Breaking Up: Fragmentation in Foreign Direct Investment

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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 multiple types of FDI. On the intensive margin, the capital expenditures of multinationals' subsidiaries have shifted away from geopolitically risky countries ("derisking") and toward geographically proximate countries, with additional evidence of reshoring. On the extensive margin, greenfield FDI primarily shows derisking, while cross-border M&A exhibits broader ideological fragmentation. At the industry level, derisking is pervasive across industries, while other forms of fragmentation are concentrated in a narrower set of sectors.

Keywords: fragmentation, geoeconomics, foreign direct investment

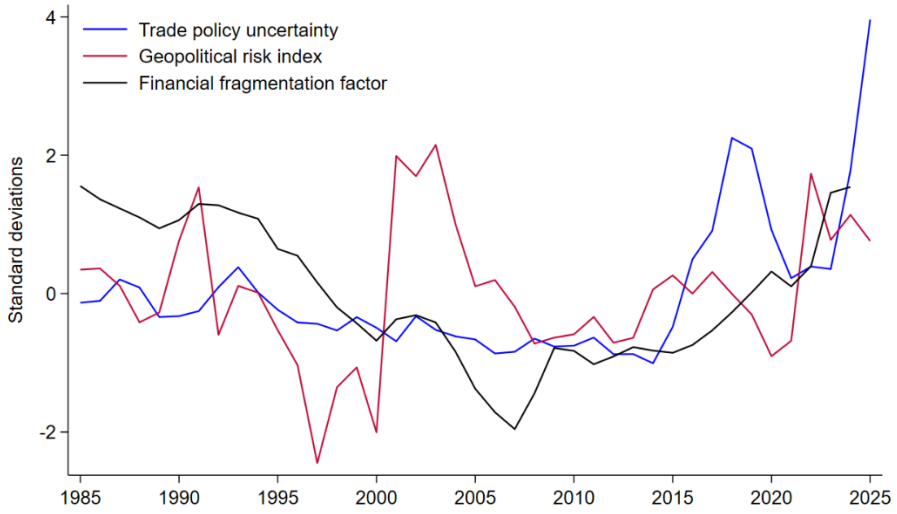
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I. Introduction

In recent years, geopolitical risks and disruptions to global supply chains have raised concerns about the fragmentation of the global economy. Geoeconomic fragmentation may reshape the allocation of capital, with implications for investment and growth (Londono, Ma, and Wilson, 2025). Measures of trade policy uncertainty and geopolitical risks have increased markedly since the 2010s (Caldara et al., 2020; Caldara and Iacoviello, 2022). Amid these new risks, the financial fragmentation factor from Fernández-Villaverde et al. (2024)—which reflects capital controls and the overall volume of global financial flows—suggests a retreat from the previous era of global financial integration.

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 take multiple forms, reflecting both ideological and geographic considerations. For ideological fragmentation, investors and firms may reallocate away from geopolitically risky countries ("derisking"), toward countries aligned with their home countries ("friendshoring"), or more broadly toward more ideologically similar countries ("ideological sorting"). 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).

This paper systematically assesses through which channels and to what extent geoeconomic fragmentation is reshaping foreign direct investment (FDI), examining each form of fragmentation

across different types of FDI: the capital expenditures of multinational enterprises, cross-border mergers and acquisitions (M&A), and greenfield FDI.

The analysis uncovers several key findings. Multinationals' capital expenditures—the intensive margin of investment—exhibit derisking and nearshoring of investment by their foreign subsidiaries. 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.

On the extensive margin, cross-border M&A activity primarily reflects derisking, with some evidence of ideological sorting and friendshoring, particularly in horizontal acquisitions. Vertical M&A and large acquisitions display especially strong derisking. In contrast, greenfield FDI exhibits derisking but no other types of fragmentation. I also document derisking in cross-border divestments, providing new evidence on a not-previously-studied margin of adjustment.

There is also substantial heterogeneity across sectors, with goods-producing industries exhibiting especially strong fragmentation in their acquisitions. Leveraging this variation, I show that industries with greater ideological sorting in their cross-border acquisitions also shift their acquisitions toward domestic targets. This pattern suggests that reshoring is closely linked to the incentives driving other forms of ideological fragmentation.

By combining and analyzing multiple datasets and margins of adjustment, this paper provides a unified empirical assessment of geoeconomic fragmentation in global FDI. In doing so, it contributes to a growing literature on the economic consequences of geopolitical and trade risks by documenting how investors and firms reconfigure their international investment strategies in response to an increasingly fragmented global environment.

In the remainder of this paper, section II reviews the small but growing literature on recent fragmentation and this paper's contributions. Section III describes the data, and section IV presents the empirical results. Section V 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 greenfield FDI and cross-border M&A, but their specification misses other forms of fragmentation.

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 ideological sorting is concentrated in a few goods-producing sectors, but derisking and friendshoring are occurring more broadly. Ideological fragmentation in greenfield FDI and multinationals' capital expenditures is concentrated in a few sectors, and nearshoring in capital expenditures is driven by the consumer goods sector. 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. One potential explanation for

[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.

the discrepancies between these results—beyond the different sources and types of data—is that Tan (2024) relies on data through 2021, which does not capture fragmentation following the onset of the war in Ukraine.

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 the only other paper testing for this, Mulabdic and Nayyar (2024) reported significant reshoring of investment for the U.S., by comparing cross-state (between U.S. states) greenfield FDI projects against cross-border (between countries) greenfield FDI.

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] 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. Industries that engaged in ideological sorting in M&A after 2018 also increased their domestic M&A shares. Moreover, these reshoring results apply to countries beyond just the U.S.

None of the existing literature on fragmentation considers the role of divestment, another margin to respond to these risks. In this paper, I find significant evidence of derisking and nearshoring in cross-border divestments; after 2018, firms became more likely to divest from their foreign subsidiaries in rival geopolitical blocs, and less likely to divest from subsidiaries in geographically proximate countries.

III. Data

In this paper, we conduct a comprehensive analysis of potential fragmentation in different types of FDI. On the extensive margin, we explore cross-border mergers and acquisitions (M&A), as well as greenfield FDI. On the intensive margin, we analyze the capital expenditures of the subsidiaries of multinational enterprises.

These data sources have distinct advantages over the standard measures of foreign direct investment between countries. First, FDI between pairs of countries is subject to mismeasurement bias due to the role of tax havens and investment hubs. For example, investments between the U.S. and China using a Cayman Islands subsidiary would appear as investment between China and the Cayman Islands and as investment between the Cayman Islands and the U.S. Tax havens are especially important to financial flows for FDI, so this mismeasurement can be substantial. By comparison, all the analyses in this paper are conducted using the country of the investment and the country of the ultimate investor, bypassing this investment hub mismeasurement problem.

[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).

Second, we can analyze subsets of the data for relevant heterogeneity, such as by industry or the type of investment.

III.A. Mergers and Acquisitions

To test for fragmentation in cross-border M&A, we use the deals data from LSEG Data and Analytics (formerly Refinitiv).[3] This database provides microdata on M&A deals, identifying relevant information on each deal. We aggregate these into M&A flows—measuring either the number of deals or the total value of deals—between pairs of countries in each year. 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 subcategories of M&A to explore heterogeneity. First, we separately tabulate large M&A deals, where the deal value exceeds $50 million, as these typically account for almost all aggregate values of M&A deals.[4] Second, we isolate horizontal M&A, where the acquirer and target are in the same (non-financial, non-government) industry, following Alfaro and Charlton (2009). Third, we consider vertical M&A, where the acquirer and target are in different (non-financial, non-government) 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.[5] Although deal values are the more relevant metric for FDI, count data are less noisy. For our main series, we use both counts and values. However, for subcomponent series with fewer observations per source-destination-year, we rely on deal counts.

We drop any country-pairs that never report any M&A between them, as these will be fully absorbed by country-pair fixed effects in our regressions. We also exclude acquisitions by governments and government agencies.

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

[4] Definitions of large deals vary. The $50 million cutoff includes "medium" or "mid-market" deals, in addition to all "large" and "mega" deals.

[5] Aiyar, Malacrino and Presbitero (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.

III.B. Greenfield FDI

Also on the extensive margin of cross-border investment, we investigate potential fragmentation in new FDI projects, or greenfield FDI. The data for this analysis comes from fDi Markets, a service owned by the Financial Times. It tracks new physical FDI projects, as well as expansions of existing FDI, in company announcements, news, and other primarily publicly available sources. The data used for this analysis have been aggregated by the country of the investment, the source country (of the ultimate investor), the industry and the year.

Several studies from the IMF have used this data, evaluating the role of ideological distance (Aiyar, Malacrino, and Presbitero, 2024) and bloc fragmentation since 2022 (Gopinath et al., 2025). Relative to these papers, we also study the changing roles of ideological and geographic distance, as well as heterogeneity by industry.

For our analysis, we focus on the number of new FDI projects. Although fDi Markets also provides data on capital expenditures and jobs created, these measures are unreliable.[6] Table 15 presents the summary statistics for this measure, as well as the ideal point distance and geographic distance.

III.C. Multinationals

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. We use a log transformation (rather than dividing by assets or PPE) to make the coefficients comparable in interpretation to those in our analysis of M&A and greenfield FDI.[7] 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.

[6] Aiyar, Malacrino and Presbitero (2024) show that the investment measure is reasonably well correlated with FDI according to official IMF statistics, when aggregated at the country level. This is not accurate at the country pair level, for which the correlation between capital expenditures and the number of projects is weaker. Moreover, firms may overestimate investment and job creation for public relations, and fDi Markets imputes capital expenditures and jobs (when not reported) using an algorithm that does not account for selection bias.

[7] The M&A and greenfield FDI analyses rely on count data, so we estimate them using Poisson regressions with a log link function. By using the log of capital expenditures, all of our coefficient estimate can be interpreted as log effects on the investment outcome variables.

We combine this with the S&P Business Entity Cross Reference Services (BECRS) file, which links each company to its ultimate parent company.[8] Using the BECRS file, we identify multinational enterprises as the ultimate parent companies with affiliates in multiple countries. We restrict our analysis to subsidiaries of MNEs, disregarding unitary firms (single companies, with no separate parents or subsidiaries), multi-subsidiary domestic enterprises (multiple affiliates of the same group, all in a single country), and the MNE parent companies (reporting consolidated financial statements).

III.D. Measuring Distance

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 ideal point distance (IPD) measure from Bailey, Strezhnev and Voeten (2017)—which is based on the similarity of voting in the UN—lagged by one year.[9] To test for friendshoring and derisking, we classify countries into a U.S. bloc, a China bloc, or nonaligned, as in Gopinath et al. (2025).[10] We then flag when country pairs belong to the same (U.S. or China) bloc, to rival blocs (U.S. vs. China), or involve a nonaligned country.

Finally, to test for nearshoring, we use the geographic distance between countries and an indicator for sharing a contiguous border, both from the CEPII Gravity database (Conte, Cotterlaz, and Mayer, 2022).

III.E. Summary Statistics

Table 1 presents the summary statistics for each of the datasets used in the analysis. The panels for cross-border M&A and for greenfield FDI have been tabulated by source and destination countries and by year. The panels for subsidiaries of multinational enterprises have not been aggregated.

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[8] 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 studied in the M&A analysis. We thus consider this analysis as a study of the intensive margin.

[9] 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.

[10] 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, Zimbabwe, Nicaragua, Venezuela, Cuba, Syria, Iran, Pakistan, Laos, and Cambodia.
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 definitions of the U.S. and China blocs.

Table 1. Summary Statistics

Variable	Obs	Mean	SD	Min	Median	Max
Cross-border M&A						
M&A values ($m)	42968	489.869	2899.231	0	5.9745	136269.6
M&A deal counts	156711	1.798	12.160	0	0	788
Big deal counts	156711	0.245	1.956	0	0	170
Divestment counts	156711	0.665	4.220	0	0	258
Horizontal deal counts	156711	0.610	4.048	0	0	263
Vertical deal counts	156711	0.588	4.387	0	0	274
Ideal point distance	131347	1.036	0.864	2.38E-07	0.890	4.818
Geographic distance	153987	6.388	4.542	0.008	5.877	19.806
Greenfield FDI						
Number of projects	177056	1.705	10.042	0	0	497
Ideal point distance	160418	1.032	0.860	1.7E-05	0.868	4.818
Geographic distance	175516	6.047	4.400	0.055	5.309	19.930
Foreign subsidiaries of multinational enterprises						
log(CapEx)	78194	1.680	2.633	-16.108	1.751	10.709
log(PPE)	78194	3.518	2.702	-13.968	3.573	11.639
Cash/Assets	78194	0.129	0.153	0.000	0.076	0.996
Leverage	78194	0.224	0.227	0.000	0.166	0.883
Revenue growth (logs)	78194	0.075	0.291	-0.632	0.059	0.818
Ideal point distance	67755	1.059	0.816	0.000	0.963	4.436
Geographic distance	77451	6.604	5.308	0.055	5.852	19.629
All subsidiaries of multinational enterprises						
log(CapEx)	188328	1.974	2.758	-16.108	2.066	10.824
log(PPE)	188328	3.901	2.784	-13.968	3.984	12.587
Cash/Assets	188328	0.119	0.146	0.000	0.067	0.996
Leverage	188328	0.243	0.230	0.000	0.195	0.883
Revenue growth (logs)	188328	0.075	0.291	-0.632	0.060	0.818

M&A data come from LSEG Data and Analytics, 2003-2024. Divestment counts are tabulated by the country of the target and the country of the target's ultimate parent company.All other measures are tabulated by the country of the target and the country of the acquirer's ultimate parent company.
Data on new FDI projects come from fDi Markets, 2003-2024. The projects are tabulated by the country of the project, the country of the ultimate investor, and the year.
MNE data come from Capital IQ, 2000-2024, and multinational enterprises are identified using S&P Business Entity Cross Reference Services. 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 (in thousands of kilometers between the most populated city of each country) is from the CEPII Gravity database.

Table 2 presents the breakdown of each sample into different groupings based on the country of the investment or target and the country of the ultimate investor: country pairs in the same geopolitical bloc, country pairs in rival geopolitical blocs, and pairs where at least one country is nonaligned. For multinationals, we also have domestic affiliates, and groupings are made based on the country of the affiliate and the country of its ultimate parent. The sample is also tabulated based on the pre-fragmentation period (2000-2017 for the MNE data, and 2003-2017 for the M&A and

greenfield FDI data), the period of initial trade tensions between the U.S. and China (2018-2021), and the period beginning with the Russian invasion of Ukraine.

Table 2. Country Pair Sample Allocations

	2003-17	2018-21	2022-24
Cross-border M&A			
Same bloc	5.58	1.49	1.12
Different blocs	2.95	0.79	0.59
With nonaligned	59.65	15.91	11.93
Greenfield FDI			
Same bloc	5.35	1.43	1.07
Different blocs	1.93	0.52	0.39
With nonaligned	60.90	16.24	12.18
Subsidiaries of multinational enterprises			
Domestic	44.78	8.77	4.92
Same bloc	15.46	3.04	1.44
Different blocs	1.16	0.27	0.14
With nonaligned	14.07	3.71	2.23

IV. Fragmentation Analysis

IV.A. Empirical Specifications

In this paper, we consider two general types of fragmentation—ideological and geographic—and different approaches to measure these. For each type of investment, we conduct two forms of regressions, one using continuous (ideological and geographic) distance measures and the other using grouping indicator variables.

For the regressions using continuous distance measures, fragmentation generally would be indicated by negative coefficients on the distance measures interacted with a dummy variable that indicates the "post" period, as in the following "generic" specification between a source country s and destination country d. Our specifications include source-year, destination-year, and source-destination fixed effects. These control for all permanent bilateral ties, as well as all push and pull factors for each country in each year.

$$Investment_{s,d,t} = \beta_S \mathbf{1}\{t \geq 2018\} * IPD_{s,d,t-1} + \beta_N \mathbf{1}\{t \geq 2018\} * GeoDist_{s,d} + \gamma' X_{s,d,t-1} + \phi_{s,t} + \psi_{d,t} + \mu_{s,d} + \epsilon_{s,d,t}$$

One potential drawback of the continuous measure approach is that it could miss nonlinearities and nuances in fragmentation, or that these distance measures may be imperfect proxies for whatever true distance measure matters.[11] For ideological distance, there is also some potential for

[11] For example, Airaudo et al. (2025) document issues in how ideal point distance is measured based on UN voting patterns. Geographically, the "right" distance measure could conceivably be the length of the shortest sea-based route between countries, rather than distance measured as the crow flies.

endogeneity, as noted by Kleinman, Liu and Redding (2024), who found that strengthening trade dependence also brings countries closer geopolitically. In principle, bilateral investment could conceivably bring countries closer geopolitically as well. To address this, the robustness tables in the appendix rerun the regressions using the average value of IPD over 2000-2017. Because we also use country-pair fixed effects in our regressions, this alternative specification would not be affected by this bias. Our results are robust to this alternative.

Instead of measuring fragmentation using continuous distance variables, we can also use the bloc specification approach from Gopinath et al. (2025), identifying country pairs as belonging to the same geopolitical bloc, to rival geopolitical blocs, or involving at least one nonaligned country. We adopt a similar approach, augmented to include an indicator for countries sharing a border, and thus not requiring sea transportation between them and less vulnerable to global shipping disruptions. The specification below identifies friendshoring as investment shifting toward countries in the same geopolitical bloc relative to nonaligned countries, and derisking as investment shifting away (negative coefficient) from countries in the rival geopolitical bloc. The coefficient on the contiguity indicator interaction provides an alternative measure for nearshoring. For the MNE capital expenditure regressions, we can also include domestic affiliates of the multinational, to directly detect reshoring of investment.

$$
\begin{aligned}
Investment_{s,d,t} &= \beta_F \mathbf{1}\{t \geq 2018\} * SameBloc_{s,d} + \beta_D \mathbf{1}\{t \geq 2018\} * DiffBlocs_{s,d} \\
&+ \beta_H \mathbf{1}\{t \geq 2018\} * Contiguous_{s,d} + \beta_R \mathbf{1}\{t \geq 2018\} * \mathbf{1}\{s = d\} + \gamma' X_{s,d,t-1} \\
&+ \phi_{s,t} + \psi_{d,t} + \mu_{s,d} + \epsilon_{s,d,t}
\end{aligned}
$$

IV.B. Fragmentation in Extensive Margin FDI

Table 3 explores fragmentation in the main measures of extensive margin FDI. The first column examines the number of cross-border acquisitions, and the second column examines the total value of these acquisitions, using a $\log(1 + X)$ transformation to address the skewness of deal values—which are driven by the right tail of large deals and mega-deals—while not dropping zero values. The third column examines the number of greenfield FDI projects between countries. The top panel presents the results of the continuous fragmentation specification, and the bottom panel presents the bloc fragmentation specification. For the first and third columns, the outcome variable is a count measure, so we use Poisson regressions with a log link function. The Pearson dispersion coefficients reported in the table indicate only mild overdispersion.

The first two columns indicate statistically significant ideological fragmentation, shown by the negative coefficients on the interaction between the period dummy and ideal point distance. In the bottom panel, ideological fragmentation occurs through both friendshoring—the positive coefficient on the period dummy interacted with the same bloc dummy—and derisking—the negative coefficient on the period dummy interacted with the different bloc dummy. Perhaps

surprisingly, the results are not consistent with nearshoring; if anything, extensive margin FDI has shifted further from the investor's country in recent years.

Table 3. Regression Results: Extensive Margin FDI

Variable type	Number of acquisitons	log(1+Value of acquisitions)	Greenfield FDI projects
Regression type	Poisson	OLS	Poisson
Fixed effects	Source-destination, source-year, destination-year		
$\{t \geq 2018\} \times IPD$	-0.063***	-0.165***	-0.019
	(0.017)	(0.054)	(0.019)
$\{t \geq 2018\} \times GeoDist$	0.013***	0.002	0.030**
	(0.003)	(0.010)	(0.012)
Observations	107675	35757	142434
Adj. (pseudo) R-sq	0.839	0.422	0.823
Pearson dispersion	1.264	0.000	1.243
$\{t \geq 2018\} \times SameBloc$	0.115**	0.400***	0.019
	(0.047)	(0.126)	(0.052)
$\{t \geq 2018\} \times DiffBlocs$	-0.263***	-0.172	-0.155**
	(0.081)	(0.181)	(0.078)
$\{t \geq 2018\} \times Contiguous$	-0.053	-0.028	-0.088***
	(0.032)	(0.124)	(0.033)
Observations	125483	40748	156043
Adj. (pseudo) R-sq	0.836	0.416	0.817
Pearson dispersion	1.256	0.000	1.238

*These regressions model the changing roles of ideological and distance factors on M&A deals and greenfield FDI projects between pairs of countries over time, for 2003-2024. The first two columns are tabulated by the country of the target and of the ultimate acquirer. The third column is tabulated by the country of the project and the country of the ultimate investor. The first and third columns 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.*

We find significant derisking in the number of new FDI projects. This effect is stronger when using 2022 as the cutoff, as in Gopinath et al. (2025).

The coefficients imply economically large derisking behavior; since 2018, there have been 23 percent fewer cross-border acquisitions and 14 percent fewer greenfield FDI projects between countries in rival geopolitical blocs, compared to deals involving nonaligned countries. However, we find no overall evidence of broader ideological sorting or friendshoring. Moreover, the wrong signs for the nearshoring coefficients resemble those in the analysis of M&A deals. It appears that extensive margin cross-border investments have been shifting further from the home countries of the investors.

Table 4 considers four special types of M&A that may behave differently from overall M&A. The first column considers the opposite of acquisitions: divestments, tabulating the number of deals by

the country of the target and the country of the target's ultimate parent whenever these differ. The results—which should display the opposite signs on the coefficient estimates if fragmentation is occurring—show evidence of derisking (positive coefficient on the different bloc interaction) and strong evidence of nearshoring (positive coefficient on geographic distance and negative coefficient on the contiguity interaction). Firms have become more likely to divest from their foreign subsidiaries if those subsidiaries are more geographically distant or in geopolitically rival countries, and less likely to divest from subsidiaries in their neighboring countries. This nearshoring result in divestments contrasts with the "farshoring" results in cross-border acquisitions.

Table 4: Regression Results: Special Types of M&A

Variable type	Divestments	Large acquistions	Horizontal acquisitions	Vertical acquisitions
Regression type	Poisson	Poisson	Poisson	Poisson
Fixed effects	Source-destination, source-year, destination-year			
$\{t \geq 2018\} \times IPD$	0.008	-0.053**	-0.123***	-0.040*
	(0.022)	(0.025)	(0.024)	(0.021)
$\{t \geq 2018\} \times GeoDist$	0.017***	0.011**	0.013***	0.007**
	(0.004)	(0.005)	(0.005)	(0.004)
Observations	72041	42125	71489	59998
Adj. (pseudo) R-sq	0.686	0.582	0.706	0.738
Pearson dispersion	1.205	1.156	1.228	1.195
$\{t \geq 2018\} \times SameBloc$	0.051	0.025	0.284***	0.045
	(0.062)	(0.079)	(0.065)	(0.062)
$\{t \geq 2018\} \times DiffBlocs$	0.239***	-0.410***	-0.300***	-0.437***
	(0.082)	(0.115)	(0.116)	(0.103)
$\{t \geq 2018\} \times Contiguous$	-0.070*	-0.104*	-0.027	-0.102***
	(0.039)	(0.056)	(0.043)	(0.034)
Observations	84141	48843	81011	68249
Adj. (pseudo) R-sq	0.700	0.589	0.700	0.733
Pearson dispersion	1.214	1.160	1.222	1.198

*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.*

The second column of Table 4 considers the number of large transactions, defined as those with values exceeding $50 million (which technically also includes many medium-size deals); these are the main drivers of M&A values. The third column considers horizontal M&A; in the context of cross-border deals, these are generally used to grow a company's market share (by acquiring a competitor) or to expand into new markets. The fourth column considers vertical M&A, which reflects supply chain integration.

Large, horizontal, and vertical transactions all display ideological sorting and derisking. For horizontal transactions, this comes from both friendshoring and derisking. For large and vertical transactions, this comes entirely from derisking, not friendshoring. While derisking appears across all these types of M&A, the reactions of large and of vertical transactions are notably greater in magnitude, underscoring the particular risks of supply chain exposure.

IV.C. FDI Fragmentation and Reshoring in Multinational Investment

Because this analysis uses firm-level microdata, the empirical specifications use a slight variation on the equations displayed above. In these regressions, we have data on an affiliate i owned by ultimate parent company j. 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 $c(j)$. As in the analysis above, 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.

For the dependent variable, we use the log of capital expenditures, controlling for the (lagged) log of property, plant and equipment. This specification ensures that the coefficient estimates have the same interpretation as those in section IV.B. We also control for the lagged cash-to-asset ratio, the lagged debt-to-asset ratio, and log revenue growth.

Table 5 reports the results of these regressions. The first two columns restrict the analysis to the foreign subsidiaries of MNEs. Like in the M&A and greenfield FDI analysis above, the identification comes from the relative allocation of foreign investment across countries. These regressions show significant nearshoring (negative coefficient on geographic distance) and derisking. The coefficient estimate on geographic distance implies a modest impact from nearshoring; a one standard deviation increase in the distance between the affiliate country and the parent country is associated with 6.7 percent lower capital expenditures after 2018 compared to the pre-fragmentation period. By comparison, the coefficient estimate for derisking implies an economically large impact of 30.9 percent lower capital expenditures in rival blocs relative to nonaligned countries, compared to the pre-fragmentation period.

The remaining columns expand the analysis to include domestic subsidiaries, setting the distance measures to zero for column 3 and adding a domestic indicator in column 4. Column 5 uses only the period interacted with the domestic indicator to measure reshoring as the post-fragmentation shift in domestic capital expenditures relative to foreign capital expenditures of multinationals. The nearshoring results are strengthened by the inclusion of domestic subsidiaries, and columns 4 and 5 display significant evidence of reshoring, with the capital expenditures of domestic

subsidiaries higher post-fragmentation by 9.5 percent relative to all foreign subsidiaries (column 5) and by 18.1 percent relative to foreign subsidiaries in nonaligned countries (column 4).

The results in the appendix show these nearshoring and reshoring results are generally robust to alternative (stronger or weaker) fixed effects, to excluding U.S. multinationals, and to defining 2022 as the beginning of the fragmentation period.

Table 5. Regression Results: MNE Capital Expenditures

Dependent variable:	log(CapEx)				
Sample	MNE foreign affiliates		All MNE affiliates		
$\{t \geq 2018\}$ × *IPD*	-0.049		-0.022		
	(0.035)		(0.024)		
$\{t \geq 2018\}$ × *GeoDist*	-0.013**		-0.012***		
	(0.006)		(0.004)		
$\{t \geq 2018\}$ × *SameBloc*		-0.042		0.050	
		(0.081)		(0.048)	
$\{t \geq 2018\}$ × *DiffBlocs*		-0.359***		-0.014	
		(0.113)		(0.087)	
$\{t \geq 2018\}$ × *Contiguous*		0.129		0.202***	
		(0.083)		(0.060)	
$\{t \geq 2018\}$ × *Domestic*				0.161***	0.091***
				(0.042)	(0.034)
log(PPE)	0.846***	0.841***	0.862***	0.859***	0.859***
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Cash/Assets	0.295***	0.350***	0.506***	0.526***	0.526***
	(0.061)	(0.058)	(0.039)	(0.038)	(0.038)
Leverage	-0.229***	-0.217***	-0.291***	-0.280***	-0.281***
	(0.042)	(0.040)	(0.025)	(0.024)	(0.024)
Revenue growth	0.643***	0.647***	0.727***	0.723***	0.723***
	(0.033)	(0.030)	(0.019)	(0.019)	(0.019)
Fixed effects	Country-year, MNE-year				
Observations	48,414	56,252	141,380	150,876	150,876
Adjusted R-squared	0.783	0.786	0.807	0.805	0.805

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the affiliates of MNEs, for 2000-2024. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as are the ratio of cash to assets and leverage. Leverage is defined as the debt-to-asset ratio. Revenue growth is computed in logs. The ideal point distance measure 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.*

IV.D. Fragmentation Heterogeneity Across Industries

Tan (2024) found that fragmentation was concentrated in high-tech industries but not more broadly. To test this in our data sources, we conduct lower-level aggregations of M&A and greenfield FDI by source country, destination country, macroeconomic sector, and year, and we regress these on

industrial sector dummies interacted with the post-2018 indicator and the fragmentation variables from section IV.B.[12] For the MNE capital expenditure regressions, we make a similar adjustment to the regressions, without having to deal with aggregation issues.

Table 6. Fragmentation by Sector

Cross-border M&A

	Ideological fragmentation			Geographic fragmentation	
Industry	Derisking	Friendshoring	Sorting	Distance	Contiguity
Consumer Goods	0.141**	0.208***	0.11**	-0.018***	-0.095***
Consumer Services	0.555***	-0.043	0.065	-0.014***	-0.059*
Energy & Materials	0.588***	0.175***	0.282***	-0.015***	-0.347***
Financials	0.247***	0.113**	-0.033	-0.013***	-0.166***
High Tech	0.326***	0.134***	0.148***	-0.01***	-0.028
Industrials	0.141**	0.134***	0.087*	-0.003	0.065*
Other	0.328***	0.143***	0.113**	-0.014***	0.006

Greenfield FDI

	Ideological fragmentation			Geographic fragmentation	
Industry	Derisking	Friendshoring	Sorting	Distance	Contiguity
Consumer Goods	-0.112	0.183*	-0.028	-0.016	-0.006
Consumer Services	-0.115	0.211*	0.063*	-0.043*	0.041
Energy & Materials	0.342***	0.402***	0.191***	-0.01	-0.213***
Financials	0.504***	0.231***	-0.1***	-0.055***	-0.188***
High Tech	0.289**	-0.259***	0	0.023*	0
Industrials	-0.018	0.034	0.012	-0.027**	-0.111***
Other	0.212*	0.024	0.039***	-0.047***	-0.118***

MNE Capital Expenditures

	Ideological fragmentation			Geographic fragmentation		
Industry	Derisking	Friendshoring	Sorting	Distance	Contiguity	Reshoring
Consumer Goods	-0.002	-0.089	0.031	0.024***	0.449***	0.133***
Consumer Services	0.240	-0.259	-0.079	0.022	-0.294	-0.050
Energy & Materials	-1.046**	0.371*	-0.060	-0.018	0.307	-0.084
Financials	0.541***	-0.114	0.078	0.010	-0.095	-0.006
High Tech	-0.388	0.419	0.573***	-0.001	0.008	0.006
Industrials	0.776***	-0.071	0.051	0.016*	0.098	0.246***
Other	-0.910***	0.086	-0.092	0.006	0.555*	0.212**

*These regressions model the changing roles of ideological and distance factors on FDI by industry between pairs of countries over time. All coefficients come from the interactions between the post-2018 dummry and the counterpart measures: ideal point distance for ideological sorting, the different-bloc indicator for derisking, the same-bloc indicator for friendshoring, the log geographic distance for distance-based nearshoring, the contiguity indicator for discrete nearshoring, and the domestic indicator for reshoring. All coefficient estimates have been normalized so that positive values are consistent with expected signs for fragmentation. The M&A and greenfield FDI coefficients come from Poisson count regressions, and the MNE CapEx estimates come from OLS using the log of CapEx. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels, computed using standard errors clustered by source-destination and industry.*

[12] The industrial sector definitions are defined for comparability across datasets, with a cross-walk in the appendix.

To control for the additional sectoral variation (on top of the source-destination-year variation), the M&A and greenfield FDI regressions 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 6. For brevity, the table only displays the coefficients and stars for statistical significance, and coefficients are normalized so that positive coefficients indicate fragmentation. The first panel presents results for cross-border M&A, the second panel for greenfield FDI, and the third panel for multinationals' capital expenditures.

In contrast to Tan (2024), we find widespread derisking and friendshoring in cross-border M&A, as well as robust farshoring. Only ideological sorting exhibits notable heterogeneity.

For greenfield FDI, ideological fragmentation is driven by energy and materials and the financial sector, and no sectors exhibit nearshoring.

For multinationals' capital expenditures, derisking among their foreign subsidiaries is concentrated in the financial sector and industrials, while ideological sorting is concentrated in high-tech. The nearshoring result appears driven by consumer goods, consistent with this sector being most impacted by shipping problems in 2020 and 2021. The reshoring results are driven by consumer goods, industrials, and other industries.

IV.E. Reshoring in M&A

In principle, reshoring would achieve all the goals of friendshoring, nearshoring and derisking. However, testing for reshoring in M&A is challenging. For multinational capital expenditures, reshoring is identifiable by comparing domestic and foreign subsidiaries of the same multinational group, but M&A data lack a comparable structure. Moreover, a purely domestic acquisition does not constitute an investment flow, unlike cross-border M&A. Finally, 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 overcome these challenges, we utilize the previous subsection's result that not all industries exhibit fragmentation in their M&A, obtaining identification through heterogeneity. We first estimate the propensity of each of 78 industries—which we aggregated into the sectors in the previous subsection—to engage in ideological sorting using M&A counts by source-destination-industry-year, with fixed effects by source-destination-industry, source-year, destination-year, and industry-year.[13] We then interact these industry-specific fragmentation coefficient estimates (normalized so positive coefficients indicate fragmentation) with a time period dummy variable to explore whether the industries experiencing stronger ideological sorting in their cross-border

[13] 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 fragmentation: industrial conglomerates, other consumer staples, other healthcare, and other media and entertainment.

acquisitions since 2018 also increase their domestic M&A shares. Additional information on the first-stage coefficient estimates and their distribution are in the appendix.

The results of these reshoring regressions are in Table 7. The first two columns use the ideological sorting coefficients estimated as described above. The positive and significant coefficient estimates mean that industries that engaged in stronger ideological sorting post-2018 we also more likely to acquire domestic companies than to acquire foreign companies. The second column uses country-year fixed effects to control for all M&A push factors.

Table 7. Regression Results: Reshoring in M&A

Dependent variable	Deal-level domestic indicator				
Regression type	Logistic (binary)				
Coef estimation method	Main	Main	Weaker FE	T-stats	Training sample
$\{t \geq 2018\} \times SortingCoef$	0.384***	0.431**	0.172**	0.022***	0.252
	(0.147)	(0.200)	(0.067)	(0.008)	(0.165)
Industry FE	x	x	x	x	x
Country FE	x		x	x	x
Year FE	x		x	x	x
Country x Year FE		x			
Observations	905555	902339	905555	905555	453002
Adj. (pseudo) R-sq	0.135	0.138	0.135	0.135	0.135
Pearson dispersion	1.004	1.005	1.004	1.004	1.004

*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 by regressing the number of cross-border acquisitions on the IPD interacted with the post-2018 dummy and the detailed industry dummies. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

The remaining three columns consider alternative methods to estimate these first-stage coefficients. The third column uses weaker fixed effects (source-destination instead of source-destination-industry) when estimating the coefficients, and the results are robust to this.[14] Because the standard errors on the ideological sorting coefficients vary by industry (and those with larger standard errors should be considered less informative), the fourth column uses the t-statistics instead of the sorting coefficients. For the fifth column, we randomly split the sample; the sorting coefficients were estimated on one half of the sample, and the reshoring results were estimated on the other half. This method generates similar coefficient estimates, but with somewhat larger

[14] We also estimated this using stronger fixed effects, or equivalently separate regressions by industry. This method generates much greater variation—likely noise, not signal— in the coefficient estimates. The second stage reshoring coefficient remains positive and significant but is much smaller, reflecting the bias induced by that greater noise in the first stage.

standard deviations (a result of Poisson regressions being less accurate with smaller counts in general).

V. Conclusion

Foreign direct investment is fragmenting along both ideological and geographic lines. Across multiple margins of FDI, I find widespread evidence of derisking as firms and investors specifically reduced exposure to countries in a rival geopolitical bloc.

Other forms of fragmentation exhibit greater heterogeneity. In cross-border acquisitions, we find evidence of ideological sorting and limited evidence of friendshoring. By comparison, multinationals' capital expenditures in their foreign affiliates exhibit nearshoring and derisking. Greenfield FDI only exhibits derisking. Cross-border divestments display derisking and nearshoring, the first evidence on this margin for adjustment.

I also provide new evidence of reshoring, one of the first papers to do so. Multinationals have shifted the allocation of their capital expenditures toward their domestic subsidiaries. In M&A, industries that engaged in greater ideological sorting also increased their domestic acquisitions.

A changing landscape for foreign direct investment may have important implications going forward. Reduced or inefficient direct investments could limit productivity spillovers and growth for developing countries, along with production inefficiencies for firms reacting to geopolitical risks (Adarov and Pallan, 2025).

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 and geopolitical risks in 2026, these patterns of fragmentation could deepen or shift in new ways.

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.

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.

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.

fDi Markets. Global FDI by Source, Destination & Sector, https://www.fdimarkets.com/, August 2025.

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 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.

Kleinman, Benny, Ernest Liu, and Stephen J. Redding (2024). “International Friends and Enemies.” *American Economic Journal: Macroeconomics*, vol. 16 no. 4, pp. 350-385.

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.

Mulabdic, Alen, and Gaurav Nayyar (2024). “Is the U.S. Friend-Shoring, Nearshoring, or Reshoring? Evidence from Greenfield Investment Announcements.” World Bank Policy Research working paper no. 11006.

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.

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.

Appendix

Table A1 presents the industrial definitions used in section IV.D. The sectors have been defined to be maximally comparable across our three main datasets. For the M&A data, we drop governments and agencies.

Table A1. Industrial Sector Definitions

LSEG M&A data	Capital IQ firm data	fDi Marjets new FDI projects
Consumer Durables		
Home furnishings; Food and beverage; Household & personal products; Textiles & apparel; Tobacco; Other consumer products; Other consumer staples	Household durables; Household products; Food products; Beverages; Personal care products; Textiles, apparel and luxury goods; Tobacco	Consumer products; Consumer electronics; Ceramics & glass; Food & beverages; Textiles
Consumer Services		
Educational services; Employment services; Legal services; Travel services; Hospitals; Healthcare providers & services (HMOs); Other healthcare; Broadcasting; Cable; Casinos & gaming; Hotels & lodging; Motion pictures/audio visual; Publishing; Recreation & leisure; Other media & entertainment	Diversified consumer services; Health care providers and services; Media and entertainment; Entertainment; Interactive Media and services; Media; Hotels, restaurants and leisure; Leisure products; Passenger airlines	Healthcare; Hotels & tourism; Leisure & entertainment
Energy & Materials		
Power; Alternative energy sources; Pipelines; Oil & gas; Metals & mining; Other materials	Independent power and renewable electricity producers; Oil, gas and consumable fuels; Metals and mining	Coal, oil & gas; Metals; Minerals; Renewable energy
Financials		
Alternative financial investments; Asset management; Banks; Brokerage; Credit institutions; Diversified financials; Government sponsored enterprises; Insurance; REITs; Real estate management & development;	Financial services; Capital markets; Banks; Consumer finance; Insurance; Diversified REITS; Health care REITs; Hotel and resort REITs; Real estate management and development; Mortgage real estate investment trusts	Financial services; Real estate

Residential; Nonresidential; Other financials; Other real estate	(REITs); Industrial REITs; Office REITs; Residential REITs; Retail REITs; Specialized REITs	
High Tech		
Computers & peripherals; IT consulting & services; Internet software & Services; Semiconductors; Software; Biotechnology; Pharmaceuticals; Other high technology	Technology hardware, storage and peripherals; IT services; Health care technology; Life sciences tools and services; semiconductors and semiconductor equipment; Software; Biotechnology; Pharmaceuticals	Semiconductors; Software & IT services; Biotechnology; Pharmaceuticals
Industrials		
Electronics; Healthcare equipment & supplies; Aerospace & defense; Automobiles & components; Building/construction & engineering; Industrial conglomerates; Machinery; Chemicals; Construction materials; Containers & packaging; Petrochemicals; Paper & forest products; Space and satellites; Telecommunications equipment; Other industrials	Aerospace and defense; Automobile components; Automobiles; Construction and engineering; Industrial conglomerates; Machinery; Building products; Health care equipment and supplies; Electrical equipment; Electronic equipment, instruments and components; Chemicals; Construction materials; Containers and packaging; Paper and forest products; Communications equipment; Energy equipment and services	Aerospace; Automotive OEM; Automotive components; Building materials; Business machines & equipment; Chemicals; Electronic components; Engines & turbines; Industrial equipment; Medical devices; Non-automotive transport OEM; Plastics; Rubber; Space & defense; Wood products; Paper, printing & packaging
Other		
Agriculture & livestock; Professional services; Water and waste management; Other energy & power; Ecommerce/B2B; Advertising & marketing; Apparel retailing; Automotive retailing; Computers & electronics retailing; Discount and department store retailing; Food & beverage retailing; Home improvement retailing; Internet and catalog retailing; Other retailing; Transportation &	Broadline retail; Consumer staples distribution and retail; Air freight and logistics; Distributors; Ground transportation; Marine transportation; Specialty retail; Trading companies and distributors; Transportation infrastructure; Professional services; Commercial services and supplies; Diversified telecommunication services; Wireless telecommunication services; Electric utilities;	Business services; Transportation & warehousing; Communications

infrastructure; Telecommunications services; Wireless; Other telecom	Water utilities; Gas utilities; Multi-utilities	

Table A2 presents the sensitivity analysis for the M&A fragmentation results, focusing on the number of cross-border acquisitions. The first column uses the current value of ideal point distance instead of the lagged value, and the second column uses log distance measures instead of linear distances. The third column addresses the potential endogeneity of ideal point distance by using the 2000-2017 average value. The fourth column uses 2022 as the beginning of the fragmentation period instead of 2018. The results are broadly robust to these alternatives.

Table A2. Robustness Results: Continuous Fragmentation in M&A

Variable type	All acquisitions			
Regression type	Poisson			
Fixed effects	Source-destination, source-year, destination-year			
$\{t \geq 2018\} \times IPD_t$	-0.053***			
	(0.018)			
$\{t \geq 2018\} \times log(IPD_{t-1})$		-0.032***		
		(0.008)		
$\{t \geq 2018\} \times IPD_{perm}$			-0.070***	
			(0.018)	
$\{t \geq 2022\} \times IPD_{t-1}$				-0.054***
				(0.019)
$\{t \geq 2018\} \times GeoDist$	0.011***		0.014***	
	(0.003)		(0.003)	
$\{t \geq 2018\} \times log(GeoDist)$		0.027**		
		(0.012)		
$\{t \geq 2022\} \times GeoDist$				0.019***
				(0.003)
Observations	103904	107675	107829	107675
Adj. (pseudo) R-sq	0.837	0.839	0.839	0.839
Pearson dispersion	1.290	1.265	1.264	1.264

*These regressions model the changing roles of ideological and geographic distance on M&A deals between pairs of countries over time, for 2003-2024. All columns are tabulated by the countries of the target and the acquirers ultimate parent company. All columns use Poisson regressions for the number of deals. 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 A3 presents the sensitivity analysis for the bloc specifications for M&A fragmentation. The first column uses 2022 as the beginning of the fragmentation period, and the second column uses wider bloc definitions, with countries assigned to blocs based on being in the top quartile of UN voting agreement with the U.S. or with China each year. The third column repeats the main

regression, but omitting the contiguity indicator. The derisking and friendshoring results are moderately robust to these alternatives.

Table A3. Robustness Results: Bloc Fragmentation in M&A

Variable type	All acquisitions		
Regression type	Poisson		
Fixed effects	Source-destination, source-year, destination-year		
Bloc definition	Narrow	Wide	Narrow
$\{t \geq 2018\}$ × *SameBloc*		0.141***	0.099**
		(0.042)	(0.046)
$\{t \geq 2018\}$ × *DiffBlocs*		-0.052	-0.255***
		(0.055)	(0.080)
$\{t \geq 2018\}$ × *Contiguous*		-0.020	
		(0.032)	
$\{t \geq 2022\}$ × *SameBloc*	0.062		
	(0.057)		
$\{t \geq 2022\}$ × *DiffBlocs*	-0.408***		
	(0.107)		
$\{t \geq 2022\}$ × *Contiguous*	-0.116***		
	(0.032)		
Observations	125483	119539	125483
Adj. (pseudo) R-sq	0.836	0.835	0.836
Pearson dispersion	1.257	1.290	1.256

*These regressions model the changing roles of blocs on M&A deals between pairs of countries over time, for 2003-2024. All columns are tabulated by the countries of the target and the acquirers ultimate parent company. All columns use Poisson regressions for the number of deals. 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.*

We now consider sensitivity analyses for the results of multinational capital expenditures, focusing on the fragmentation regressions for their foreign subsidiaries and on the reshoring specification comparing domestic against foreign subsidiaries. Table A4 presents results using either weaker fixed effects (MNE instead of MNE-year, first three columns) or stronger fixed effects (adding subsidiary fixed effects, last three columns). The nearshoring and derisking results are moderately robust, and the reshoring results are robust to these alternative specifications.

Table A4. Robustness Results: Alternative Fixed Effects for MNE CapEx

Dependent variable:	log(CapEx)					
Sample	Foreign affiliates		All	Foreign affiliates		All
$\{t \geq 2018\}$ × *IPD*	-0.013			0.022		
	(0.016)			(0.037)		
$\{t \geq 2018\}$ × *GeoDist*	-0.006**			0.009		
	(0.003)			(0.006)		
$\{t \geq 2018\}$ × *SameBloc*		0.021			-0.159*	
		(0.032)			(0.089)	
$\{t \geq 2018\}$ × *DiffBlocs*		-0.036			-0.282**	
		(0.054)			(0.118)	
$\{t \geq 2018\}$ × *Contiguous*		0.104***			0.005	
		(0.035)			(0.079)	
$\{t \geq 2018\}$ × *Domestic*			0.063***			0.066**
			(0.015)			(0.034)
log(PPE)	0.789***	0.771***	0.803***	0.367***	0.371***	0.425***
	(0.004)	(0.004)	(0.002)	(0.014)	(0.013)	(0.008)
Cash/Assets	0.361***	0.431***	0.616***	0.309***	0.310***	0.432***
	(0.043)	(0.040)	(0.027)	(0.072)	(0.069)	(0.045)
Leverage	-0.448***	-0.444***	-0.428***	-0.360***	-0.329***	-0.442***
	(0.030)	(0.028)	(0.018)	(0.056)	(0.052)	(0.034)
Revenue growth	0.601***	0.600***	0.690***	0.383***	0.379***	0.419***
	(0.020)	(0.018)	(0.011)	(0.027)	(0.025)	(0.016)
Fixed effects	Country-year, MNE			Country-year, MNE-year, Firm		
Observations	85,747	105,568	254,827	47,191	54,909	147,228
Adjusted R-squared	0.801	0.797	0.814	0.889	0.891	0.898

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the affiliates of MNEs, for 2000-2024. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as are the ratio of cash to assets and leverage. Leverage is defined as the debt-to-asset ratio. Revenue growth is computed in logs. The ideal point distance measure is lagged by one year. The first three regressions use country-year and MNE fixed effects, while the other three regressions use country-year, MNE-year, and firm fixed effects. Standard errors are robust. *, ** and *** denote statistical significance at the 10, 5 and 1 percent confidence levels.*

Table A5 repeats the analysis, but excluding U.S. multinationals. The results are robust to this (although with slightly smaller coefficient magnitudes), demonstrating that this is not unique the U.S.

Table A5. Robustness Results: Excluding U.S. MNEs for MNE CapEx

Dependent variable:	log(CapEx)		
Sample	MNE foreign affiliates		
$\{t \geq 2018\}$ × *IPD*	-0.033		
	(0.037)		
$\{t \geq 2018\}$ × *GeoDist*	-0.014**		
	(0.006)		
$\{t \geq 2018\}$ × *SameBloc*		-0.034	
		(0.083)	
$\{t \geq 2018\}$ × *DiffBlocs*		-0.226**	
		(0.112)	
$\{t \geq 2018\}$ × *Contiguous*		0.161*	
		(0.090)	
$\{t \geq 2018\}$ × *Domestic*			0.067*
			(0.039)
log(PPE)	0.847***	0.842***	0.851***
	(0.006)	(0.005)	(0.003)
Cash/Assets	0.297***	0.370***	0.600***
	(0.069)	(0.065)	(0.047)
Leverage	-0.211***	-0.193***	-0.277***
	(0.046)	(0.043)	(0.029)
Revenue growth	0.635***	0.642***	0.725***
	(0.036)	(0.033)	(0.022)
Fixed effects		Country-year, MNE-year	
Observations	40,982	48,478	120,036
Adjusted R-squared	0.780	0.781	0.788

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the affiliates of MNEs, for 2000-2024. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as are the ratio of cash to assets and leverage. Leverage is defined as the debt-to-asset ratio. Revenue growth is computed in logs. The ideal point distance measure 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.*

Finally, Table A6 presents the results using 2022 as the beginning of the fragmentation period instead of 2018. The magnitudes of the coefficient estimates are robust to this alternative, but the standard errors are larger.

Table A6. Robustness Results: Post-2022 Fragmentation for MNE CapEx

Dependent variable:	log(CapEx)		
Sample	MNE foreign affiliates		
$\{t \geq 2022\} \times IPD$	-0.028		
	(0.053)		
$\{t \geq 2022\} \times GeoDist$	-0.007		
	(0.010)		
$\{t \geq 2022\} \times SameBloc$		-0.087	
		(0.134)	
$\{t \geq 2022\} \times DiffBlocs$		-0.307	
		(0.200)	
$\{t \geq 2022\} \times Contiguous$		0.322**	
		(0.137)	
$\{t \geq 2022\} \times Domestic$			0.097*
			(0.058)
log(PPE)	0.846***	0.841***	0.859***
	(0.005)	(0.005)	(0.003)
Cash/Assets	0.296***	0.350***	0.526***
	(0.061)	(0.058)	(0.038)
Leverage	-0.229***	-0.218***	-0.281***
	(0.042)	(0.040)	(0.024)
Revenue growth	0.643***	0.648***	0.723***
	(0.033)	(0.030)	(0.019)
Fixed effects	Country-year, MNE-year		
Observations	48,414	56,252	150,876
Adjusted R-squared	0.783	0.785	0.805

*These regressions model the changing roles of ideological, distance and bloc factors for capital expenditures by the affiliates of MNEs, for 2000-2024. The dependent variable is the log of capital expenditures. The log of PPE is lagged by one year, as are the ratio of cash to assets and leverage. Leverage is defined as the debt-to-asset ratio. Revenue growth is computed in logs. The ideal point distance measure 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.*

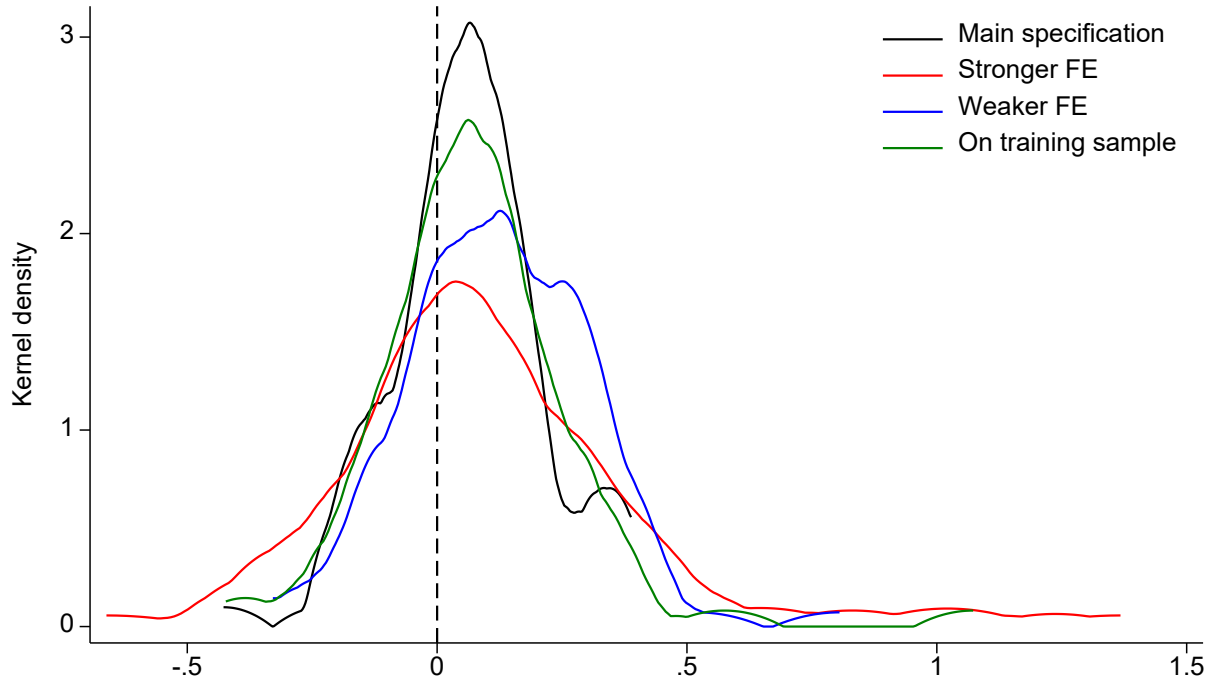
Table A7 presents summary statistics of the different industry-level (normalized) coefficients of ideological sorting from the first stage of the M&A reshoring analysis. The first row is for the main specification. The second row is run using separate industry-level regressions; although these are still positive on average, they are so noisy as to lose information. The third row uses weaker fixed effects. The fourth row uses the same fixed effects as the main specification, but is estimated on the training sample instead of the full sample (evenly selected at random). The fifth row presents information on the t-statistics instead of the coefficient estimates. The right column shows the correlation of each set of measures with those of the main specification.

Table A7. Summary Statistics for First-Stage Ideological Sorting by Detailed Industry

	Mean	StdDev	Main corr
Main specification	0.062	0.151	1
More fixed effects	9.008	59.980	0.170
Fewer fixed effects	0.123	0.188	0.246
From training sample	0.076	0.203	0.760
t-statistics	0.955	2.190	0.945

Figure A1 presents the kernel densities of the ideological sorting normalized coefficient estimates.

Figure A1. Kernel Densities of Ideological Sorting Estimates, by Detailed Industry



The density with stronger fixed effects has been constrained to [-1, 1.5] due to extreme values.