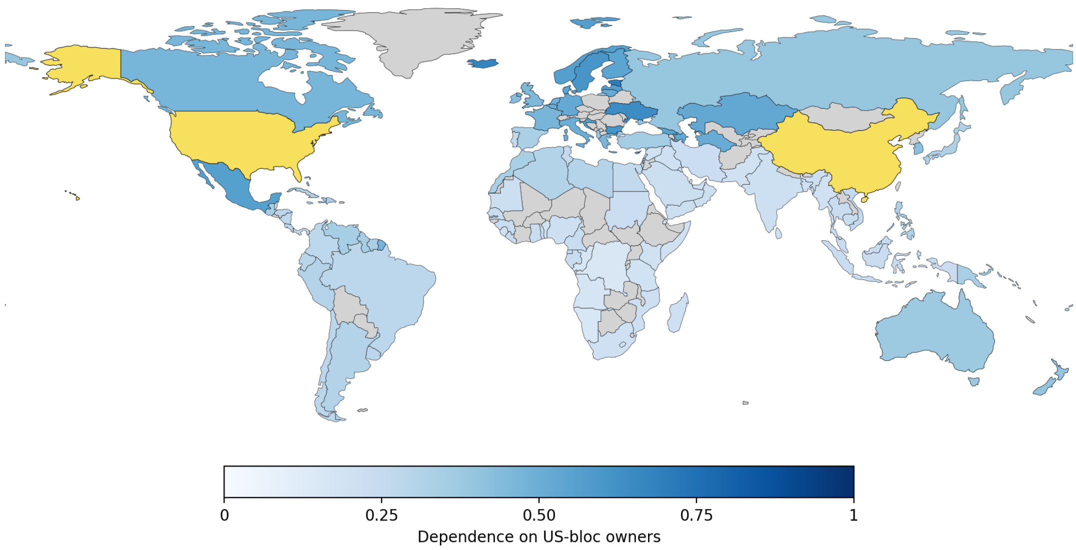
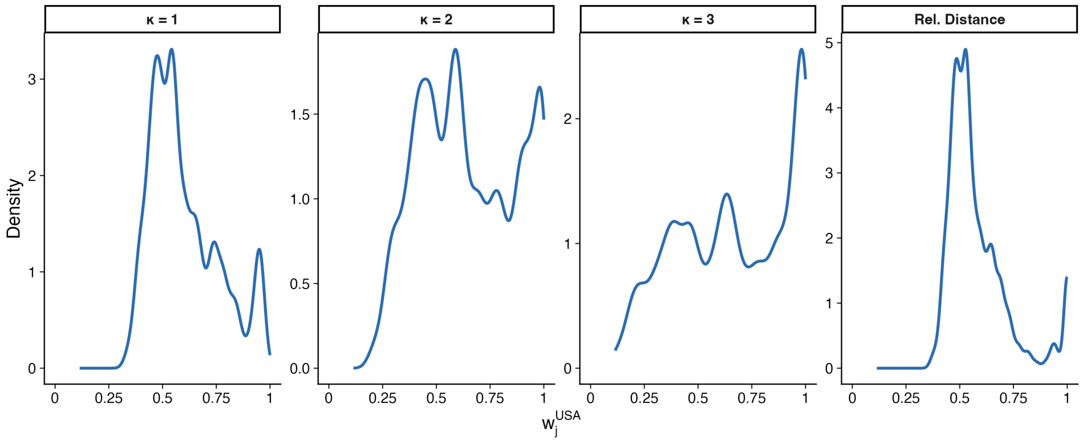
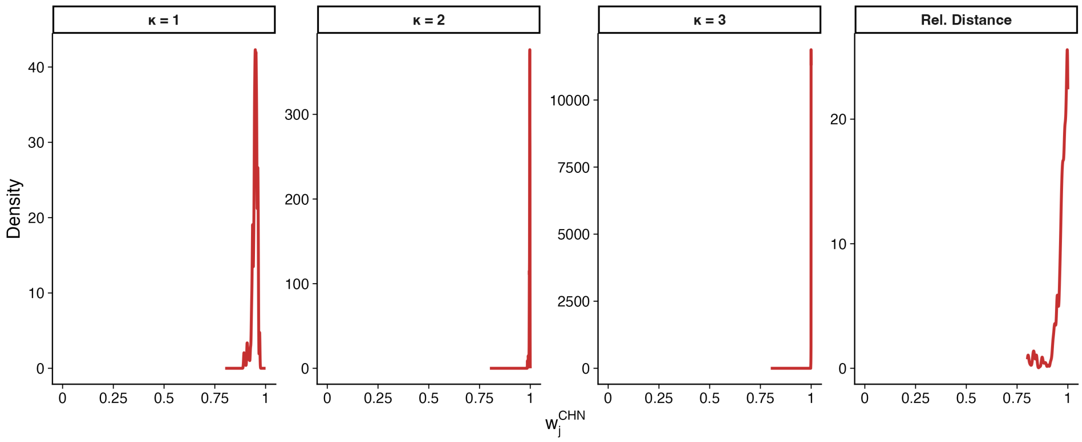


Figure 15: Distribution of Alignment Weights by Baseline Bloc

(a) US Bloc



(b) China Bloc



Note: Panels report kernel densities of alignment weights within baseline investor blocs, computed on the estimation sample. Top row: $w_{j,t}^{USA}$ among US-bloc investors; bottom row: $w_{j,t}^{CHN}$ among China-bloc investors. Each panel uses its own y-axis scale.