Board of Governors of the Federal Reserve System

International Finance Discussion Papers

ISSN 1073-2500 (Print)
ISSN 2767-4509 (Online)

Number 1413

July 2025

Breaking Up: Fragmentation in Foreign Direct Investment

Cody Kallen

Please cite this paper as:
Kallen, Cody (2025). "Breaking Up: Fragmentation in Foreign Direct Investment," International Finance Discussion Papers 1413. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/IFDP.2025.1413.

Breaking Up: Fragmentation in Foreign Direct Investment

Cody Kallen[*]

Federal Reserve Board

This draft: July 10, 2025

Abstract

Rising geopolitical tensions and supply chain vulnerabilities have driven recent fragmentation of foreign direct investment (FDI). This paper provides systematic evidence of FDI fragmentation along ideological and geographic lines across five dimensions: shifting away from ideologically distant countries (ideological sorting), prioritizing politically aligned countries (friendshoring), reducing exposure to specific high-risk countries (derisking), moving production closer to the home country (nearshoring), and returning investment to the home country (reshoring). Measures of FDI based on financial transactions reveal evidence of ideological sorting and nearshoring. The capital expenditures of multinational enterprises and their affiliates display ideological sorting, derisking, nearshoring, and reshoring. Cross-border M&A deals reflect patterns of derisking, while horizontal (but not vertical) M&A exhibits broader ideological realignment. At the industry level, derisking and ideological sorting appear widely distributed. By contrast, friendshoring and nearshoring of M&A remain concentrated in goods-producing sectors.

Keywords: fragmentation, geoeconomics, foreign direct investment

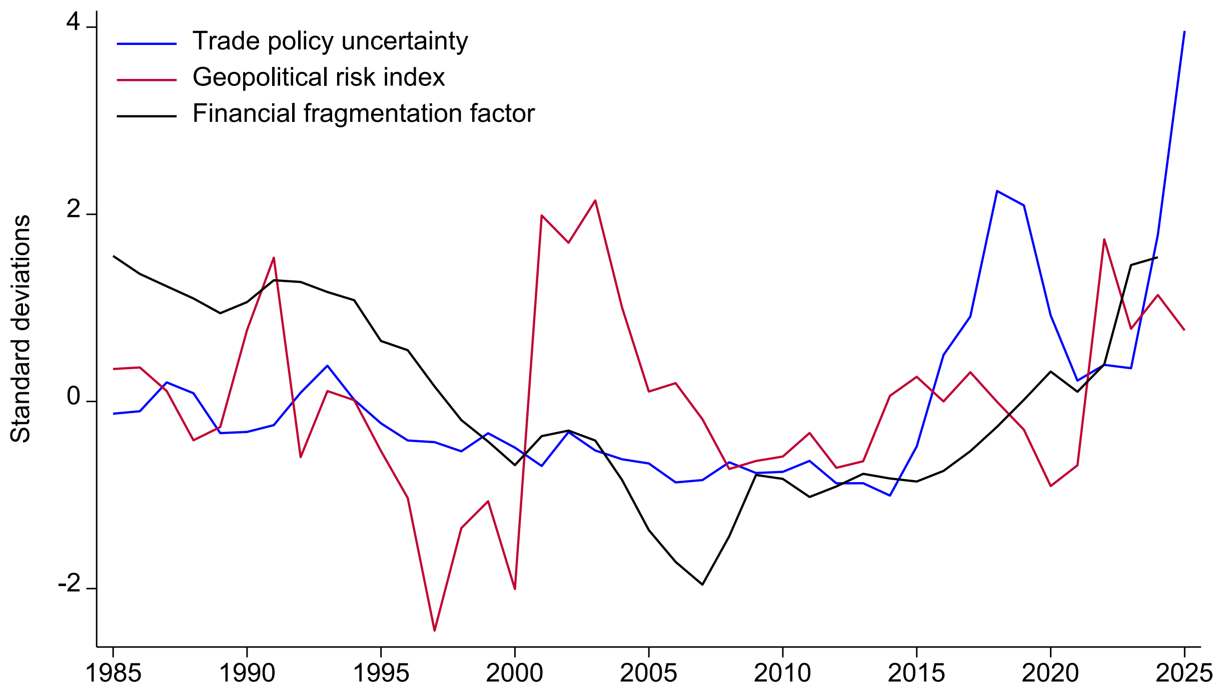
JEL classifications: F21; F23; F36; F50; F65

[*] Email: cody.f.kallen@frb.gov. The views in this material are solely the responsibility of the author and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or other members of its staff. The author is grateful to Carol Bertaut, Daniel Beltran, Florencia Airaudo, Ruth Judson, and seminar participants for their comments.

I. Introduction

In recent years, geopolitical risks and financial fragmentation have become central concerns. Tensions between the U.S. and China caused trade policy uncertainty to surge in the late 2010s (Figure 1, blue line), and again in 2025 (Caldara et al., 2020). The news-based Geopolitical Risk Index from Caldara and Iacoviello (2022) spiked after the Russian invasion of Ukraine in 2022 (red line) and remains elevated. Meanwhile, the financial fragmentation factor from Fernández-Villaverde et al. (2024), which reflects capital controls and the overall volume of global financial flows, began rising in in the late 2010s before accelerating in 2022. Persistently elevated policy uncertainty may have adverse implications for investment and production around the world (Londono, Ma, and Wilson, 2025; Aiyar et al., 2023; Adarov and Pallan, 2025).

Figure 1. International Risks and Financial Fragmentation



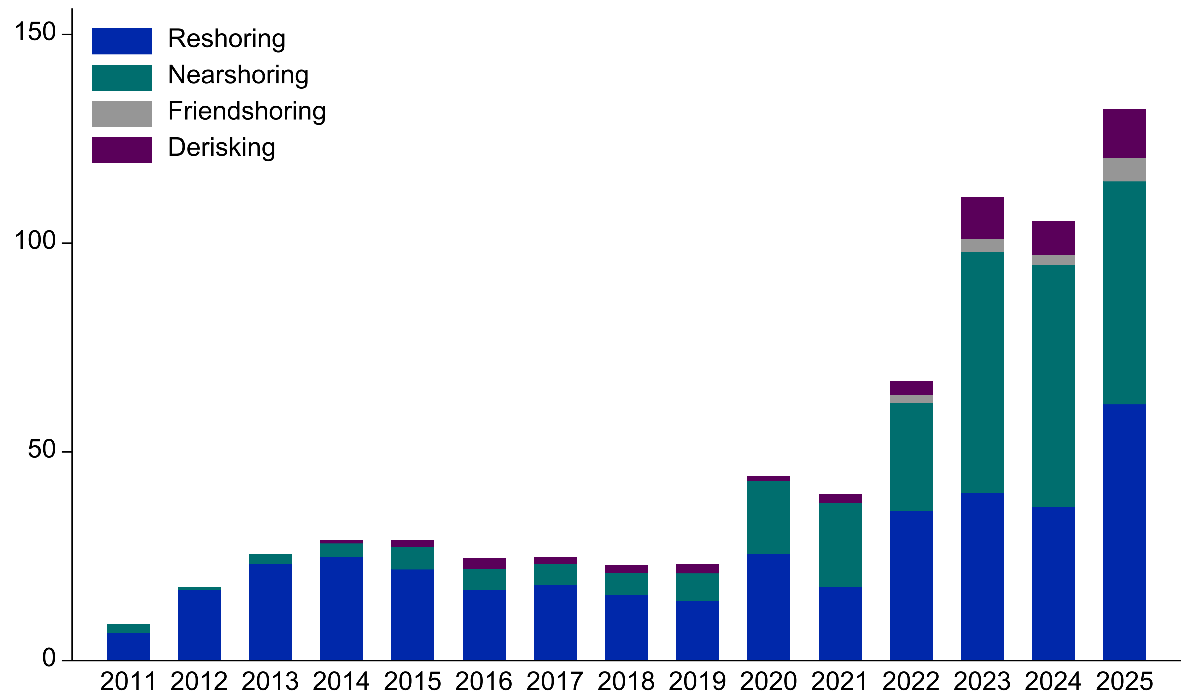
Source: Geopolitical Risk Index (log-standardized) from Caldara and Iacoviello (2022), Trade Policy Uncertainty (log-standardized) from Caldara et al. (2020), and the financial fragmentation factor (standardized) from Fernández-Villaverde et al. (2024). The chart shows annual averages.

Geoeconomic fragmentation may involve different forms of potentially overlapping ideological and geographic realignments, depending on the novel risks confronting investors. To avoid risks from conflicts and sanctions, firms can shift production toward more ideologically similar countries ("ideological sorting"), potentially by divesting from specific geopolitically risky countries ("derisking") or moving investment to countries allied with the home country and sharing similar values ("friendshoring"). Empirically, we find support for all three of these types of ideological realignments, although with heterogeneity across types of FDI.

In addition to policy-related risks, snarled supply chains in 2020 and 2021 revealed potential costs of geographically distant supply chains, which firms can mitigate by moving investment and production to geographically proximate countries ("nearshoring"). Investors could also potentially shift investment and production back to their home countries ("reshoring"), which could address both geopolitical and geographical risks (Kallen, 2025).

These examples of fragmentation are now prominent in public discourse. Shown in Figure 2, Google searches for "nearshoring" and "reshoring" began to grow in 2020, and interest in all these measures picked up after the Russian invasion of Ukraine in 2022.

Figure 2. Growing Public Awareness of Fragmentation



Source: Google Trends. Note: Google Trends scores the monthly popularity of search terms, on a scale up to 100 (max popularity). The chart shows the annual averages of these monthly scores, for U.S. searches.

In this paper, I systematically explore each form of fragmentation in many types of direct investment. Much of the fragmentation narrative has focused on the United States. Accordingly, we first test for fragmentation in U.S. outward FDI, which exhibits nearshoring and ideological sorting, but not derisking. Next, we test for fragmentation globally. Changes in bilateral FDI positions since 2018 exhibit ideological sorting and nearshoring without derisking.

These initial results—ideological sorting and nearshoring but not derisking—appear in official FDI statistics, which attempt to measure bilateral FDI through how investments are financed: debt, reinvested earnings, or other equity. This approach, however, may not correspond to the investments actually made and is complicated by measurement issues linked to tax havens. Directly measuring the investments made using microdata may reveal different patterns of fragmentation.

In contrast to the aggregate financial measures of FDI, developments in cross-border mergers and acquisitions are primarily consistent with derisking, with some evidence of ideological sorting. Horizontal M&A, which reflects expansions into new markets and competition, exhibits much stronger ideological realignment (sorting, derisking and friendshoring) than vertical M&A, which pertains to supply chain organization. Investors in goods-producing industries display particularly strong fragmentation in their acquisitions. Exploiting this heterogeneity, industries with M&A showing stronger ideological sorting, friendshoring and nearshoring also redirected their acquisitions toward domestic targets, consistent with reshoring being driven by the same incentives driving other types of fragmentation.

The capital expenditures of multinational enterprises exhibit ideological sorting, derisking and nearshoring. Since 2018, multinationals have also engaged in significant reshoring of investment, with their domestic capital expenditures growing more rapidly than their foreign capital expenditures or the capital expenditures by local subsidiaries of foreign multinationals.

These results provide systematic evidence of fragmentation in foreign direct investment and reveal substantial heterogeneity in the nature and drivers of fragmentation across types of FDI.

Section II reviews the small but growing literature on recent fragmentation and this paper's contributions. Section III explores fragmentation in financial measures of foreign direct investment, both from the U.S. and worldwide. Section IV explores fragmentation in cross-border M&A, as well as testing for reshoring of M&A. Section V tests for fragmentation in the allocation of multinationals' capital expenditures across their foreign subsidiaries as well as reshoring of investment. Section VI concludes.

II. Related Literature

The fragmentation of international flows is a relatively recent phenomenon. Most of the existing research on fragmentation focuses on testing for effects of tariffs on trade flows and global value chains, as well as quantifying the potential costs of trade reallocation, largely due to timelier data and well-established trade models (Reyes-Heroles, Traiberman & van Leemput, 2020; Timmer et al., 2021; Aiyar et al., 2023; Cerdeiro et al., 2021; Felbermayr, Mahlkow & Sandkamp, 2023; Javorcik et al., 2024; Airaudo et al., 2025). Several papers have also explored fragmentation in portfolio investment and banking flows (Catalán, Fendoglu and Tsurunga, 2024; Correa et al., 2023; Airaudo et al., 2025).

Instead, this paper contributes to the small but growing literature on FDI fragmentation.

Aiyar, Malacrino and Presbitero (2024) explore the role of geopolitical alignment in the numbers of "greenfield" foreign direct investments between pairs of countries, finding a significant role for ideological alignment in these FDI projects.[1] In particular, countries that are further apart ideologically—measured using the ideal point distance score from Bailey, Strezhnev and Voeten (2017)—have fewer FDI projects between them and lower FDI expenditures. This relationship is particularly important for emerging markets, although not for advanced economies. They find similar results for mergers and acquisitions, although their M&A data only reaches 2019 and thus predates much of the recent fragmentation.

The results in Aiyar, Malacrino and Presbitero (2024) provide an important baseline result: Ideological distance matters for FDI. By comparison, in this paper I explore ideological *realignment*, through the lens that ideological distance may have become more important in recent years, amid rising trade tensions, supply chain disruptions, and sanctions.

Gopinath et al. (2025) utilize this same greenfield FDI data (as well as bilateral trade data) to explore the idea of fragmentation across geopolitical blocs. Sorting countries into a U.S.-aligned bloc, a China-aligned bloc, and nonaligned countries, they find that cross-bloc FDI declined after the Russian invasion of Ukraine relative to previous years. They also identify a new role for "connector countries," such as Mexico, India, and Vietnam, that may be intermediating trade between the U.S. and China. Their results build on a previous analysis, which also sought to quantify potential costs of fragmentation (IMF Research Department, 2023).

In this paper, I build on the approach from Gopinath et al. (2025) to explore ideological realignment over time, and I adapt their empirical bloc specification to test for derisking and friendshoring. I also take a broader approach to studying different types of FDI. Their empirical results, which indicate derisking in new FDI projects, are consistent with my findings of derisking in M&A but inconsistent with the absence of derisking in overall FDI flows.

Unlike the papers previously mentioned, Tan (2024) finds that FDI fragmentation is not widespread but rather is confined to several strategically sensitive industries, likely reflecting targeted national security policies. In my M&A analysis, I find that friendshoring and nearshoring are concentrated in a few sectors (consumer goods and industrials), but derisking and ideological sorting are occurring more broadly. Tan (2024) also finds that U.S. outward FDI has decoupled from China, but FDI from other countries has not fragmented. In contrast, I find significant evidence of ideological realignment of FDI and nearshoring even when excluding the U.S. and China.

[1] Their data, from fDi Markets, is of new FDI projects, but it is not clear that these projects necessarily meet the definition of greenfield FDI. In particular, the number and value of FDI projects in the U.S. (from this dataset) are only weakly correlated with new greenfield investments according to the Bureau of Economic Analysis; it is more strongly correlated with the reinvested earnings component of FDI, suggesting these may be financed from the returns on previous investments rather than a new infusion of capital.

One limitation in the fragmentation literature comes from an inability to test for reshoring, as datasets on trade or FDI inherently lack comparable measures of domestic activity, and it may be more challenging to control for relevant push and pull factors when comparing foreign and domestic investments. In this paper, I offer the first systematic evidence of reshoring of M&A and of multinationals' capital expenditures as a part of global financial fragmentation.[2] Industries that engaged in friendshoring and nearshoring in M&A after 2018 also increased their domestic M&A shares, but derisking seems unrelated to reshoring. After 2018 (and more so after 2022), multinationals increased their domestic capital expenditures, relative to investments by their foreign subsidiaries and by foreign multinationals in their country.

III. Fragmentation in Financial Measures of Foreign Direct Investment

Financial measures of foreign direct investment, following the BPM5 and BPM6 conventions, measure FDI on the basis of "transactions", consisting of debt-financed FDI, retained earnings, and other equity-financed FDI.[3] This measurement approach provides a picture of cross-border investment based on how it is financed, rather than measuring the investments directly.

Anecdotally, discussions of geopolitical fragmentation have focused on the role of the U.S. and its trade and sanction policies, especially regarding the U.S.-China relationship (Sullivan, 2023; Strahan et al., 2025). Kallen (2025) finds that U.S. investors shifted from China and Hong Kong and toward Mexico and India, and Tan (2024) finds that U.S. outward FDI has relocated more strongly than FDI from Europe. Accordingly, we begin with an empirical analysis of fragmentation in U.S. outward FDI.

III.A. Data: U.S. Outward Foreign Direct Investment

This analysis of U.S. fragmentation draws on the Bureau of Economic Analysis (BEA) data on U.S. Direct Investment Abroad (USDIA). The USDIA dataset reports annual outward direct investment flows (transactions) to other countries, as well as historical direct investment positions and FDI income, by detailed counterpart country. We scale FDI transactions by the lagged FDI position. Because much of FDI consists of retained earnings, we control for the income rate of return on the FDI position.

The USDIA data are relatively timely and thorough, but they suffer from measurement problems induced by investment hubs (mainly tax havens). As with FDI data more generally, direct investments that will ultimately be made in one country (e.g., China) are often implemented using

[2] Faber et al. (2025) find reshoring in the sourcing of intermediate inputs in response to uncertainty shocks in developing countries, but only in highly robotized industries (i.e., automatable).

[3] For FDI accounting, the primary difference between BPM5 ("directional basis") and BPM6 ("asset/liability basis") is in the treatment of debt-financed reverse FDI, or loans from foreign subsidiaries to the parent or other affiliates in the home country of a multinational.

subsidiaries in intermediate countries (e.g., Hong Kong). In such situations, the investment is recorded as going to the intermediate country instead of the ultimate destination. We address this issue in sections IV and V, as our M&A and MNE data do not suffer from this problem.

Empirically, we want to test for ideological realignment of FDI through ideological sorting, friendshoring, and derisking, as well as nearshoring. To test for ideological sorting of FDI, we use the U.S. agreement score from Bailey, Strezhnev and Voeten (2017)—which is based on the share of U.N. votes in which a given country voted with the U.S.—from the prior year.[4] Alternatively, to test for friendshoring and derisking, we can classify countries into a U.S. bloc, a China bloc, or nonaligned, as in Gopinath et al. (2025).[5] Finally, to test for nearshoring, we use the (log) geographic distance from the U.S. from the CEPII Gravity database (Conte, Cotterlaz, and Mayer, 2022).

For controls common to the regressions, we use GDP growth, exchange rate depreciation against the U.S. dollar, and trade openness (exports and imports as a share of GDP) from the World Bank's World Development Indicators. These controls are common in the FDI literature, and the important country-specific factors are absorbed by country fixed effects (Blonigen and Piger, 2014). As additional controls for some regressions, we use the counterpart country's openness to FDI (total inward FDI scaled by GDP), the country's investment rate (gross fixed capital formation as a percent of GDP), the inflation rate (measured using the GDP deflator), and a rule of law measure, all from the World Development Indicators. We also use the country's U.S. export exposure, measured as that country's exports to the U.S. (from the CEPII Gravity database) divided by its total exports (from the World Development Indicators). Appendix A provides additional details of the data sourcing and preparation.

Table 1 reports the summary statistics for this dataset, covering 2009 through 2023. FDI positions are all lagged by one year. Appendix A reports the sample breakdown by time and by geopolitical bloc.

---

[4] The regressions use the agreement share linearly, but one could imagine that marginal changes in agreement with the U.S. matter more when the country already agrees with the U.S. more often, or the opposite case. The results are robust to using a log transformation or squaring it, but we do not have enough power to robustly identify any nonlinearity.

[5] The U.S. bloc consists of the U.S., Canada, Belgium, the Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, Great Britain, Australia, New Zealand, Japan, Israel, South Korea, and Taiwan. The China bloc consists of China, Hong Kong, Macau, Russia, Belarus, Eritrea, Mali, Nicaragua, and Syria. All other countries are in the nonaligned bloc. These blocs resemble the "narrow" bloc definition in Gopinath et al. (2025), with some modifications to improve the definition of the U.S. bloc.

Table 1. Summary Statistics for USDIA Dataset

Variable	Obs	Mean	SD	Min	Median	Max
FDI Transactions/Position	1742	0.050	0.163	-0.317	0.044	0.453
FDI Income/Position	1742	0.088	0.107	-0.136	0.079	0.364
US Agreement	1728	0.280	0.160	0.000	0.212	0.944
log(GeoDist)	1741	8.888	0.562	6.321	8.927	9.692
GDP growth	1742	2.895	3.502	-5.795	3.022	9.399
ΔExchange rate	1742	0.030	0.066	-0.052	0.002	0.196
Trade openness	1742	0.886	0.412	0.349	0.805	1.788
FDI openness	1724	0.061	0.303	-4.401	0.027	4.522
US export share	1381	0.091	0.127	0.000	0.041	0.743
Rule of law	1735	0.166	0.954	-1.923	0.008	2.125
Inflation rate	1742	4.869	5.713	-2.674	3.199	21.774
Investment rate	1553	22.939	6.413	5.359	22.266	70.109

FDI transactions, income and positions are from the BEA's U.S. Direct Investment Abroad data by detailed country, 2009-2023. The U.S. agreement score is from Bailey, Strezhnev and Voeten (2017). GDP growth, the exchange rate, trade openness, FDI openness, rule of law, inflation, and the aggregate investment rate are computed from the World Development Indicators. The U.S. export share is computed from the CEPII Gravity database. FDI position terms are all lagged by one year, as is the U.S. agreement score. The FDI transactions-to-position ratio, income-to-position ratio, GDP growth, trade openness, exchange rate change (in logs), and inflation have all been winsorized at the 5th and 95th percentiles.

III.B. Fragmentation in U.S. Direct Investment Abroad

To test for potential geopolitical fragmentation, we use the following regression specifications. The first specification regresses on the U.S. agreement score from Bailey, Strezhnev, and Voeten (2017), interacted with a dummy indicating the post-2018 period, when trade tensions rose. The coefficient β_S measures how strongly ideological alignment (based on UN voting) starts to matter for U.S. outward FDI beginning in 2018. We use the lagged value as in Aiyar et al. (2024), reflecting the relatively long times required for direct investments to adjust.

$$\frac{FDI_{i,t}}{FDIposition_{i,t-1}} = \beta_S \mathbf{1}_{\{t\geq 2018\}} USAgreement_{i,t-1} + \gamma' X_{i,t} + \mu_i + \alpha_t + \epsilon_{i,t}$$

The second specification uses the bloc approach from Gopinath et al. (2025). The coefficient β_F measures friendshoring as a shift in investment to the U.S.-aligned countries relative to nonaligned countries, and β_D measures derisking as a shift of FDI away from China-aligned countries relative to nonaligned ($\beta_D < 0$).

$$\frac{FDI_{i,t}}{FDIposition_{i,t-1}} = \beta_F \mathbf{1}_{\{t\geq 2018\}} USbloc_i + \beta_D \mathbf{1}_{t\geq 2018} CHbloc_i + \gamma' X_{i,t} + \mu_i + \alpha_t + \epsilon_{i,t}$$

The third specification uses geographic distance to test for nearshoring. The log transformation reflects that among geographically distant countries, marginal differences likely matter little.

$$\frac{FDI_{i,t}}{FDIposition_{i,t-1}} = \beta_N \mathbf{1}_{\{t\geq 2018\}} \log(GeoDist_i) + \gamma' X_{i,t} + \mu_i + \alpha_t + \epsilon_{i,t}$$

All these regressions use the ratio of FDI transactions to the lagged FDI position to address heteroscedasticity. We include country and year fixed effects, and each regression controls for FDI income scaled by the lagged FDI position (which drives the retained earnings component of FDI), GDP growth, exchange rate depreciation, and openness to trade. These regressions exclude tax havens to mitigate the misattribution problem of investment hubs.[6]

Table 2 presents the regression results, with standard errors clustered by country. The first column shows that U.S. outward FDI has shifted reflecting ideological sorting. This result is robust to controlling for the destination country's openness to FDI, to its export exposure to the U.S., and to a larger set of macroeconomic controls (last three columns). This ideological sorting of U.S. outward FDI applies on top of any broader shifts of worldwide FDI to that country as well as any realignment of trade with the U.S. As shown in Appendix Table B.1, this ideological sorting result is robust to many more specifications: using the current year's UN agreement score instead of the lagged value; using nonlinear but monotonic transformations of the agreement score; including tax havens; using 2022 as the beginning of the fragmentation period instead of 2018; and excluding 2018-2019 on account of the anomalous repatriation flows resulting from the Tax Cuts and Jobs Act of 2017 (Smolyansky, Suarez, and Tabova, 2019).

The second column—the specification based on Gopinath et al. (2025)—finds evidence of friendshoring, but not of derisking of U.S. outward FDI; however, these results are sensitive to alternative bloc definitions and the inclusion of tax havens.

The third column finds evidence of nearshoring, with U.S. FDI moving toward more geographically proximate countries beginning in 2018. Appendix Table B.2 shows that this result is robust to using linear distance instead of log distance, to using 2022 as the cutoff instead of 2018, to including tax havens, and to excluding 2018-2019.

The magnitudes of the coefficient estimates imply that after 2018, one standard deviation higher UN voting agreement with the U.S. is associated with higher U.S. FDI into that country by 1.9 percent of the existing stock of historical U.S. FDI to that country. This is large relative to both average and median FDI flows (5.0 and 4.4 percent respectively), but small relative to the volatility of FDI flows. The coefficient estimate for geographic distance implies a similar magnitude impact of a one standard deviation difference in log distance.

[6] Our tax havens are Bermuda, the British Virgin Islands, Cayman Islands, Ireland, the Netherlands, Switzerland, Luxembourg, Hong Kong, Jersey, Singapore, the United Arab Emirates, Malta, Cyprus, Barbados, Seychelles, and Mauritius. This group combines those appearing on multiple tax haven lists, focusing on corporate tax havens rather than individual tax havens or secrecy havens.

Table 2. Regression Results: U.S. Direct Investment Abroad

Dependent variable	U.S. Outward FDI Transactions/Position					
$\{t \geq 2018\} \times$ *USAgree*	0.119***			0.120***	0.126**	0.124***
(sorting)	(0.045)			(0.045)	(0.048)	(0.044)
$\{t \geq 2018\} \times$ *USbloc*		0.041***				
(friendshoring)		(0.015)				
$\{t \geq 2018\} \times$ *CHbloc*		0.062**				
(derisking)		(0.030)				
$\{t \geq 2018\} \times$ *log(GeoDist)*			-0.028**			
(nearshoring)			(0.012)			
FDI income/Position	0.981***	0.984***	0.988***	0.976***	0.975***	0.964***
	(0.063)	(0.063)	(0.063)	(0.064)	(0.066)	(0.071)
GDP growth	-0.001	-0.001	-0.001	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
ΔExchange rate	-0.038	-0.036	-0.036	-0.042	-0.054	-0.057
	(0.077)	(0.076)	(0.076)	(0.078)	(0.085)	(0.072)
Trade openness	0.034	0.033	0.044	0.027	0.022	0.025
	(0.046)	(0.044)	(0.045)	(0.049)	(0.046)	(0.048)
FDI openness				0.076		
				(0.078)		
US export share					0.070	
					(0.164)	
Rule of law						-0.028
						(0.026)
Inflation rate						-0.001
						(0.001)
Investment rate						0.001
						(0.001)
Fixed effects	Country, year					
Observations	1,559	1,572	1,572	1,540	1,236	1,392
Adj. R-sq	0.376	0.375	0.374	0.370	0.386	0.336

*These regressions model the changing roles of ideological and distance factors for U.S. FDI abroad, for 2009-2023. The dependent variable is the ratio of FDI transactions for outward FDI to the lagged FDI position; the lagged position is also used in the FDI income ratio. The U.S. agreement score is lagged by one year. Tax havens are excluded. All regressions use fixed effects by country and by year. Standard errors are clustered by country. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

III.C. Data: Bilateral Foreign Direct Investment

We now broaden the analysis to explore fragmentation in worldwide FDI flows. In addition to the potential for fragmentation beyond the U.S., the broader set of countries allows for a more exhaustive set of fixed effects, as in Gopinath et al. (2025), to control for all push and pull factors, potentially obtaining better identification of any fragmentation.

We implement this analysis of bilateral flows worldwide using the International Monetary Fund's Direct Investment Positions by Counterpart Economy (DIPCE) database (formerly the Coordinated Direct Investment Survey).

The IMF's DIPCE data report bilateral FDI positions ($P_{s,d,t}$) between source country (s) and destination country (d) in year (t) from 2009 through 2023. In addition to overall FDI positions, the DIPCE data also report equity and debt FDI positions, although these are not as well-populated as the overall positions. We use these positions to construct implied flow measures, as follows:

$$FDIflow_{s,d,t} \equiv \frac{P_{s,d,t} - P_{s,d,t-1}}{P_{s,d,t} + P_{s,d,t-1}}$$

This flow measure is similar to dividing FDI by either the lagged position or the current position, but the resulting measure is on the scale between -1 and 1, making the results robust to the treatment of outliers.[7]

As an alternative, we also consider FDI (the change in the position) scaled by the GDP of the destination country. Although this specification is less appropriate than scaling by the FDI position,[8] it allows a more direct comparison of FDI fragmentation to trade fragmentation, as measured by the IMF's International Trade in Goods database (formerly the Direction of Trade Statistics).

To measure ideological distance, we use the ideal point distance (IPD) measure from Bailey, Strezhnev and Voeten (2017), and we continue to use the geographic distance measure from the CEPII Gravity database.

Table 3 reports the summary statistics for this dataset.

III.D. Fragmentation in Worldwide Foreign Direct Investment

To test for fragmentation, we regress each flow measure on the post-2018 dummy interacted with the relevant distance or bloc measures, as well as source-destination fixed effects, destination-year fixed effects, and source-year fixed effects. These control for all permanent bilateral ties, as well as all common push and pull factors for FDI.

[7] We exclude all observations with negative gross FDI positions.
[8] The magnitude and volatility of FDI flows scale almost one-for-one with lagged FDI positions. Although the GDP of the destination country and of the source country both matter for the scale of FDI flows, they are an order of magnitude less important. Scaling by GDP effectively over-weights the investment hubs and countries that are more open to FDI, and any regression results become sensitive to cutoffs when winsorizing and to the inclusion or exclusion of investment hubs.

Table 3. Summary Statistics for Bilateral FDI and Trade Data

Variable	Obs	Mean	SD	Min	Median	Max
FDI flow	124967	0.047	0.382	-1.000	0.016	1.000
Debt FDI flow	75918	0.040	0.480	-1.000	0.010	1.000
Equity FDI flow	109167	0.049	0.361	-1.000	0.017	1.000
FDI/GDP	108853	0.220	1.150	-1.826	0.000	4.154
Debt FDI/GDP	63454	0.048	0.528	-1.192	0.000	1.688
Equity FDI/GDP	99702	0.203	0.923	-1.290	0.001	3.419
Exports/GDP	352975	1.630	5.646	0.000	0.041	41.148
Imports/GDP	401407	2.134	7.164	0.000	0.045	51.789
Ideal point distance	383919	0.987	0.752	0.000	0.871	4.818
log(Geographic distance)	452302	8.671	0.822	0.693	8.854	9.900

FDI data come from the IMF's Direct Investment Positions by Counterpart Country (formerly CDIS), 2009-2023. The FDI flow measures are computed as the change in position divided by the sum of the new and old position, as in the equation above. We also compute FDI (changes in FDI positions) scaled by GDP of the destination country. Exports and imports are from the IMF's International Trade in Goods (formerly DOTS), also scaled by GDP of the destination country. All variables scaled by GDP are also multiplied by 1000. GDP is from the World Bank's World Development Indicators. Ideal point distance is from Bailey, Strezhnev and Voeten (2017), and geographic distance is from the CEPII Gravity database. All flow measures that have been scaled by GDP have all been winsorized at the 5th and 95th percentiles.

Table 4 reports the regression results, using the preferred scaling for FDI flows. The top panel uses the IPD measure to test for sorting of FDI along ideological lines. The coefficient estimates are negative, significant and common across types of financing (columns), suggesting that FDI worldwide has shifted consistent with ideological sorting. The second panel considers potential nonlinearity, as marginal changes in UN voting patterns may be more important when countries generally vote similarly. The coefficient estimates remain negative and significant. The third panel considers fragmentation through blocs, as in Gopinath et al. (2025); equity-financed FDI displays friendshoring, but friendshoring and derisking do not appear more broadly. The final panel considers geographic distance; the negative coefficient estimates suggest that nearshoring in FDI applies to FDI flows worldwide.

These coefficient estimates imply that a one standard deviation increase in ideological distance between countries is associated with 2.3 percent lower FDI flows relative to FDI positions since 2018. For geographic distance, a one standard deviation increase is associated with 4.9 percent lower FDI flows relative to FDI positions. As with U.S. outward FDI, these magnitudes are large relative to mean and median FDI flows but small relative to the volatility of these flows.

As in the regressions for U.S. outward FDI, these regressions exclude tax havens. Appendix B shows that the ideological alignment and nearshoring results are robust to this decision, as well as to using 2022 as the cutoff year instead of 2018. Notably, the results are also robust to excluding the U.S. and China, the countries receiving the most attention in discussions of fragmentation.

Table 4. Regression Results: Bilateral FDI Flows

Variable type	All DI	Equity DI	Debt DI
Fixed effects	Source-destination, source-year, destination-year		
$\{t \geq 2018\}$ × *IPD*	-0.015***	-0.021***	-0.020***
	(0.004)	(0.004)	(0.007)
Observations	87,211	76,242	52,430
Adj. R-sq	0.052	0.075	0.025
$\{t \geq 2018\}$ × *log(IPD)*	-0.008***	-0.008***	-0.011***
	(0.002)	(0.002)	(0.003)
Observations	87,211	76,242	52,430
Adj. R-sq	0.052	0.075	0.025
$\{t \geq 2018\}$ × *SameBloc*	0.013	0.039***	0.023
	(0.011)	(0.011)	(0.018)
$\{t \geq 2018\}$ × *DiffBlocs*	0.000	0.018	-0.017
	(0.015)	(0.016)	(0.025)
Observations	94,121	82,378	55,550
Adj. R-sq	0.054	0.078	0.028
$\{t \geq 2018\}$ × *log(GeoDist)*	-0.030***	-0.029***	-0.043***
	(0.003)	(0.003)	(0.005)
Observations	91,394	79,942	54,320
Adj. R-sq	0.054	0.077	0.028

*These regressions model the changing roles of ideological and distance factors on FDI flows between pairs of countries over time, for 2009-2023. The dependent variable is constructed from positions as in the equation above. Ideal point distance is lagged by one year. Country pairs with tax havens are excluded. All regressions use source-destination, source-year, and destination-year fixed effects. Standard errors are clustered by source-destination. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Table 5 repeats this analysis but uses FDI flows scaled by the destination country's GDP. For comparison, the last two columns consider exports from s to d and imports in s from d. The coefficient estimates for IPD and its log transformation remain negative for overall FDI and equity-financed FDI but not for debt-financed FDI. The third panel shows evidence of friendshoring, but not of derisking; FDI within blocs is growing relative to FDI with nonaligned countries, but cross-bloc FDI is not decreasing relative to FDI with nonaligned countries. The results in the fourth panel suggest that nearshoring is still occurring, but primarily for debt-financed FDI.

The discrepancies between equity-financed and debt-financed FDI may reflect their underlying components. Debt-financed FDI occurs either when a foreign investor lends a sufficiently large amount to a firm, or through loans between related affiliates of the same multinational group. This intercompany debt arises from a multinational group's use of its internal capital market to reallocate financing across subsidiaries, often using financing subsidiaries in tax havens; thus, bilateral intercompany debt flows likely do not reflect actual reallocation of financing within the MNE network. By comparison, equity FDI consists of reinvested earnings, which generally track past FDI, as well as net new equity, which is the mostly likely component to display fragmentation.

Table 5. Regression Results: Bilateral FDI and Trade

Variable type	All DI	Equity DI	Debt DI	Exports	Imports
Fixed effects	Source-destination, source-year, destination-year				
$\{t \geq 2018\} \times IPD$	-0.039***	-0.030***	-0.010	-0.178***	-0.177***
	(0.010)	(0.008)	(0.007)	(0.027)	(0.027)
Observations	78,648	72,503	44,745	257,664	291,325
Adj. R-sq	0.146	0.187	0.014	0.875	0.916
$\{t \geq 2018\} \times \log(IPD)$	-0.012**	-0.011***	-0.004	-0.056***	-0.057***
	(0.005)	(0.004)	(0.003)	(0.011)	(0.011)
Observations	78,648	72,503	44,745	257,664	291,325
Adj. R-sq	0.146	0.187	0.014	0.875	0.916
$\{t \geq 2018\} \times SameBloc$	0.125***	0.085***	0.041*	0.678***	0.571***
	(0.039)	(0.032)	(0.023)	(0.109)	(0.104)
$\{t \geq 2018\} \times DiffBlocs$	-0.013	-0.007	-0.005	-0.308**	-0.475**
	(0.046)	(0.038)	(0.022)	(0.152)	(0.218)
Observations	81,889	75,649	46,188	294,132	337,725
Adj. R-sq	0.141	0.185	0.015	0.870	0.912
$\{t \geq 2018\} \times \log(GeoDist)$	-0.021**	-0.006	-0.014**	-0.015	-0.019
	(0.010)	(0.009)	(0.007)	(0.031)	(0.034)
Observations	81,099	74,934	45,859	294,108	337,693
Adj. R-sq	0.145	0.186	0.015	0.870	0.911

*These regressions model the changing roles of ideological and distance factors on FDI flows between pairs of countries over time, for 2009-2023. The dependent variables are scaled by GDP of the destination country, multiplied by 1000, and winsorized. For the FDI measures, the same is restricted to country pairs reporting strictly positive FDI positions in the current and prior years, and observations with tax havens are excluded. All regressions use source-destination, source-year, and destination-year fixed effects. Standard errors are clustered by source-destination. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

By comparison, bilateral trade flows show clear and robust evidence of ideological sorting, friendshoring and derisking, but not nearshoring. Although the coefficient estimates are much larger, this reflects the generally greater magnitude of trade flows relative to FDI flows; the standardized coefficient estimates are very similar in magnitude.

Overall, FDI flows between country pairs show strong evidence of ideological sorting and nearshoring, as well as tentative evidence of friendshoring. However, derisking—reducing cross-bloc investment relative to investment involving nonaligned countries—is not apparent. These fragmentation results broadly resemble those in U.S. outward direct investment.

IV. Fragmentation in Mergers and Acquisitions

Of the three major components of FDI (debt, retained earnings, other equity), the other equity component is the most likely to show signs of fragmentation, and its most important sub-component is cross-border M&A.

IV.A. M&A Data

To test for fragmentation in cross-border M&A, we use the deals data from LSEG Data and Analytics (formerly Refinitiv).[9] This database provides microdata on M&A deals, identifying relevant information on each deal. We aggregate these into M&A flows between pairs of countries in each year, creating a structure resembling the bilateral FDI flow data in section III.

Beginning with the microdata offers several advantages over already aggregated FDI in the DIPCE data. First, we can overcome the standard investment hub misattribution problem in FDI data, as LSEG collects the locations of the target company, the acquirer, the target's ultimate parent company, and the acquirer's ultimate parent company. We can use this to reallocate M&A from the acquirer's country to the acquirer's ultimate parent country whenever these differ. Moreover, we can identify cross-border divestments as deals where the target's ultimate parent country differs from the target country (e.g., a Japanese company selling off its Chinese subsidiary).

We also conduct the source-destination-year aggregation for three subcategories of M&A to explore heterogeneity. First, we separately tabulate large M&A deals, where the deal value exceeds \$100 million, as these typically account for almost all aggregate values of M&A deals.[10] Second, we isolate horizontal M&A, where the acquirer and target are in the same (non-financial) industry, following Alfaro and Charlton (2009). Third, we consider vertical M&A, where the acquirer and target are in different (non-financial) industries. The industry definitions for horizontal and vertical M&A use the 85 midlevel industry classifications from LSEG.

However, one notable limitation comes from the discrepancy between count data and values. Not all deals report the deal value, although value coverage for large deals is more complete than for smaller deals. Moreover, the distribution of (reported) M&A deal values closely resembles a lognormal distribution, with strong skewness. This skewness is particularly important whenever the number of deals per observation is small and the law of large numbers does not apply.[11] Although deal values are the more relevant metric for FDI, count data are less noisy. For our main

---

[9] We exclude leveraged buyouts, recapitalizations, share repurchases, spinoffs, self-tender offers, and exchange offers, as in Gregoriou et al. (2021).

[10] Definitions of large deals vary. The \$100 million cutoff includes all "large" and "mega" deals across all definitions, but may include some "mid-market" deals under some definitions.

[11] Aiyar et al. (2024) and others have argued that count data are reasonably representative of FDI values, using data aggregated at the country-year level. For medium and large countries, this is generally true, but the correlation between counts and values is weak at the country-pair-year level or for small countries.

series, we use both counts and values. However, for subcomponent series with fewer observations per source-destination-year, we rely on deal counts.

Table 6 presents the summary statistics for M&A deals by source-destination-year, excluding any country pairs with no M&A between them.

Table 6. Summary Statistics for Bilateral M&A

Variable	Obs	Mean	SD	Min	Median	Max
M&A values ($m)	40675	472.884	2730.109	0	5.405	107550
M&A deal counts	159386	1.507	10.446	0	0	707
M&A deal counts (by AUP)	159386	1.843	12.656	0	0	841
Big deal counts	159386	0.182	1.485	0	0	130
Divestment counts	159386	0.696	4.433	0	0	263
Horizontal deal counts	159386	0.601	4.021	0	0	262
Vertical deal counts	159386	0.585	4.390	0	0	280
Ideal point distance	144674	1.050	0.846	2E-07	0.913	4.818
log(Geographic distance)	156276	8.394	0.999	0.693	8.676	9.894

M&A data come from LSEG Data and Analytics, 2003-2024. The first two rows—M&A values and counts—are tabulated by the country of the target and the country of the acquirer. Divestment counts are tabulated by the country of the target and the country of the target's ultimate parent company. The remaining count measures—counts (by AUP), big counts, horizontal counts, and vertical counts—are tabulated by the country of the target and the country of the acquirer's ultimate parent company. Ideal point distance is from Bailey, Strezhnev and Voeten (2017), and geographic distance is from the CEPII Gravity database.

IV.B. Fragmentation in Bilateral M&A

Table 7 repeats the regression approach from section IV, with several modifications. Instead of constructing a flow measure from positions, we use the number of M&A deals or the log value of M&A. For the regressions using count data, we use Poisson regressions (with a log link function); the coefficients should be interpreted as the changes in log-points to the expected number of deals. All regressions use source-destination, source-year, and destination-year fixed effects.

In the first column, M&A deals are tabulated by the country of the target and the country of the acquirer. The second column uses M&A deals tabulated by the country of the target and the country of the acquirer's ultimate parent company. Both metrics show evidence of ideological sorting and derisking. Correcting for the location of the acquirer's ultimate parent company produces some support for friendshoring and removes the significant "farshoring" result from the first column.

The third and fourth columns consider the value of transactions and their main driver, the number of large transactions. The number of large transactions shows very strong derisking and some evidence of ideological sorting. By comparison, M&A transaction values show no significant results, even though the coefficient estimates are of similar magnitude (and because of the log-link function, would have similar interpretations). At a sufficiently disaggregated level, M&A values may be so volatile that any regression may lack the statistical power to identify fragmentation.

Table 7. Regression Results: Bilateral M&A

Variable type	Immediate acquisitions	Ultimate acquisitions	log(Values)	Large acquistions
Regression type	Poisson	Poisson	OLS	Poisson
Fixed effects	Source-destination, source-year, destination-year			
$\{t \geq 2018\} \times IPD$	-0.031*	-0.040**	-0.047	-0.053*
	(0.016)	(0.016)	(0.065)	(0.028)
Observations	112342	115470	22301	38570
Adj. (pseudo) R-sq	0.818	0.840	0.419	0.536
Pearson dispersion	1.230	1.269	0.000	1.143
$\{t \geq 2018\} \times log(IPD)$	-0.033***	-0.029***	-0.020	-0.025
	(0.008)	(0.008)	(0.037)	(0.018)
Observations	112342	115470	22301	38570
Adj. (pseudo) R-sq	0.818	0.840	0.419	0.536
Pearson dispersion	1.229	1.269	0.000	1.143
$\{t \geq 2018\} \times SameBloc$	0.053	0.082*	-0.019	0.000
	(0.046)	(0.043)	(0.166)	(0.082)
$\{t \geq 2018\} \times DiffBlocs$	-0.275***	-0.280***	-0.401	-0.412***
	(0.081)	(0.079)	(0.277)	(0.123)
Observations	124798	128130	24728	42293
Adj. (pseudo) R-sq	0.814	0.836	0.412	0.541
Pearson dispersion	1.222	1.256	0.000	1.146
$\{t \geq 2018\} \times log(GeoDist)$	0.022**	0.012	-0.012	0.042**
	(0.011)	(0.011)	(0.045)	(0.020)
Observations	121718	125065	23612	41103
Adj. (pseudo) R-sq	0.819	0.841	0.418	0.549
Pearson dispersion	1.232	1.266	0.000	1.152

*These regressions model the changing roles of ideological and distance factors on M&A deals between pairs of countries over time, for 2003-2024. The first and third columns are tabulated by the countries of the target and the acquirer. The second column is tabulated by the countries of the target and the acquirer's ultimate parent company. The fourth column is tabulated by the countries of the target and the target's ultimate parent company. The first, second and fourth columns all use Poisson count regressions. All regressions use source-destination, source-year, and destination-year fixed effects. Standard errors are clustered by source-destination. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

The magnitudes of the coefficient estimates imply much stronger derisking behavior than ideological sorting. For example, in the first column, a one standard deviation increase in ideological distance between countries is associated since 2018 with a 2.6 percent decrease in the expected number of acquisitions (in each direction). By comparison, the coefficient estimate for derisking implies that since 2018 there has been a 24 percent decrease in the expected number of deals for countries in rival blocs (in each direction) compared to deals involving nonaligned countries.

Table 8 considers three special types of M&A that may behave differently from M&A overall. The first column of Table 7 considers the opposite of acquisitions: divestments. The results—which should display the opposite signs on the coefficient estimates if fragmentation is occurring—show some evidence of ideological sorting, and strong evidence of derisking and of nearshoring. This suggests that the nearshoring results in FDI data may reflect divestments from existing investments in distant countries rather than new investments into closer countries.

Table 8. Regression Results: Different Types of M&A

Variable type	Divestments	Horizontal M&A	Vertical M&A
Regression type	Poisson	Poisson	Poisson
Fixed effects	Source-destination, source-year, destination-year		
$\{t \geq 2018\} \times IPD$	0.046**	-0.094***	-0.028
	(0.020)	(0.021)	(0.020)
Observations	78010	75519	63961
Adj. (pseudo) R-sq	0.694		0.730
Pearson dispersion	1.217	1.228	1.201
$\{t \geq 2018\} \times log(IPD)$	0.025**	-0.041	-0.009
	(0.011)	(0.389)	(0.011)
Observations	78010	75519	63961
Adj. (pseudo) R-sq	0.694		0.730
Pearson dispersion	1.217	1.229	1.201
$\{t \geq 2018\} \times SameBloc$	0.020	0.261***	0.008
	(0.058)	(0.063)	(0.058)
$\{t \geq 2018\} \times DiffBlocs$	0.246***	-0.307***	-0.459***
	(0.081)	(0.117)	(0.102)
Observations	86808	82866	70172
Adj. (pseudo) R-sq	0.704	0.693	0.727
Pearson dispersion	1.217	1.220	1.206
$\{t \geq 2018\} \times log(GeoDist)$	0.062***	0.002	0.018
	(0.013)	(0.016)	(0.012)
Observations	84250	80576	68208
Adj. (pseudo) R-sq	0.712	0.700	0.733
Pearson dispersion	1.222	1.226	1.207

*These regressions model the changing roles of ideological and distance factors on specific types of M&A between pairs of countries over time, for 2003-2024. All measures are tabulated by the countries of the target and the acquirer's ultimate parent company. All estimations use Poisson count regressions. All regressions use source-destination, source-year, and destination-year fixed effects. Standard errors are clustered by source-destination. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Horizontal M&A shows strong evidence of ideological realignment along all three dimension of ideological sorting, friendshoring, and derisking. Horizontal acquisitions are generally intended either to expand a company's market share (by acquiring a competitor) or to reach into new markets. These results suggest firms are reducing their efforts to expand their access to new markets in rival geopolitical blocs and are instead expanding in geopolitically aligned countries.

Vertical M&A—which reflects supply chain integration—only shows evidence of derisking. This underscores the particular risks of supply chain exposure to geopolitical rivals and mirrors the diminishment of trade between the U.S. and China after 2018. The lack of friendshoring or broader ideological sorting beyond derisking likely reflects that producing in the primarily advanced economies in the U.S. bloc may not be a viable substitute to producing in China.

While derisking appears across all these types of M&A, the reactions of large and vertical transactions are notably greater in magnitude. Other forms of ideological realignment are concentrated in large and horizontal M&A, and no subcategories of M&A display nearshoring.

Tan (2024) found that fragmentation was concentrated in high-tech industries but not more broadly. To test this in M&A data, we regress M&A counts by source country, destination country, macroeconomic sector (of the acquiring company) and year on industry dummies interacted with the post-2018 indicator and the fragmentation variables as in the analyses in Tables 7 and 8. To control for the additional sectoral variation (on top of the source-destination-year variation), we use source-destination-sector, source-year, destination-year, and sector-year fixed effects. The regressions generate sector-specific estimates of each fragmentation metric, shown in Table 9. For brevity, the table only displays the coefficients and stars for statistical significance, and coefficients are normalized so that positive coefficients indicate fragmentation (i.e., coefficients on *DiffBloc*, *logDist*, and *logIPD* are multiplied by -1).

In contrast to Tan (2024), we find that fragmentation in M&A may be relatively widespread. The evidence of fragmentation is strongest in the industrials and the consumer products and services sectors, which exhibit significant derisking, friendshoring, nearshoring, and ideological sorting.

M&A from most sectors is consistent with derisking. By contrast, evidence of friendshoring is concentrated in the goods-producing sectors. Half of the sectors show signs of ideological sorting. Notably, acquisitions display more heterogeneity in terms of nearshoring, consistent with the insignificant or wrong-sign coefficients in the pooled estimates in Table 7.

When testing for fragmentation by industry, the coefficient estimates are inherently less robust for individual industries than for total M&A, an issue explored further in Appendix B. However, the widespread derisking result and friendshoring being concentrated in goods-producing industries also occur with alternative estimation approaches. By contrast, most of the nearshoring coefficients are not robust, except for the "farshoring" results for the financial and materials sectors.

Table 9. Regression Results: M&A Fragmentation, by Sector

Industry	Derisking	Friendshoring	Sorting	Nearshoring
Consumer Products & Services	0.311**	0.115***	0.168***	0.05***
Consumer Staples	0.234***	0.091*	0.044	-0.048***
Energy & Utilities	0.706***	-0.064	0.097***	0.005
Financials	0.251***	0.073	-0.057	-0.07***
Healthcare	0.098	0.023	0.065	0.068***
High Tech	0.473***	0.004	0.148***	0.007
Industrials	0.187**	0.19***	0.088**	0.021*
Materials	0.162	0.122*	0.159***	-0.06***
Median & Entertainment	0.408***	0.033	-0.005	-0.056***
Real Estate	-0.003	-0.067	0.072*	0.004
Retail	0.483***	-0.089**	0.004	-0.043***
Telecommunications	1.08***	-0.055	0.033	-0.028*

*These regressions model the changing roles of ideological and distance factors on M&A deals by industry between pairs of countries over time, for 2003-2024. All measures are tabulated by the acquirer's industry and the countries of the target and the acquirer's ultimate parent company. The derisking and friendshoring estimates come from regressing on the interaction between the post-2018 dummy and the same-bloc and different-bloc indicators. The sorting estimate comes from regressing on the post-2018 dummy interacted with ideal point distance, and the nearshoring estimate comes from regressing on the post-2018 dummy interacted with log geographic distance. All regressions use Poisson count regressions. All regressions use source-destination-industry, industry-year, source-year, and destination-year fixed effects. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels, computed using standard errors clustered by source-destination and industry. The coefficients for derisking, realignment and nearshoring have been multiplied by -1, so positive coefficients indicate fragmentation.*

IV.C. Reshoring in M&A

In principle, reshoring—shifting investment toward one's home country—would achieve all the goals of friendshoring, nearshoring and derisking. However, testing for reshoring is difficult. First, foreign direct investment datasets obviously lack comparable measures of domestic investments by entities engaging in FDI. Some aggregated datasets covering multinationals include some relevant measures, but these are often too sparse or infrequent to test for reshoring empirically. Moreover, unlike the analysis of bilateral FDI flows, testing for reshoring (comparing domestic vs foreign investment) lacks the same ability to control for push and pull factors that get absorbed by source-year and destination-year fixed effects.

To test for reshoring, we utilize the previous subsection's result that not all industries exhibit fragmentation in their M&A. We first estimate the propensity of each of 73 industries—which LSEG aggregates into the economic sectors in the previous subsection—to engage in friendshoring and derisking, in ideological sorting, and in nearshoring, using M&A counts by source-destination-industry-year, with fixed effects by source-destination-industry, source-year, destination-year, and industry-year.[12] We then interact these industry-specific fragmentation coefficient estimates with a time period dummy variable to explore whether the industries experiencing stronger fragmentation in their cross-border acquisitions since 2018 also increase their domestic M&A shares.

Table 10 reports the results of these reshoring regressions. The dependent variable is an indicator for whether a deal is domestic, defined as cases where the country of the target is same as the acquirer's ultimate parent company. Each column corresponds to a different fragmentation metric, normalized so that positive values imply fragmentation. Regressions in the top panel use country, industry and year fixed effects; those in the bottom panel use country-year and industry fixed effects.

Table 10. Regression Results: M&A Reshoring

Dependent variable	Deal-level domestic indicator			
Regression type	Logistic (binary)			
Fragmentation type	Derisking	Friendshoring	Sorting	Nearshoring
$\{t \geq 2018\} \times$ *Fragmentation*	-0.015	0.172**	0.556***	0.910**
	(0.015)	(0.087)	(0.214)	(0.376)
Fixed effects	Country, Year, Industry			
Observations	970480	970480	970480	970480
Pearson dispersion	1.006	1.006	1.006	1.006
$\{t \geq 2018\} \times$ *Fragmentation*	-0.014	0.163	0.601**	0.876**
	(0.017)	(0.107)	(0.252)	(0.397)
Fixed effects	Country * Year, Industry			
Observations	967010	967010	967010	967010
Pearson dispersion	1.007	1.007	1.007	1.007

*These regressions model potential reshoring of M&A deals by industry and country over time, for 2003-2024. The dependent variable is and indicator taking values of 1 if the target and the acquirer's ultimate parent company are in the same country, and values of 0 otherwise. The fragmentation measures are computed as in Table 10 but by detailed industry. Regressions in the top panel use country, industry and year fixed effects, and standard errors are clustered by country (of acquirer's ultimate parent) and industry (of the acquirer). Regressions in the bottom panel use country-year and industry fixed effects, and standard errors are clustered by industry. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

The significant positive coefficients indicate that industries with M&A showing greater ideological sorting, friendshoring and nearshoring after 2018 also raised their domestic shares of M&A. By contrast, these results do not hold for derisking, which appears unrelated to reshoring.

Note that the fragmentation coefficients used in this analysis are estimated and thus contain measurement error. Measurement error in the industry-level fragmentation analysis generally

[12] We use the 85 mid-level industry classification of the acquirer, excluding governments and agencies as well as all industries with insufficient cross-border M&A variation to test for derisking or friendshoring: cable, diversified financial, government-sponsored enterprises, home improvement retail, industrial conglomerates, other consumer staples, other healthcare, other media & entertainment, other telecommunications, and tobacco.

would bias the coefficient estimates in the reshoring analysis toward zero and raise the standard errors. These results should plausibly be considered lower bounds on reshoring. However, such errors could also reduce the robustness of the results; Appendix B explores this further.

In the results in Table 9, nearshoring and friendshoring were concentrated in the consumer products and services and industrials sectors, while derisking and sorting were more broadly distributed. The connection between nearshoring and friendshoring with reshoring shown in Table 10 thus suggests that the reshoring result is likely concentrated in goods-producing industries as well.

V. Fragmentation in Multinationals' Capital Expenditures

A major caveat to any FDI fragmentation results comes from mismeasurement induced by investment hubs, such as U.S. direct investments ultimately destinated for China being routed through Hong Kong or Singapore and thus not recorded as U.S. investment into China. Moreover, the official FDI measures of financial transactions with a country may not be consistent with capital investments made in the country.

In this section, we overcome these problems by analyzing the allocation of capital investments across the affiliates of multinational enterprises.

V.A. Data: Multinationals and their Foreign Affiliates

To study the activities of multinational enterprises, we draw upon two data sources (both from S&P Global Market Intelligence).

Capital IQ provides financial accounting data (balance sheet, income statement, and cash flow statement items) for private and public companies around the world. Our outcome of interest is each company's capital expenditures, a measure of physical investments (rather than financial investments) for future use in production. We control for lagged property, plant and equipment (PPE). As investments likely depend on financial factors, we also control for the firm's lagged cash-to-asset ratio and debt-to-asset ratio. We control for the firm's growth prospects using revenue growth.

We combine this with the S&P Business Entity Cross Reference Services (BECRS) file, which links each company to its ultimate parent company.[13] Using the BECRS file, we identify multinational enterprises as the ultimate parent companies with affiliates in multiple countries. We restrict our analysis to affiliates of MNEs, disregarding unitary firms (single companies, with

[13] The link in the BECRS file is based on October 1, 2016. Although this does not allow for dynamic changes in group structures from acquiring or divesting from subsidiaries, those extensive margin responses are already studied in section IV. We thus consider this analysis as a study of the intensive margin.

no separate parents or subsidiaries) and multi-subsidiary domestic enterprises (multiple affiliates of the same group, all in a single country).

Table 11 reports the summary statistics for the resulting dataset. The top panel covers foreign affiliates of MNEs, which are used when testing for ideological sorting, friendshoring, derisking, and nearshoring. The bottom panel covers all MNE affiliates, which we use when testing for reshoring.

Table 11. Summary Statistics for MNE Investment

Variable	Obs	Mean	SD	Min	Median	Max
			Foreign affiliates of multinational enterprises			
log(CapEx)	74697	1.700	2.611	-12.071	1.767	10.709
log(PPE)	74697	3.519	2.692	-13.968	3.570	11.442
Cash/Assets	74697	0.130	0.153	0.000	0.076	0.997
Leverage	74697	0.215	0.216	0.000	0.161	1.000
Revenue growth (logs)	74697	0.084	0.412	-1.764	0.061	2.172
Ideal point distance	68929	1.081	0.804	0.000	1.039	4.436
log(Geographic distance)	73995	8.276	1.191	4.007	8.675	9.885
			All affiliates of multinational enterprises			
log(CapEx)	241106	2.545	2.856	-13.823	2.645	13.705
log(PPE)	241106	4.432	2.880	-13.968	4.555	15.816
Cash/Assets	241106	0.115	0.138	0.000	0.069	0.997
Leverage	241106	0.242	0.212	0.000	0.208	1.000
Revenue growth (logs)	241106	0.086	0.395	-1.764	0.064	2.172

MNE data come from Capital IQ, 2000-2023, and multinational enterprises are identified using S&P Business Entity Cross Reference Services. The top panel includes only foreign affiliates of MNEs, and the bottom panel includes all affiliates of MNEs. Capital expenditures, PPE, cash/assets, leverage (debt/assets) and log revenue growth all come from Capital IQ, and PPE and cash/assets are lagged by one year. Ideal point distance is from Bailey, Strezhnev and Voeten (2017), and geographic distance is from the CEPII Gravity database.

V.B. Fragmentation in MNE Capital Expenditures

We test for the different types of fragmentation with specifications similar to those in sections III and IV. However, because the analysis in this section uses firm-level microdata, we employ firm-level controls and a different set of fixed effects. The data structure consists of data on company i, which is an affiliate of MNE j, in year t. In our regressions, the relevant distance and bloc variables are for the country where the company is located $c(i)$ and the country of its ultimate parent company $c(j)$.

As in sections III and IV, we use country-year fixed effects to control for all reasons a firm might invest in country $c(i)$ in year t. However, instead of source-year fixed effects, we use MNE-year fixed effects. With these fixed effects, the identifying variation in these specifications comes from how a MNE changes the allocation of its capital expenditures across countries, relative to how other companies are investing in that country.

$$\log\left(CapEx_{i,j,t}\right) = \beta_S \mathbf{1}_{\{t\geq 2018\}} IdealPointDist_{c(i),c(j),t-1} + \gamma X_{i,j,t} + \mu_{j,t} + \alpha_{c(i),t} + \epsilon_{i,j,t}$$

$$\log\left(CapEx_{i,j,t}\right) = \beta_F \mathbf{1}_{\{t\geq 2018\}} SameBloc_{c(i),c(j)} + \beta_D \mathbf{1}_{t\geq 2018} DiffBloc_{c(i),c(j)} + \mu_{j,t} + \alpha_{c(i),t} + \epsilon_{i,j,t}$$

$$\log\left(CapEx_{i,j,t}\right) = \beta_N \mathbf{1}_{\{t\geq 2018\}} \log\left(GeoDist_{c(i),c(j),t}\right) + \gamma X_{i,j,t} + \mu_{j,t} + \alpha_{c(i),t} + \epsilon_{i,j,t}$$

Table 12 reports the results of these regressions, restricting the analysis to the foreign affiliates of MNEs. We find significant evidence of ideological realignment in the allocation of capital expenditures, driven by ideological sorting and derisking but not friendshoring. The fourth column shows evidence of nearshoring in capital expenditures.

Table 12. Regression Results: Capital Expenditures by MNEs' Foreign Affiliates

Dependent variable:	log(CapEx)			
Sample	MNE foreign affiliates			
$\{t \geq 2018\}$ × *IPD*	-0.073**			
	(0.036)			
$\{t \geq 2018\}$ × *log(IPD)*		-0.033*		
		(0.017)		
$\{t \geq 2018\}$ × *SameBloc*			0.011	
			(0.084)	
$\{t \geq 2018\}$ × *DiffBlocs*			-0.443***	
			(0.130)	
$\{t \geq 2018\}$ × *log(GeoDist)*				-0.087***
				(0.026)
log(PPE)	0.837***	0.838***	0.836***	0.835***
	(0.005)	(0.005)	(0.005)	(0.005)
Cash/Assets	0.351***	0.351***	0.420***	0.381***
	(0.061)	(0.061)	(0.059)	(0.059)
Leverage	0.022	0.022	0.037	0.043
	(0.044)	(0.044)	(0.042)	(0.042)
Revenue growth	0.427***	0.427***	0.435***	0.435***
	(0.024)	(0.024)	(0.023)	(0.023)
Fixed effects	Country-year, MNE-year			
Observations	49,506	49,506	53,777	53,082
Adjusted R-squared	0.786	0.786	0.786	0.786

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the foreign affiliates of MNEs, for 2000-2023. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as is the ratio of cash to assets. Leverage is defined as the debt-to-asset ratio, constrained to be less than 1. Revenue growth is computed in logs. The U.S. agreement score is lagged by one year. All regressions use fixed effects by country-year and MNE-year. Standard errors are robust. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

The coefficient estimates imply nontrivial changes in the allocation of capital expenditures. For ideal point distance, a one standard deviation increase in the ideological distance between the subsidiary's country and its ultimate parent country is associated with 5.7 percent lower capital expenditures relative to the multinational's other affiliates and relative to other investors in that country. The implied magnitude for geographic distance is modestly larger, with 6.8 percent lower capital expenditures. By comparison, the coefficient estimate from the bloc specification implies that having the subsidiary in a rival bloc from the parent is associated with 35.8 percent lower capital expenditures since 2018.

Notably, across all these regressions, cash and revenue growth appear as significant, positive predictors of investment, but not leverage. The insignificant coefficients on leverage reflect the unusual nature of debt in multinational enterprises, where borrowing by affiliates often reflects relative tax rates and the internal capital markets of multinational groups (Desai, Foley and Hines, 2005).

Appendix B explores the sensitivity and robustness of these results. These results are moderately robust to replacing the MNE-year fixed effects with MNE fixed effects as well as to excluding U.S. multinationals, although this reduces the magnitude of the coefficients. When using 2022 as the cutoff instead of 2018, the derisking coefficient becomes larger in magnitude, but the other coefficient estimates shrink. We can also compare larger MNEs, defined as those with annual consolidated revenue of at least $2 billion as in the Forbes Global 2000, against smaller MNEs, which generally have fewer foreign affiliates and are less geographically diversified. Smaller MNEs exhibit stronger ideological sorting and friendshoring but not derisking. Small MNEs do not exhibit significant nearshoring, although this may reflect their relatively limited capacity to shift activity across their few foreign affiliates.

The analysis above focused on the reallocation of capital expenditures between foreign subsidiaries of a multinational group. We now consider the allocation of capital expenditures across domestic vs. foreign affiliates of the MNE, using the following specification. As before, we use country-year and MNE-year fixed effects, and we add fixed effects for the affiliate type (foreign subsidiary, domestic subsidiary, parent company). The coefficient β_R measures how much MNEs have increased their domestic capital expenditures, relative to their foreign capital expenditures and relative to the investments in the MNE's home country by foreign multinationals.

$$\log\left(CapEx_{i,j,t}\right) = \beta_R \mathbf{1}_{\{t\geq 2018\}} \mathbf{1}_{\{c(i)=c(j)\}} + \gamma X_{i,j,t} + \mu_{j,t} + \alpha_{c(i),t} + \theta_{type(i)} + \epsilon_{i,j,t}$$

Table 13 reports the results of this regression. We obtain significant positive estimates of β_R. In the second column, this result also holds when excluding U.S. multinationals, indicating that reshoring is a worldwide phenomenon. The effect is concentrated in large multinationals (revenue of at least $2b), with insignificant results for small MNEs. When using 2022 as the cutoff instead of 2018, the coefficient estimates are larger, but not significantly larger (not shown).

Table 13. Regression Results: Reshoring in MNE Capital Expenditures

Dependent variable	log(CapEx)			
Included entities	All MNE affiliates			
Subsample	All	No US MNEs	Big MNEs	Small MNEs
$\{t \geq 2018\}$ × *Domestic*	0.098***	0.096***	0.119***	0.060
	(0.022)	(0.026)	(0.029)	(0.054)
log(PPE)	0.855***	0.847***	0.877***	0.804***
	(0.002)	(0.003)	(0.003)	(0.005)
Cash/Assets	0.600***	0.685***	0.454***	0.643***
	(0.031)	(0.038)	(0.044)	(0.059)
Leverage	0.012	0.028	-0.029	0.029
	(0.020)	(0.024)	(0.029)	(0.040)
Revenue growth	0.483***	0.487***	0.485***	0.448***
	(0.012)	(0.014)	(0.020)	(0.021)
Fixed effects	Country-year, MNE-year, affiliate type			
Observations	240,781	191,344	103,404	69,955
Adjusted R-squared	0.844	0.829	0.870	0.771

*These regressions domestic allocation of capital expenditures by all affiliates of MNEs, for 2000-2023. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as is the ratio of cash to assets. Leverage is defined as the debt-to-asset ratio, constrained to be less than 1. Revenue growth is computed in logs. All regressions use fixed effects by country-year and MNE-year, as well as affiliate type fixed effects (foreign subsidiary, domestic subsidiary, parent company). Standard errors are robust. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

VI. Discussion and Conclusion

Foreign direct investment is shifting along ideological and geographic lines, summarized in Table 14. Financial transaction measures of FDI, either U.S. outward FDI or bilateral FDI flows (even excluding the U.S.), exhibit recent signs of ideological sorting and nearshoring. Cross-border M&A deals exhibit strong evidence of derisking, as well as broad ideological realignment of horizontal (within-industry) M&A. Moreover, M&A in industries that engaged in nearshoring and friendshoring (primarily goods-producing industries) also exhibited increases in their domestic M&A shares. The allocation of capital investment by multinational enterprises displays ideological and geographic realignment, through ideological sorting, derisking, nearshoring, and reshoring.

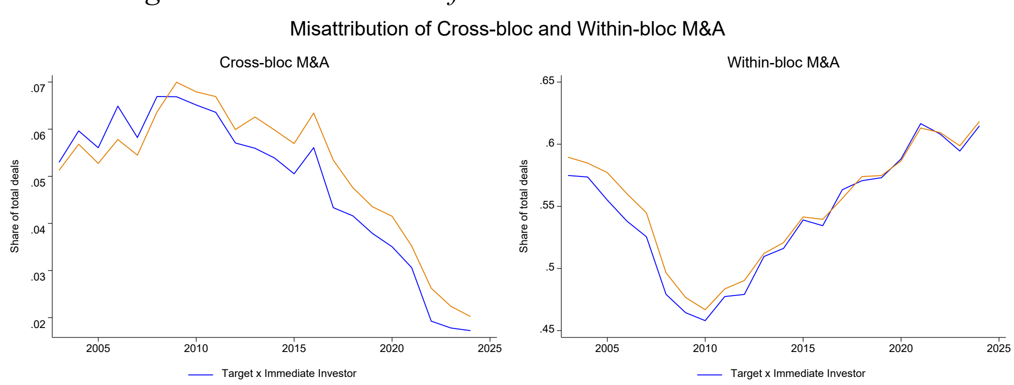
This analysis reveals substantial heterogeneity in how different forms of cross-border investments respond to new geopolitical risks. The financial transaction approach to measuring FDI—which includes new equity-financed investments, but also reinvested earnings and intra-firm debt—displays fragmentation differently from more direct measures of investment, such as capital expenditures and M&A. And, while some types of fragmentation (friendshoring) may be concentrated in specific goods-producing sectors, other types of fragmentation appear in many datasets and across many industries.

Table 14. Summary of the Fragmentation Results

	Ideological sorting	Derisking	Friendshoring	Nearshoring	Reshoring
Financial transactions					
U.S. outward FDI	Yes	No	Maybe	Yes	
Bilateral FDI	Yes	No	Maybe	Yes	
Equity-financed	Yes	No	Yes	Yes	
Debt-financed	Yes	No	No	Yes	
M&A	Yes	Yes	No	No	Yes
Large M&A deals	Yes	Yes	No	No	
Horizontal M&A	Yes	Yes	Yes	No	
Vertical M&A	No	Yes	No	No	
Divestments	Yes	Yes	No	Yes	
MNE CapEx	Yes	Yes	No	Yes	Yes

Notably, financial measures of FDI show no evidence of derisking (cross-bloc flows), despite significant, robust, and economically large reductions in cross-bloc M&A and capital investments. This puzzle may occur due to the role of investment hubs in cross-bloc FDI and the misattribution problem in financial FDI measures, whereby a U.S.-to-China (cross-bloc) investment implemented using a Singaporean affiliate would be counted as U.S.-to-Singapore and Singapore-to-China (nonaligned). The magnitude of this problem is difficult to assess in general, but Figure 3 explores this problem using our M&A data. The left panel plots the aggregate number of cross-bloc M&A deals as a share of total worldwide deals each year, which began to decline sharply in the late 2010s. The blue line assigns the cross-bloc status using the country of the target and the country of the acquirer, whereas the orange line uses the country of the acquirer's ultimate parent company. Since around 2010, the gap between these lines represents the number of deals that would be erroneously assigned to the nonaligned category in the bloc regressions, and the gap has decreased during the fragmentation period. By contrast, since 2012, within-bloc M&A has not suffered from this misattribution problem, with the immediate and ultimate assignments moving in tandem.

Figure 3. Misattribution of Cross-bloc and Within-bloc M&A



Source: LSEG Data and Analytics, and author's calculations.

In the bloc regression specification, identification of derisking comes from the comparison of cross-bloc deals to those involving nonaligned countries; with misattribution, some of the decrease in cross-bloc M&A would be erroneously attributed to the nonaligned category, mechanically raising the estimated coefficients on the cross-bloc indicator and on the within-bloc indicator. This bias would make it more difficult to detect derisking, as well as implying possible friendshoring even if that is not occurring.

A changing landscape for foreign direct investment may have important implications going forward. Reduced direct investments could reduce productivity spillovers and growth for developing countries, along with production inefficiencies for firms reacting to geopolitical risks (Adarov and Pallan, 2025). These losses may be especially severe for developing countries that rely heavily on FDI (IMF Research Department, 2023).

However, just as the FDI landscape has changed from the pre-2018 era, the post-2018 landscape may be reshaping anew. Amid elevated uncertainty and trade pressures in 2025, these new risks may deepen or redirect the fragmentation already in motion.

References

Adarov, Amat, and Hayley Pallan (2025). “Foreign Direct Investment in Retreat: Policies to Turn the Tide,” in World Bank, 2025, “Global Economic Prospects: June 2025,” Washington DC: World Bank Group.

Airaudo, Florencia, Francois De Soyres, Keith Richards, and Ana Maria Santacreu (2025). “Measuring Geopolitical Fragmentation: Implications for Trade, Financial Flows, and Economic Policy,” International Finance Discussion Papers no. 1408, Board of Governors of the Federal Reserve System.

Aiyar, Shekhar, Anna Ilyina, and others (2023). "Geoeconomic Fragmentation and the Future of Multilateralism," International Monetary Fund Staff Discussion Note SDN/2023/001.

Aiyar, Shekhar, Davide Malacrino, and Andrea Presbitero (2024). “Investing in friends: The role of geopolitical alignment in FDI flows,” *European Journal of Political Economy* 83.

Alfaro, Laura, and Andrew Charlton (2009). “Intra-industry Foreign Direct Investment,” *American Economic Review* 99(5), pp. 2096-2119.

Bailey, Michael, Anton Strezhnev and Eric Voeten (2017). “Estimating Dynamic State Preferences from United Nations Voting Data,” *The Journal of Conflict Resolution* 62(2), pp. 430-456.

Blonigen, Bruce and Jeremy Piger (2014). “Determinants of foreign direct investment,” *The Canadian Journal of Economics* 47(3), pp. 775-812.

Caldara, Dario and Matteo Iacoviello (2022). “Measuring Geopolitical Risk,” *American Economic Review* 112(4), pp. 1194-1225.

Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo (2020). “The Economic Effects of Trade Policy Uncertainty,” *Journal of Monetary Economics* 109, pp. 38-59.

Catalán, Mario, Salih Fendoglu, and Tomohiro Tsuruga (2024). “A Gravity model of Geopolitics and Financial Fragmentation,” IMF Working Paper no. 2024/196, https://doi.org/10.5089/9798400280337.001 .

Cerdeiro, Diego A., Johannes Eugster, Rui C. Mano, Dirk Muir, and Shanaka J. Peiris (2021). "Sizing Up the Effects of Technological Decoupling," International Monetary Fund Working Paper 21/69.

Conte, Maddalena, Pierre Cotterlaz and Thierry Mayer (2022). “The CEPII Gravity database,” CEPII Working Paper no. 2022-05.

Correa, Ricardo, Julian di Giovanni, Linda Goldberg, and Camelia Minoiu (2023). "Trade Uncertainty and U.S. Bank Lending," International Finance Discussion Papers no. 1383, Board of Governors of the Federal Reserve System, https://doi.org/10.17016/IFDP.2023.1383.

Desai, Mihir, C. Fritz Foley, and James Hines (2005). "A Multinational Perspective on Capital Structure Choice and Internal Capital Markets," *Journal of Finance* 59(6), pp. 2451-2487.

Faber, Marius, Kemal Kilic, Gleb Kozliakov, and Dalia Marin (2025). "Global value chains in a world of uncertainty and automation," *Journal of International Economics* 155.

Felbermayr, Gabriel, Hendrik Mahlkow, and Alexander Sandkamp (2023). "Cutting through the value chain: the long-run effects of decoupling the East from the West." *Empirica* 50, pp. 75–108, https://doi.org/10.1007/s10663-022-09561-w.

Fernández-Villaverde, Jesús, Tomohide Mineyama, and Dongho Song (2024). "Are We Fragmented Yet? Measuring Geopolitical Fragmentation and Its Causal Effect," NBER working paper no. 32638.

Gopinath, Gita, Pierre-Olivier Gourinchas, Andrea Presbitero and Petia Topalova (2025). "Changing global linkages: A new Cold War?" *Journal of International Economics* 153.

Gregoriou, Andros, Binh Duy Nguyen, Tung Duy Nguyen, Huong Le, and Robert Hudson (2021). "Economic policy uncertainty and cross-border mergers and acquisitions," *International Review of Financial Analysis* 78.

International Monetary Fund. Direct Investment Positions by Counterpart Country, https://data.imf.org/en/datasets/IMF.STA:IMTS.

International Monetary Fund. International Trade in Goods by Partner Country, https://data.imf.org/en/datasets/IMF.STA:IMTS.

International Monetary Fund Research Department (2023). "Chapter 4. Geoeconomic Fragmentation and Foreign Direct Investment." In *World Economic Outlook, April 2023: A Rocky Recovery*, International Monetary Fund, https://doi.org/10.5089/9798400224119.081.CH004.

Javorcik, Beata, Lucas Kitzmüller, Helena Schweiger, and Muhammed Yıldırım (2024). "Economic costs of friendshoring," *The World Economy*, vol. 47 no. 7, pp. 2871–2908, https://doi.org/10.1111/twec.13555.

Kallen, Cody (2025). "How is Geopolitical Fragmentation Reshaping U.S. Foreign Direct Investment?" FEDS Notes, https://doi.org/10.17016/2380-7172.3764.

Londono, Juan, Sai Ma, and Beth Anne Wilson (2025). "Costs of Rising Uncertainty," FEDS Notes, https://doi.org/10.17016/2380-7172.3779.

LSEG Data & Analytics. SDC Platinum SFTP Feed and Workspace for Investment banking with Deals Module, http://www.thomsonone.com.

Reyes-Heroles, Ricardo, Sharon Traiberman, and Eva Van Leemput (2020). "Emerging Markets and the New Geography of Trade: The Effects of Rising Trade Barriers," *IMF Economic Review*, vol. 68 no. 3, pp. 456-508, September.

Smolyansky, Michael, Gustavo Suarez, and Alexandra Tabova (2019). "U.S. Corporations' Repatriation of Offshore Profits: Evidence from 2018," FEDS Notes. Washington DC: Board of Governors of the Federal Reserve System.

Strahan, Matt, Ole Moehr, and Daniel Tannebaum (2025). "Navigating Global Financial System Fragmentation," World Economic Forum Insight Report, January, https://reports.weforum.org/docs/WEF_Navigating_Global_Financial_System_Fragmentation_2025.pdf.

Sullivan, Jake (2023). "Renewing American Economic Leadership," Brookings Institution, April 27.

S&P Global Market Intelligence. Business Entity Cross Reference Services, https://marketintelligence.spglobal.com/client-solutions/data/reference-data/cross-reference-services.

S&P Global Market Intelligence. Capital IQ Platform, Wharton Research Data Services, http://wrds.wharton.upenn.edu/.

Tan, Joanne (2024). "How Widespread is FDI Fragmentation?" IMF Working Paper no. 2024/179, https://www.imf.org/en/Publications/WP/Issues/2024/08/16/How-Widespread-is-FDI-Fragmentation-551132.

Timmer, Marcel, Bart Los, Robert Stehrer, and Gaaitzen Vries (2021). "Supply Chain Fragmentation and the Global Trade Elasticity: A New Accounting Framework," *IMF Economic Review*, vol 69 no. 4, pp. 656-680, December.

"World Development Indicators", the World Bank, Washington, DC.

Appendix A. Data Construction

Data Preparation: U.S. Foreign Investment

The data on U.S. Direct Investment Abroad come from the BEA's U.S. Direct Investment Abroad data, specifically the annual country detail tables 2009-2019 and 2020-2023. These report positions on a historical cost basis, financial transactions for FDI, and FDI income. Observations with (*)—which are coded for nonzero values that round to zero—are recoded as zero. We scale transactions and income by the lagged FDI position, winsorized at the 5th and 95th percentiles.

For the U.S. agreement score, this comes from Bailey, Strezhnev and Voeten (2017), specifically their ideal point estimates file as of June 2024. The U.S. bloc is defined as the U.S., Canada, Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, Sweden, United Kingdom, Australia, New Zealand, Japan, Israel, South Korea and Taiwan. The China bloc consists of China, Russia, Belarus, Hong Kong, Macau, Eritrea, Mali, Nicaragua and Syria. We extend the agreement scores and blocs to subsidiary countries—Antigua, Bermuda, Gibraltar, Aruba, Curacao, Netherlands Antilles, Sint Maarten, Hong Kong, Macau, French Guiana, Saint Pierre and Miquelon, Greenland, and the Cook Islands—from their respective sovereigns—United Kingdom, the Netherlands, China, France, Denmark and New Zealand. These blocs are similar to the narrow blocs in Gopinath et al. (2025); we include Hong Kong and Macau in the China bloc, and we include several Asian countries in the U.S. while excluding some European countries that may not align well with the U.S.

Geographic distance and exports to the U.S. come from the CEPII Gravity database from November 2022. We use the distance between the main cities of each country. Because the dataset is not populated for all years, and this measure rarely changes from year to year, we take the average distance between each pair of countries, and we use that constant (over time) measure instead.

We compute exports to the U.S. as the average of the four measures of them: data from Comtrade or the IMF, and reporting from the destination and the origin country.

From the World Bank's World Development Indicators, we get GDP, GDP growth, population, imports and exports from BOP and national accounts, trade as a percent of GDP, net inward FDI, the rule of law measure, inflation measures, the exchange rate (LCU per USD) and gross fixed capital formation as a percent of GDP. For the regressions, we compute openness as exports plus imports (averaging across the BOP and NA measures) divided by GDP, filling in any missing values with the trade/GDP measure. We also compute the log change in the exchange rate (depreciation), and we compute total inward FDI as a share of GDP. We winsorize openness, inflation, GDP growth and exchange rate change at the 95h and 95th percentiles.

The tables below report the allocation across blocs and over periods for the USDIA dataset (all observations in the regressions).

Sample Allocation: U.S. Direct Investment Abroad

	2009-17	2018-21	2022-23	Total
US bloc	12.06	6.20	3.04	21.30
China bloc	2.99	1.21	0.69	4.88
Nonaligned	43.05	20.61	10.16	73.83
Total	58.09	28.01	13.89	100

Data Preparation: Bilateral FDI

Our data on bilateral FDI positions come from the IMF's Direct Investment Positions by Counterpart Country, formerly known as the Coordinated Direct Investment Survey. This reports bilateral FDI positions, overall, by debt and equity, and by directly reported positions or derived from reporting by the counterpart country. We average across the directly reported and derived positions. Negative positions are replaced as missing values. The flow measure is computed as the change in positions divided by the sum of the current and past positions, which by construction falls between -1 and 1 (and thus does not need to be winsorized). We also compute FDI flows scaled by GDP of the destination country, measured using the change in the FDI position, and winsorizing at the 5th and 95th percentiles.

For bilateral trade in goods, we use the IMF's International Trade in Goods by Partner Country, formerly known as the Direction of Trade Statistics. We scale exports and imports (cost in freight) by GDP of the destination country. We recode negative values as missing, and we winsorize at the 1st and 99th percentiles.

We obtain the ideal point distance measure from Bailey, Strezhnev and Voeten (2017), in the June 2024 file. We construct blocs and assign values so subsidiary countries as above.

We obtain GDP from the World Development Indicators, and geographic distance from the CEPII Gravity database with the same constant metric as above.

The table below reports the sample allocation across periods and blocs for observations included in the regressions.

Sample Allocation: Bilateral FDI

	2009-17	2018-21	2022-23	Total
Within US bloc	1.28	0.57	0.28	2.13
Within China bloc	0.06	0.03	0.01	0.10
Different blocs	0.66	0.29	0.15	1.10
With nonaligned	56.91	26.62	13.14	96.66
Total	58.92	27.51	13.58	100

Data Preparation: Bilateral M&A

The M&A data come from LSEG Data and Analytics (formerly Refinitiv/SDC). We follow Gregoriou et al. (2021) in excluding leveraged buyouts, recapitalizations, repurchases, spinoffs, self-tenders, and exchange offers, as these are fundamentally different from most M&A. We also exclude withdrawn deals.

We identify large M&A deals as those with values of at least $100 million. Horizontal M&A consists of deals where the acquirer and the target are in the same mid-level industry (85 industries). Vertical M&A is defined as those in different industries. Both horizontal and vertical M&A deals exclude those involving firms in the financial sector.

Immediate acquisitions (and values) are computed by summing up the number and value of transactions between the country of the acquirer and the country of the target by year. Ultimate transactions are computed by summing between the country of the acquirer's ultimate parent company and the country of the target by year. Large, horizontal and vertical M&A are tabulated like the ultimate transaction counts. Divestments are obtained by tabulating between the country of the target and the country of the target's ultimate parent company by year.

For the dataset of acquisitions by industry, we tabulate by country of the target, country of the acquirer's ultimate parent company, macro-level industry classifier (13, after dropping Government and Agencies) and year.

We restrict the sample to 2003-2024. Coverage before 2003 is spotty, and 2025 is incomplete.

Ideal point distance, blocs, and geographic distance come from Bailey, Strezhnev and Voeten (2017) and the CEPII database as above.

The table below reports the sample allocation across periods and blocs for M&A data.

Sample Allocation: M&A Flows

	2003-17	2018-21	2022-24	Total
Within US bloc	5.73	1.53	1.05	8.30
Within China bloc	0.13	0.04	0.02	0.19
Different blocs	1.70	0.46	0.25	2.41
With nonaligned	63.15	17.26	8.69	89.10
Total	70.71	19.28	10.01	100

To test for reshoring, we first produce tabulations of M&A deals by country of the target, target of the acquirer's ultimate parent company, the acquirer's mid-level industry, and year. We exclude governments and agencies, as well as industries without enough variation to run the bloc regressions (discovered via trial-and-error). After estimate fragmentation coefficients (see Appendix B for more details) by industry, we merge these into the micro-level data (not tabulating, but excluding undesired deals as above), and we flag deals as domestic if the country of the target is the same as the country of the acquirer's ultimate parent company.

Data Preparation: MNEs

The MNE dataset is built from two sources provided by S&P: firm-level financial data from Capital IQ firm industry and ownership data from the Business Entity Cross Reference Services.

For each company in CapitalIQ, we obtain total assets, cash, net property, plant and equipment, revenue, total debt and capital expenditures.[14] We use data for 2000-2023. We recode zero or negative asset values as NA. We also do this for negative values of PPE, as well as debt reported as either negative or greater than total assets. We also recode as NA any anomalous or impossible values for capital expenditures: when total capital expenditures exceed end-period PPE and when total capital expenditures are less than the change in PPE (implying negative depreciation).

Although our main dependent variable is the log of capital expenditures (controlling for lagged PPE), we also consider the ratio of capital expenditures to lagged PPE, winsorized at the 5th and 95th percentiles. We define leverage as the ratio of debt to assets; because we have excluded negative debt and debt greater than assets, we do not need to winsorize this ratio. We also compute the cash-to-asset ratio, winsorized at the 1st and 99th percentiles. We compute revenue growth as the log change in revenue from the prior year, winsorized at the 1st and 99th percentiles.

The BECRS data links a large set of companies around the world (more than 30 million) to their ultimate parent companies. It also provides each company's country and their internal industry code. We identify multinationals as the ultimate parent companies with at least two affiliates in at least two different countries. We use this link to obtain each company's ultimate parent country and ultimate parent industry. We identify foreign subsidiaries as those in countries that differ from their ultimate parent country. Domestic subsidiaries are in the same country as the ultimate parent, but are not their own ultimate parent.

Ideal point distance, blocs, and geographic distance come from Bailey, Strezhnev and Voeten (2017) and the CEPII database as above. We classify firms into blocs similarly as in the other analyses, but using the ultimate parent country as the source country. The table below reports the sample allocation across periods and blocs for the MNE data. Notably, the sample is far more heavily weighted toward the U.S. bloc (which includes many European countries) than the bilateral FDI and M&A panels.

[14] In Capital IQ, capital expenditures are pulled from the cash flow statement and enter with a negative sign as a negative cash flow. We correct for this by multiplying the Capital IQ variable by -1.

Sample Allocation: MNE Data

	2000-17	2018-23	Total
Within US bloc	35.79	8.95	44.74
Within China bloc	2.44	1.23	3.67
Different blocs	2.49	0.77	3.26
With nonaligned	35.38	12.95	48.33
Total	76.09	23.91	100

Appendix B. Robustness and Sensitivity Analysis

Sensitivity and Robustness: Financial Transaction Measure of FDI

Table B.1 tests the sensitivity of ideological sorting results for U.S. outward direct investment. The result is robust to using the current-year measure of agreement with the U.S. instead of the lagged value and to using a log transformation to address potential nonlinearity. In the third column, it is robust to including the tax havens. The fourth column keeps the tax havens but uses 2022 as the cutoff year instead of 2018; the weaker result likely reflects the lower power from using only two years of data for the post period. The last column excludes 2018 and 2019, as those years featured anomalously negative FDI outflows due to a wave of repatriations in the aftermath of the Tax Cuts and Jobs Act's elimination of the repatriation tax penalty.

Table B.1. Robustness Results for Ideological Sorting in U.S. Direct Investment Abroad

Dependent variable	U.S. Outward FDI Transactions/Position				
Sample	Main	Main	Include havens	Include havens	Exclude 2018-19
$\{t \geq 2018\} \times USAgree_{t-1}$			0.103**		0.109**
			(0.044)		(0.049)
$\{t \geq 2018\} \times USAgree_{t}$	0.119***				
	(0.044)				
$\{t \geq 2018\} \times log(USAgree_{t-1})$		0.037**			
		(0.015)			
$\{t \geq 2022\} \times USAgree_{t-1}$				0.078*	
				(0.047)	
FDI income/Position	0.981***	0.982***	0.992***	0.994***	0.967***
	(0.063)	(0.064)	(0.062)	(0.062)	(0.070)
GDP growth	-0.001	-0.001	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ΔExchange rate	-0.038	-0.039	-0.028	-0.036	0.025
	(0.077)	(0.077)	(0.074)	(0.074)	(0.081)
Trade openness	0.032	0.034	0.034	0.038	0.034
	(0.046)	(0.046)	(0.042)	(0.042)	(0.049)
Fixed effects	Country, year				
Observations	1,559	1,557	1,726	1,726	1,328
Adj. R-sq	0.376	0.376	0.380	0.378	0.373

*These regressions model the changing roles of ideological distance for U.S. FDI abroad, for 2009-2023. The dependent variable is the ratio of FDI transactions for outward FDI to the lagged FDI position; the lagged position is also used in the FDI income ratio. Tax havens are excluded from columns 1, 2 and 5. All regressions use fixed effects by country and by year. Standard errors are clustered by country. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Table B2 repeats this exercise for the nearshoring result. This result is robust to using linear geographic distance instead of the log, to including tax havens, to using 2022 as the cutoff year, and to excluding 2018 and 2019.

Table B.2. Robustness Results for Nearshoring in U.S. Direct Investment Abroad

Dependent variable	U.S. Outward FDI Transactions/Position			
Sample	Main	Include havens	Include havens	Exclude 2018-19
$\{t \geq 2018\} \times log(GeoDist)$		-0.020*		-0.032**
		(0.012)		(0.014)
$\{t \geq 2018\} \times GeoDist$	-4.947***			
	(1.891)			
$\{t \geq 2022\} \times log(GeoDist)$			-0.028**	
			(0.014)	
FDI income/Position	0.986***	0.998***	0.997***	0.975***
	(0.063)	(0.062)	(0.062)	(0.070)
GDP growth	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
ΔExchange rate	-0.035	-0.028	-0.026	0.027
	(0.076)	(0.073)	(0.074)	(0.080)
Trade openness	0.042	0.044	0.041	0.041
	(0.045)	(0.041)	(0.042)	(0.048)
Fixed effects	Country, year			
Observations	1,572	1,739	1,739	1,340
Adj. R-sq	0.374	0.378	0.378	0.373

*These regressions model the changing roles of geographic distance for U.S. FDI abroad, for 2009-2023. The dependent variable is the ratio of FDI transactions for outward FDI to the lagged FDI position; the lagged position is also used in the FDI income ratio. Tax havens are excluded from columns 1 and 4. All regressions use fixed effects by country and by year. Standard errors are clustered by country. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Note that the bloc results for friendshoring and derisking in U.S. outward FDI are not robust in general.

Tables B.3 and B.4 conduct the sensitivity analyses for ideological sorting and nearshoring in worldwide bilateral FDI flows in Table 5. The results are robust to using 2022 as the cutoff year, to including tax havens, to excluding the U.S. and China (or just one at a time, not shown), and to using linear distance instead. These results are also robust to scaling FDI flows by their lagged position instead.

Note, however, that when scaling by FDI flows by GDP, as in Table 5, the results are not robust to the treatment of tax havens or to the cutoffs using when winsorizing. That lack of robustness occurs because FDI flows generally scale with the lagged FDI position; controlling for the lagged position, source-country GDP and destination-country GDP have little importance or explanatory power for the scale of FDI flows. For these reasons, we prefer the approach and results in Table 4 over those in Table 5.

Table B.3. Robustness Results for Ideological Sorting in FDI Worldwide

Variable type	All DI		
Sample	Main	Include havens	Exclude US & China
Fixed effects	Source-destination, source-year, destination-year		
$\{t \geq 2018\} \times IPD$		-0.015***	-0.016***
		(0.003)	(0.004)
$\{t \geq 2022\} \times IPD$	-0.015***		
	(0.005)		
Observations	87,211	112,382	80,185
Adj. R-sq	0.051	0.048	0.050

*These regressions model the changing roles of ideological distance on FDI flows between pairs of countries over time, for 2009-2023. The dependent variable is constructed from the change in FDI position divided by the sum of the old and new positions. Country pairs with tax havens are excluded from the first and third columns. All regressions use source-destination, source-year, and destination-year fixed effects. Standard errors are clustered by source-destination. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Table B.4. Robustness Results for Nearshoring in FDI Worldwide

Variable type	All DI			
Sample	Main	Main	Include havens	Exclude US & China
Fixed effects	Source-destination, source-year, destination-year			
$\{t \geq 2018\} \times log(GeoDist)$			-0.026***	-0.031***
			(0.002)	(0.003)
$\{t \geq 2018\} \times GeoDist$		-6.914***		
		(0.805)		
$\{t \geq 2022\} \times log(GeoDist)$	-0.031***			
	(0.004)			
Observations	91,394	76,731	119,677	84,156
Adj. R-sq	0.053	0.049	0.051	0.052

*These regressions model the changing roles of ideological distance on FDI flows between pairs of countries over time, for 2009-2023. The dependent variable is constructed from the change in FDI position divided by the sum of the old and new positions. Country pairs with tax havens are excluded from the first and third columns. All regressions use source-destination, source-year, and destination-year fixed effects. Standard errors are clustered by source-destination. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Sensitivity and Robustness: M&A

We explore the sensitivity of the M&A reshoring results to alternative approaches. The data are the number of M&A transactions $X_{d,s,i,t}$, tabulated by the target's country (*d*), the acquirer's ultimate parent's country (*s*), the acquirer's industry (*i*), and the year (*t*). To estimate alignment, derisking, friendshoring, and nearshoring for the main specifications, we run the following regressions. These specifications use fixed effects for source-destination-industry, industry-year, destination-year, and source-year.

$$\log E[\ X_{d,s,i,t}] = -\alpha_i^d 1_{\{t\geq 2018\}} DiffBlocs_{d,s} + \alpha_i^f 1_{\{t\geq 2018\}} SameBloc_{d,s} + \mu_{d,s,i} + \gamma_{i,t} + \phi_{d,t} + \psi_{s,t}$$

$$\log E[\ X_{d,s,i,t}] = -\alpha_i^s 1_{\{t\geq 2018\}} IDP_{d,s,t-1} + \mu_{d,s,i} + \gamma_{i,t} + \phi_{d,t} + \psi_{s,t}$$

$$\log E[\ X_{d,s,i,t}] = -\alpha_i^n 1_{\{t\geq 2018\}} \log GeoDist_{d,s} + \mu_{d,s,i} + \gamma_{i,t} + \phi_{d,t} + \psi_{s,t}$$

However, we could instead use more or fewer fixed effects. The following alternative specifications use more fixed effects, by source-destination-industry, destination-industry-year, and source-industry-year, equivalent to running the main specification separately for each industry.

$$\log E[\ X_{d,s,i,t}] = -\hat{\alpha}_i^d 1_{\{t\geq 2018\}} DiffBlocs_{d,s} + \hat{\alpha}_i^f 1_{\{t\geq 2018\}} SameBloc_{d,s} + \hat{\mu}_{d,s,i} + \hat{\phi}_{d,i,t} + \hat{\psi}_{s,i,t}$$

$$\log E[\ X_{d,s,i,t}] = -\hat{\alpha}_i^s 1_{\{t\geq 2018\}} IPD_{d,s,t-1} + \hat{\mu}_{d,s,i} + \hat{\phi}_{d,i,t} + \hat{\psi}_{s,i,t}$$

$$\log E[\ X_{d,s,i,t}] = -\hat{\alpha}_i^n 1_{\{t\geq 2018\}} \log GeoDist_{d,s} + \hat{\mu}_{d,s,i} + \hat{\phi}_{d,i,t} + \hat{\psi}_{s,i,t}$$

The use of more fixed effects in these specifications controls for country-industry-specific push and pull factors, but reduces the variation available to identify the coefficients of interest, resulting in more noise. Alternatively, we could use fewer fixed effects, as in the specifications below, which do not control for source-destination-industry fixed effects.

$$\log E[\ X_{d,s,i,t}] = -\tilde{\alpha}_i^d 1_{\{t\geq 2018\}} DiffBlocs_{d,s} + \tilde{\alpha}_i^f 1_{\{t\geq 2018\}} SameBloc_{d,s} + \tilde{\mu}_{d,s} + \tilde{\gamma}_{i,t} + \tilde{\phi}_{d,t} + \tilde{\psi}_{s,t}$$

$$\log E[\ X_{d,s,i,t}] = -\tilde{\alpha}_i^s 1_{\{t\geq 2018\}} IPD_{d,s,t-1} + \tilde{\mu}_{d,s} + \tilde{\gamma}_{i,t} + \tilde{\phi}_{d,t} + \tilde{\psi}_{s,t}$$

$$\log E[\ X_{d,s,i,t}] = -\tilde{\alpha}_i^n 1_{\{t\geq 2018\}} \log GeoDist_{d,s} + \tilde{\mu}_{d,s} + \tilde{\gamma}_{i,t} + \tilde{\phi}_{d,t} + \tilde{\psi}_{s,t}$$

Finally, the coefficient estimates for each industry may not be equally well-identified across industries. To address this, we can also consider using the t-statistics of the coefficient estimates instead of the estimates themselves.

Table B.5 reports the mean and median of each measure of fragmentation, as well as the correlation between that measure and the one used in our main analysis. Consistent with Table 9, derisking coefficient estimates are broadly positive across industries, while coefficient estimates for other types of fragmentation are less robustly positive. Estimates obtained using more fixed effects are much noisier and not strongly correlated with the other measures.

Table B.6 reports the regression results for reshoring using these alternative fragmentation measures. The results from Table 11 are robust to using t-statistics instead of coefficient estimates. However, coefficient estimates obtained using different fixed effects have somewhat different implications. Those obtained using more fixed effects (better control of industry push/pull factors, less residual variation for identification) suggest that derisking and ideological sorting are associated with reshoring. Estimates obtained using fewer fixed effects (less control of industry push/pull factors, more residual variation for identification) suggest that ideological sorting of cross-border M&A is associated with reshoring, but not the other types of fragmentation.

Table B.5. Fragmentation Summary Statistics by Detailed Industry

	Mean	StdDev	Main corr
	Derisking		
Main specification	0.814	2.072	1
More fixed effects	2.260	15.887	0.4284
Fewer fixed effects	0.851	2.326	0.9725
t-statistics	4.651	16.668	0.9589
	Friendshoring		
Main specification	-0.026	0.270	1
More fixed effects	0.874	19.644	0.136
Fewer fixed effects	0.126	0.414	0.2504
t-statistics	-0.130	2.657	0.9677
	Ideological Sorting		
Main specification	0.051	0.148	1
More fixed effects	4.633	33.290	0.1497
Fewer fixed effects	0.115	0.170	0.2885
t-statistics	0.859	2.270	0.9619
	Nearshoring		
Main specification	-0.011	0.093	1
More fixed effects	0.076	4.792	0.1742
Fewer fixed effects	0.020	0.118	0.0911
t-statistics	-0.362	2.150	0.9468

Table B.6. Robustness Results for Reshoring

Dependent variable	Deal-level domestic indicator			
Regression type	Logistic (binary)			
Fragmentation type	Derisking	Friendshoring	Sorting	Nearshoring
	Fragmentation estimation with more fixed effects			
$\{t \geq 2018\} \times$ *Fragmentation*	0.004	-0.001	-0.001***	-0.002
	(0.003)	(0.002)	(0.000)	(0.002)
Observations	970480	970480	970480	970480
	Fragmentation estimation with fewer fixed effects			
$\{t \geq 2018\} \times$ *Fragmentation*	-0.018	0.041	0.294**	0.239
	(0.015)	(0.095)	(0.136)	(0.261)
Observations	970480	970480	970480	970480
	Using fragmentation t-statistics			
$\{t \geq 2018\} \times$ *Fragmentation*	-0.002	0.015*	0.030**	0.036***
	(0.002)	(0.009)	(0.012)	(0.013)
Observations	970480	970480	970480	970480

*These regressions model potential reshoring of M&A deals by industry and country over time, for 2003-2024. The dependent variable is an indicator taking values of 1 if the target and the acquirer's ultimate parent company are in the same country, and values of 0 otherwise. All regressions use country, industry and year fixed effects, and standard errors are clustered by country (of acquirer's ultimate parent) and industry (of the acquirer). *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Sensitivity and Robustness: MNE Capital Expenditures

The regressions in section V rely on country-year and MNE-year fixed effects, allowing us to control for all reasons that MNEs are investing in each country in each year, as well as all reasons that MNEs are investing overall in each year. Alternatively, we could weaken these fixed effects by replacing MNE-year fixed effects with MNE fixed effects. Table B.7 shows these results. With weaker fixed effects, the approximately doubles in size, resulting smaller coefficient estimates and standard errors. The results still show ideological sorting and nearshoring, but not derisking.

Table B.7. Robustness Results for MNE CapEx: Alternative Fixed Effects

Dependent variable:	log(CapEx)			
Sample	MNE foreign affiliates			
$\{t \geq 2018\} \times$ *IPD*	-0.024			
	(0.016)			
$\{t \geq 2018\} \times$ *log(IPD)*		-0.018**		
		(0.009)		
$\{t \geq 2018\} \times$ *SameBloc*			0.057*	
			(0.032)	
$\{t \geq 2018\} \times$ *DiffBlocs*			-0.060	
			(0.060)	
$\{t \geq 2018\} \times$ *log(GeoDist)*				-0.052***
				(0.011)
log(PPE)	0.769***	0.769***	0.766***	0.766***
	(0.004)	(0.004)	(0.004)	(0.004)
Cash/Assets	0.462***	0.462***	0.488***	0.477***
	(0.042)	(0.042)	(0.041)	(0.041)
Leverage	-0.081***	-0.081***	-0.077**	-0.076**
	(0.031)	(0.031)	(0.030)	(0.030)
Revenue growth	0.396***	0.396***	0.395***	0.398***
	(0.014)	(0.014)	(0.014)	(0.014)
Fixed effects	Country-year, MNE			
Observations	91,479	91,479	100,407	99,072
Adjusted R-squared	0.799	0.799	0.797	0.798

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the foreign affiliates of MNEs, for 2000-2023. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as is the ratio of cash to assets. Leverage is defined as the debt-to-asset ratio, constrained to be less than 1. Revenue growth is computed in logs. The U.S. agreement score is lagged by one year. All regressions use fixed effects by country-year and MNE. Standard errors are robust. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Tan (2024) argues that fragmentation is concentrated in the activities of U.S. multinationals. Table B.8 repeats the analysis of fragmentation but excluding all U.S. multinationals. The results resemble those in the main analysis.

Table B.8. Robustness Results for MNE CapEx: Excluding U.S. MNEs

Dependent variable:		log(CapEx)		
Sample		MNE foreign affiliates		
$\{t \geq 2018\} \times IPD$	-0.052			
	(0.039)			
$\{t \geq 2018\} \times log(IPD)$		-0.026		
		(0.017)		
$\{t \geq 2018\} \times SameBloc$			0.027	
			(0.085)	
$\{t \geq 2018\} \times DiffBlocs$			-0.292**	
			(0.126)	
$\{t \geq 2018\} \times log(GeoDist)$				-0.093***
				(0.028)
log(PPE)	0.839***	0.839***	0.838***	0.837***
	(0.005)	(0.005)	(0.005)	(0.005)
Cash/Assets	0.368***	0.368***	0.448***	0.407***
	(0.068)	(0.068)	(0.065)	(0.066)
Leverage	0.046	0.047	0.064	0.073
	(0.048)	(0.048)	(0.046)	(0.046)
Revenue growth	0.417***	0.417***	0.429***	0.430***
	(0.026)	(0.026)	(0.025)	(0.025)
Fixed effects		Country-year, MNE		
Observations	42,339	42,339	46,319	45,710
Adjusted R-squared	0.782	0.782	0.781	0.781

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the foreign affiliates of MNEs, for 2000-2023. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as is the ratio of cash to assets. Leverage is defined as the debt-to-asset ratio, constrained to be less than 1. Revenue growth is computed in logs. The U.S. agreement score is lagged by one year. All regressions use fixed effects by country-year and MNE-year. Standard errors are robust. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

We can also split the sample of foreign affiliates into those belonging to large multinationals and those belonging to small multinationals. Table B.9 shows these results. Small MNEs display much stronger ideological realignment in their capital expenditures. However, this realignment is driven by friendshoring instead of derisking. In fact, small MNEs appear to have increased their capital expenditures in risky countries relative to nonaligned countries. Small MNEs also do not exhibit significant nearshoring, although this may reflect the small number of foreign affiliates they have.

Table B.9. Robustness Results for MNE CapEx: Large vs. Small MNEs

Dependent variable:	log(CapEx)							
Sample	MNE foreign affiliates							
Size	Large	Small	Large	Small	Large	Small	Large	Small
$\{t \geq 2018\} \times$ *IPD*	-0.080*	-1.211***						
	(0.043)	(0.406)						
$\{t \geq 2018\} \times$ *log(IPD)*			-0.031	-0.324				
			(0.019)	(0.200)				
$\{t \geq 2018\} \times$ *SameBloc*					0.152	3.393***		
					(0.105)	(1.200)		
$\{t \geq 2018\} \times$ *DiffBlocs*					-0.395**	4.952***		
					(0.164)	(1.543)		
$\{t \geq 2018\} \times$ *log(GeoDist)*							-0.098***	-0.625
							(0.035)	(0.387)
log(PPE)	0.852***	0.789***	0.852***	0.790***	0.854***	0.783***	0.854***	0.785***
	(0.006)	(0.023)	(0.006)	(0.023)	(0.006)	(0.021)	(0.006)	(0.021)
Cash/Assets	0.323***	0.479**	0.323***	0.488**	0.342***	0.518***	0.328***	0.549***
	(0.074)	(0.192)	(0.074)	(0.192)	(0.072)	(0.187)	(0.072)	(0.189)
Leverage	-0.085	0.039	-0.084	0.045	-0.077	-0.006	-0.085*	-0.010
	(0.052)	(0.148)	(0.052)	(0.148)	(0.051)	(0.143)	(0.051)	(0.144)
Revenue growth	0.421***	0.504***	0.421***	0.501***	0.426***	0.514***	0.429***	0.508***
	(0.031)	(0.071)	(0.031)	(0.071)	(0.030)	(0.068)	(0.030)	(0.069)
Fixed effects	Country-year, MNE-year							
Observations	30,495	4,932	30,495	4,932	32,033	5,508	31,924	5,423
Adjusted R-squared	0.798	0.765	0.798	0.765	0.802	0.760	0.802	0.758

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the foreign affiliates of MNEs, for 2000-2023. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as is the ratio of cash to assets. Leverage is defined as the debt-to-asset ratio, constrained to be less than 1. Revenue growth is computed in logs. The U.S. agreement score is lagged by one year. All regressions use fixed effects by country-year and MNE-year. Standard errors are robust. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels. Large MNEs are defined as those with (parent-level) revenue of at least $2b in the given year.*

Finally, Table B.10 repeats the analysis using 2022 as the cutoff instead of 2018. Relative to the main analysis, the standard errors for ideological sorting and nearshoring are larger, reducing the significance of the results. The derisking result remain significant, and with a larger coefficient than when using 2018 as the cutoff.

Table B.10. Robustness Results for MNE CapEx: 2022 vs 2018

Dependent variable:	log(CapEx)			
Sample	MNE foreign affiliates			
$\{t \geq 2022\} \times IPD$	-0.047			
	(0.062)			
$\{t \geq 2022\} \times log(IPD)$		-0.053*		
		(0.032)		
$\{t \geq 2022\} \times SameBloc$			0.027	
			(0.150)	
$\{t \geq 2022\} \times DiffBlocs$			-0.535**	
			(0.259)	
$\{t \geq 2022\} \times log(GeoDist)$				-0.052
				(0.050)
log(PPE)	0.838***	0.838***	0.837***	0.836***
	(0.005)	(0.005)	(0.005)	(0.005)
Cash/Assets	0.353***	0.352***	0.420***	0.379***
	(0.061)	(0.061)	(0.059)	(0.059)
Leverage	0.021	0.021	0.035	0.042
	(0.044)	(0.044)	(0.042)	(0.042)
Revenue growth	0.427***	0.427***	0.435***	0.436***
	(0.024)	(0.024)	(0.023)	(0.023)
Fixed effects	Country-year, MNE			
Observations	49,506	49,506	53,777	53,082
Adjusted R-squared	0.786	0.786	0.786	0.786

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the foreign affiliates of MNEs, for 2000-2023. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as is the ratio of cash to assets. Leverage is defined as the debt-to-asset ratio, constrained to be less than 1. Revenue growth is computed in logs. The U.S. agreement score is lagged by one year. All regressions use fixed effects by country-year and MNE-year. Standard errors are robust. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*