CHAPTER 4 GEOECONOMIC FRAGMENTATION AND FOREIGN DIRECT INVESTMENT
ONLINE ANNEXES

Online Annexes 4.1–4.5 provide the data sources, methodology and complementary results referenced in the main text.

Online Annex 4.1. Geopolitical Alignment and FDI

This online annex provides the details behind the non-parametric and parametric evidence that foreign direct investment (FDI) is more likely to take place between countries that are geopolitically close. It also provides additional exhibits that complement those in the main text.

Methodology

The analysis relies on two different approaches to get at non-parametric evidence that the association between geopolitical alignment and FDI grew overtime, and parametric results that quantify in a controlled setting such relationship.

The non-parametric evidence is based on the following steps. First, countries are ranked based on their distance from the U.S. (similar results hold if another large country of reference like China is chosen). Then, countries are split in five groups $G \in \{1,2..5\}$ based on their ranking—very close (first quintile of the distance distribution), close (second quintile), at medium distance (third), far (fourth), and very far (fifth). A function from the set of countries C to the set of groups $\{1,2..5\}$ $g(.)\colon C \rightarrow \{1,2..5\}$ is such that if a country i belongs to group G then $g(i) = G$. Then, for each year in the sample FDI taking place between countries in the same group is counted. Finally, this number is divided by the total number of FDI observed in the year. Thus, the measure of FDI geopolitical concentration in year *t* ($FDIGC_t$) is obtained as:

$$FDIGC_t = \frac{\sum_j \sum_i \mathbf{1}(g(i) = g(j))FDI_{ij}}{\sum_j \sum_i FDI_{ij}}$$

where $\mathbf{1}(g(i) = g(j))$ is an indicator function taking value 1 if $g(i) = g(j)$ and 0 otherwise. As there are 25 combinations of groups from $\{1,2..5\} \times \{1,2..5\}$, while only the FDI taking place between countries belonging to the same group are counted in the numerator in the expression for $FDIGC_t$, if geopolitical distance did not matter, $FDIGC_t$ would equal 0.2, that is one in five FDI would take place between geopolitically close (aligned) countries. Upwards deviation from this number is taken as evidence that geopolitical distance matters for FDI.

The parametric evidence relies on a regression framework based on a standard gravity model, which controls for many bilateral variables and country specific time varying factors. Namely, the following equation is estimated:

$$FDI_{sdt} = f(\alpha Geopolitical\ Distance_{sdt-1} + \beta Gravity_{sd} + \tau_{st} + \upsilon_{dt}, \varepsilon_{sdt}) \qquad (1),$$

Where bilateral FDI flows (measured in USD volumes or by the number of projects) from the source country *s* to the destination country *d,* in year *t* is a function of the lagged value of a measure of geopolitical distance between countries *d* and *s.* As standard in gravity models, the specification controls for the geographical distance between source and destination countries (which could be correlated with the geopolitical distance), other standard gravity factors (common legal origins, common language, colonial or dependency relationship), and absorb any time varying push and pull unobservable factor adding source country x year and destination country x year fixed effects. These fixed effects would absorb, for instance, business cycle dynamics which could push FDI outflows from the source country and attract inflows into the destination country. Equation (1) would capture mostly cross section differences in geopolitical proximity. In other words, for the FDI from a given source country s, the coefficient α would inform how the difference in the geopolitical distance between two destination countries and the source country s affects FDI flows from country s to the two destination countries. However, the coefficient α could pick up the effect of other factors which are specific of the country-pair and are potentially correlated with the geopolitical distance and are not captured by the gravity variables. Equation (1) is then augmented to include measure of cultural and institutional distance and a historical measure of colonial ties. However, as long as these measures are time invariant, equation (1) could be fully saturated by including the country-pair fixed effects (ψ_{sd}) which would absorb all these sources of heterogeneity:

$$FDI_{sdt} = f(\alpha Geopolitical\ distance_{sdt-1} + \psi_{sd} + \tau_{st} + \upsilon_{dt}, \varepsilon_{sdt}) \qquad (2),$$

In this case, the interpretation of the coefficient α is more restrictive and within country-pair. This means that that the coefficient α picks up the effect of a deviation in political proximity between the source and the destination country on FDI flows.

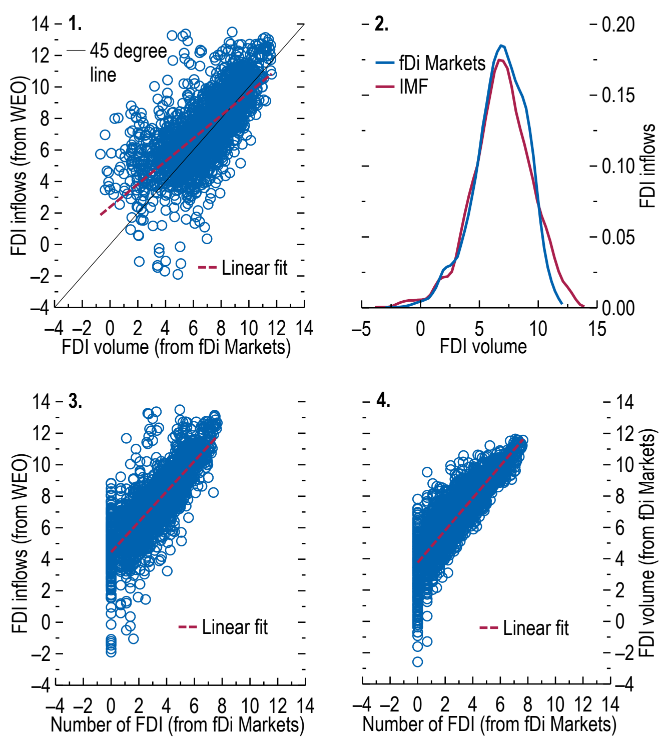
As most of the FDI_{sdt} cells are zeros, the model is estimated by Poisson pseudo-maximum likelihood (PPML, Santos Silva and Tenreyro 2006). Standard errors are clustered at the country-pair level.

Data Sources

The data on bilateral greenfield FDI comes from fDi Markets, a service from the Financial Times which tracks new physical project or expansion of an existing investment which creates new jobs and capital investment.[1] The data are collected primarily from publicly available

Online Annex Figure 4.1.1. fDi Markets versus World Economic Outlook Data, 2003–21

(Log)

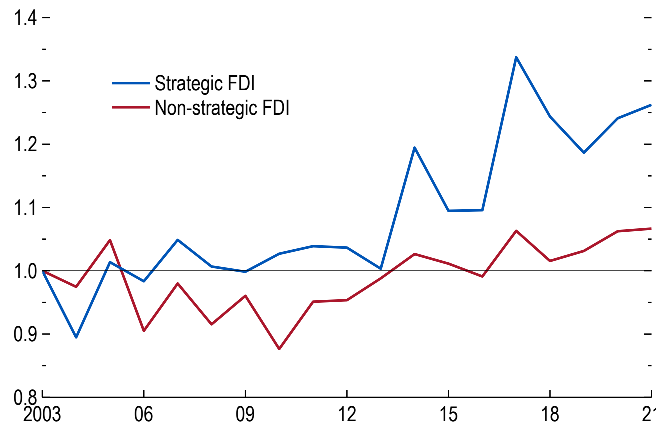


Sources: fDi Markets; and IMF staff calculations.
Note: Panels 1, 2, and 3 report FDI inflows at the country-year level from the WEO database and from fDi Market database between 2003 and 2021, both in volumes (panels 1 and 2) and in number of investments (panel 3). Panel 4 plots FDI inflows at the country-year level only from fDi Market between 2003 and 2021, comparing flows in volumes and in number of investments. FDI = foreign direct investment; WEO = *World Economic Outlook*.

[1] fDi Markets does not track mergers and acquisitions and other international equity investments, investment projects that do not create new jobs, companies which establish a foreign subsidiary without a physical company presence.

sources (e.g., media sources, industry organizations, investment promotion agencies newswires) and report investment-level information for over 300,000 FDI between January 2003 and December 2022. For each investment, the dataset reports the source and destination countries, as well as the sector, activity (e.g., business services, sales, R&D), type (new investment or expansion), volume (in USD) and number of jobs created. The volume of the capital investment and the associated jobs are often estimated. The reliability of these data is tested by aggregating the volumes at the destination country-year level and contrasting them with gross FDI inflows as published in the World Economic Outlook (WEO). Online Annex Figure 4.1.1 shows that the two sets of data are highly correlated, and the two distributions show a large degree of overlap. In addition, the number and value of bilateral investment are highly correlated. Both variables, once aggregated at the source-destination-year level, are top-winsorised with a threshold corresponding to the 0.01 percent of the observations.

Online Annex Figure 4.1.2. Geopolitics Became More Relevant for Strategic FDI
(Probability ratios, 2003 = 1)



Sources: Atlantic Council; Bailey, Strezhnev, and Voeten (2017); Centre d'études prospectives et d'informations internationales; fDi Markets; NL Analytics; and IMF staff calculations.
Note: Figure shows probability ratio of strategic FDI and non-strategic FDI taking place between country pairs geopolitically close (that is, in the same quintile of the distribution of the ideal point distance). FDI = foreign direct investment.

The measure of geopolitical distance used in the analysis is the Ideal Point Distance (IPD) constructed by Bailey and others (2017). It is based on the votes at the United Nation General Assembly between 1946 and 2021. The measure is built by first estimating an ordered logit over the three voting choices (yea, abstain, nay), where the choice depends on the parameters of the model combined with a latent vote specific preference of each country in a given year. The latent process is estimated imposing a Bayesian prior on the preferences and employing a Metropolis-Hastings/Gibbs sampler algorithm to infer the parameters of the logit model and then the posterior distribution of the latent preferences parameters. The distance between two countries in each year is then computed as the absolute value of the difference between the inferred vote specific preference parameter. More details on the measurement and the estimation are provided in Bailey and others (2017).[2]

The CEPII gravity dataset provides standard gravity variables including geographical distance, common language, legal framework and colonial ties.

Data on earnings calls from NL Analytics (Hassan and others 2019) and a study from the Atlantic Council are combined to obtain the definition of strategic sectors. Specifically, the chapter defines strategic sectors at the 3-digit industry level, based on the following approach. First, a list proposed by the Atlantic Council is used to identify as strategic these sectors:

[2] The distance is not estimated but taken directly as available from this link: https://dataverse.harvard.edu/dataverse/Voeten which provides the most updated version of the distance for all the country pairs.

semiconductors, telecommunications and 5G infrastructure, equipment needed for green transition, pharmaceutical ingredients, and strategic and critical minerals.[3] These sectors are mapped into the 3-digit industry classification based on ISIC Revision 4. Second, amongst manufacturing and mining sectors, the 3-digit industry groups which fall in the top-3 deciles of mentions of reshoring-related terms in companies earnings calls between 2017-2022 are added to the list. The manufacture of textiles, which also falls in the top-3 deciles of reshoring terms mentions, is excluded. The final list of strategic sectors is reported in Online Annex Table 4.1.5.

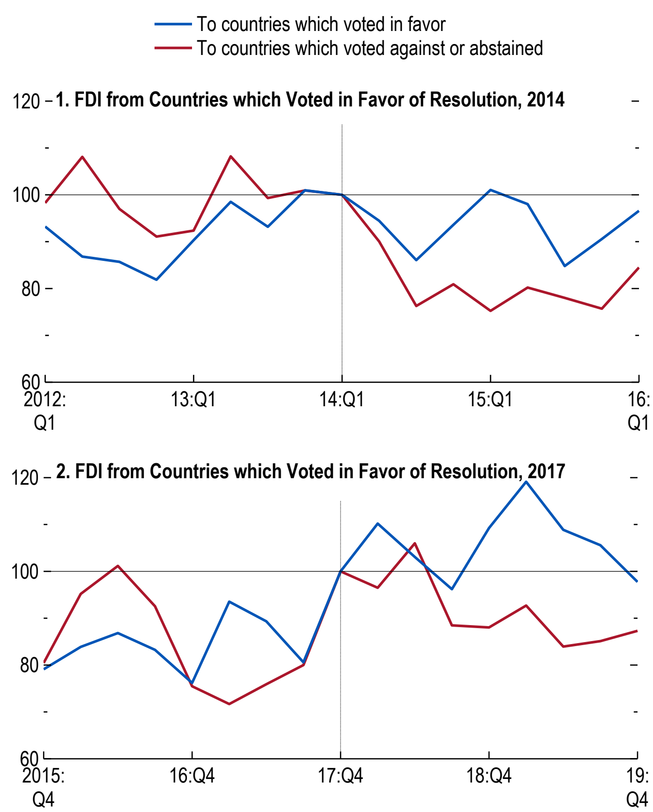
The list of 162 source countries and 180 destination countries for which we have complete data and at least one FDI sourced or received is reported in Online Annex Table 4.1.5.

Non-parametric Results

Figure 4.7 in the main text shows that our measure $FDIGC_t$ is greater than 0.2 and it is in fact well above 0.35 throughout the sample. Second, it has increased to more than 0.5 in 2021. To interpret the size of $FDIGC_t$, an analogous measure based on geographical distance is plotted in red in the same figure. The line shows that FDI takes place more frequently between geographically close countries than between countries further apart, but the red line is consistently below the blue line suggesting that geopolitical distance is relatively more important. A ratio between the two lines summarizes this relative importance. Such ratio has increased from 1.2 in 2003 (the first year of data) to 1.3 in 2021.

To gauge a sense of the different importance of geopolitical distance for different types of sectors, the same exercise is repeated focusing the count on strategic sectors and other sectors. Measures of FDI concentration are built based on geopolitical and geographic distance, and their year-by-year ratio is then normalized to one in 2003. The normalized series for the two groups of sectors is reported in Online Annex Figure 4.1.2. The chart shows that the increase in

Online Annex Figure 4.1.3. Event Studies around United Nations Resolutions
(Index, quarter of the vote = 100)



Sources: fDi Markets and IMF staff calculations.
Note: The charts plot the number of greenfield FDI in each quarter from countries which approved the United Nations General Assembly resolution to that from countries which either voted against or abstained. The series are normalized to 100 in the quarter of the vote. Panel 1 refers to resolution 68/262 (March 2014) about the territorial integrity of Ukraine. Panel 2 refers to resolution 72/191 (December 2017) on human rights in Syria. FDI = foreign direct investment.

[3] See: https://www.atlanticcouncil.org/in-depth-research-reports/issue-brief/our-guide-to-friend-shoring-sectors-to-watch/

geopolitical importance for FDI decisions was markedly higher in strategic sectors (+26 percent) than for other sectors (+6 percent).

Before turning to the parametric evidence, also looking at the behavior of FDI flows around key UN resolutions suggests that indeed geopolitics matters for the allocation of FDI. The evidence is gathered by focusing on the patterns of FDI flows from countries which approved the resolution to host countries which either voted against or abstained in the 16 quarters around two resolutions.[4] Online Annex Figure 4.1.3 shows that the two series of FDI diverge after both resolutions, with investments to opposing countries being much lower than those to countries which approved the resolutions. This evidence, while purely descriptive, suggests that geopolitical factors affect MNCs' investment decisions.

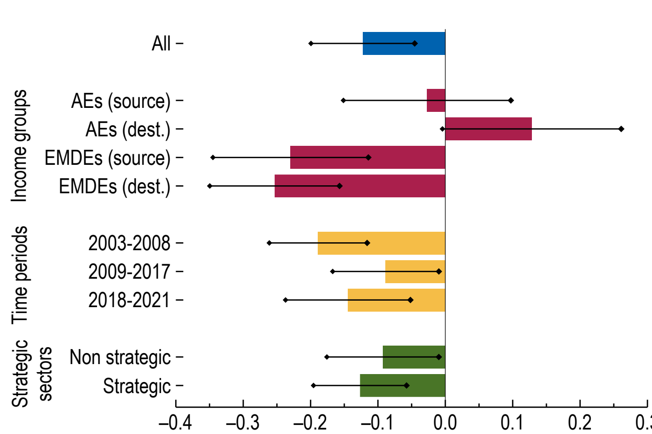
Parametric Results

Baseline findings

The results of the estimation of the gravity model are shown in Online Annex Table 4.1.1, where columns 1-3 take the number of projects as dependent variable and columns 4-6 consider their volume (in USD). The estimates show that a higher IPD is associated with lower FDI, regardless of how FDI is measured. As expected, the estimated coefficient becomes smaller when controlling for geographical distance—which is also associated with lower FDI (columns 2 and 5)—and when augmenting the model with controls for common legal origins, common language, and the presence of a colonial relationship (columns 3 and 6). While these variables are generally associated with more FDI, the coefficient on IPD remains negative and statistically significant. A quantitative interpretation of the coefficient in column 3 suggests that as the IPD measure raises from the 25th to the 75th percentile (equivalent to moving the distance from that between South Korea and Japan to that between the UK and Russia), the number of FDI between countries declines by about 15 percent.

To explore how the importance of IPD for FDI changes across samples, time and types of FDI, the main specification

Online Annex Figure 4.1.4. Heterogeneity Analysis
(Semielasticities)



Sources: Atlantic Council; Bailey, Strezhnev, and Voeten (2017); Centre d'études prospectives et d'informations internationales, Gravity database; fDi Markets; NL Analytics; and IMF staff calculations.
Note: Coefficients are estimated from a gravity model for foreign direct investment estimated with Pseudo-Poisson Maximum Likelihood. The reported coefficients refer to the ideal point distance measure from Bailey, Strezhnev, and Voeten (2017).

[4] First, the resolution 68/262 about the territorial integrity of Ukraine, which was adopted on 27 March 2014 in response to the Russian annexation of Crimea. The resolution defends the territorial integrity of Ukraine within its internationally recognized borders and underscores the invalidity of the 2014 Crimean referendum. Second, the resolution 72/191, adopted on 19 December 2017 on the situation of human rights in Syria. This resolution strongly condemns the grave deterioration of the human rights situation in Syria, the indiscriminate killing and deliberate targeting of civilians as such, including those involving the continued indiscriminate use of heavy weapons and aerial bombardments.

(Online Annex Table 4.1.1, column 3) is re-estimated by interacting the coefficient on IPD with various dummies or restricting the sample appropriately. FDI responds to IPD especially when an EMDE country is involved either as the source or destination. The relevance of geopolitical distance for FDI was declining up to 2017 but started increasing again after then. Finally, the coefficient of the ideal point distance is larger for FDI in strategic sectors than in other sectors. These results are reported in Online Annex Figure 4.1.4. The blue bars in the chart show that the negative relationship between FDI and IPD is non significantly different from zero if the source or destination country is an AE, while it is larger than average (approximately twice as large) if the destination or source country is an EMDE. Further analysis reveals that the impact of IPD on FDI flows is especially driven by South-South flows, that is in cases when both the source and the destination country is an EMDE. The red bars show that the importance of IPD for FDI has changed over time. The U-shape of the negative coefficients captures the fact that the negative relation between IPD and FDI was declining between the beginning of the sample (2003, soon after China joined the WTO) and 2017, while it increased after 2018 and until 2021, coinciding with the resurgence of tensions between China and the U.S. Importantly, the difference in the semielasticities between the 2009-17 and 2018-21 periods is statistically significant. Finally, the green bars report the coefficient on IPD from two different regressions: one in which only FDI that are classified as strategic are included in the sample, and one in which only FDI in other sectors are included. The results show that the importance of IPD for FDI is larger for strategic sectors than for other sectors.

Robustness and Extensions

The main results are robust to alternative samples, alternative measures of geopolitical distance, and to the inclusion of additional control variables.

As shown in Online Annex Table 4.1.2, the main findings hold when restricting the sample to only manufacturing (column 1) or services (column 2) FDI, and they remain valid when excluding country pairs that never registered a FDI during the sample period (column 3). The results are also robust to excluding international financial centers,[5] or China (columns 4 and 5).

Results are similar if the IPD measure is replaced with the rank of the destination country with respect to the source country in the IPD distribution, or with alternative indicators of geopolitical distance, such as the *S* score or the *Pi* (π) scores proposed by Signorino and Ritter (1999) and Häge (2011)—which are used in Chapter 3 of the April 2023 *Global Financial Stability Report* (Online Annex Table 4.1.2, columns 1-3).

Columns 4 to 7 in Online Annex Table 4.1.2 address the concern that geopolitical distance could pick up other factors which could vary across country pair and affect FDI flows. Results are also robust to the inclusion of: (1) the announcement and implementation of bilateral trade barriers, as measured by Global Trade Alerts (column 4); (2) the intensity of trade flows, measured by bilateral imports (column 5); and (3) the yearly change in the bilateral exchange rate (column 6).

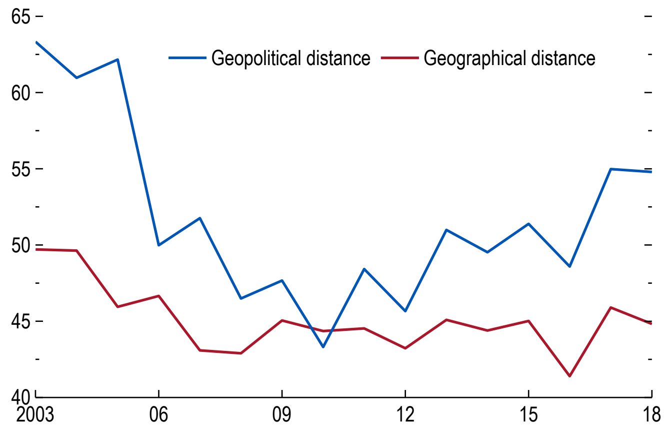
---

[5] Singapore, Luxembourg, The Netherlands and Ireland, with the addition of Bahamas, Malta and Cyprus, see column 4. The other countries classified as international financial centers by Daamgard and others (2019) are also excluded from our baseline sample as other variables included in the specification are not available for those countries

In column 7 the model is saturated with country-pair fixed effects. In that specification, which is very restrictive and only exploits the variation in IPD within country pairs, the coefficient of the IPD variable becomes smaller in size and loses significance when FDI is measured by the number of projects (top panel), but not when FDI is measured in value (bottom panel).[6]

Finally, although the chapter focuses exclusively on greenfield FDI, key findings from the chapter hold for brownfield FDI (i.e., cross-border M&As). Specifically, replacing country-year level greenfield FDI measures with corresponding brownfield FDI measures up to 2018 from the SDC Platinum database, Online Annex Figure 4.1.5 confirms the robustness of the results reported in Figure 4.7 in the main text, and Online Annex Table 4.1.4 show qualitatively identical results to Online Annex Table 4.1.1.

Online Annex Figure 4.1.5. Foreign Direct Investment between Geographically and Geopolitically Close Countries: Brownfield FDI (Merger and Acquisition)
(Percent)



Sources: Atlantic Council; Bailey, Strezhnev, and Voeten (2017); Centre d'études prospectives et d'informations internationales; SDC Platinum database; and IMF staff calculations.
Note: Figure shows the annual share of strategic brownfield foreign direct investments (merger and acquisition) between country pairs that are similarly distant (that is, in same quintile of distance distribution), geopolitically and geographically, from the United States.

[6] However, restricting the sample to EMDE destination countries shows that an increase in geopolitical distance is associated with a subsequent decline in FDI, regardless of measuring in value of by the number of projects. Quantitatively, in the baseline specification in the EMDEs-destination-countries sample moving the IPD measure from the 25th to the 75th percentiles is associated with a decline of about 30 percent in the number of FDI, and this is reduced to 15 percent in the model saturated with country pairs fixed effects.

Online Annex Table 4.1.1. Main Results

Dependent Variable:	FDI (number of projects)			FDI (USD million)		
	(1)	(2)	(3)	(4)	(5)	(6)
Ideal point distance, lagged	-0.3570***	-0.1448***	-0.1162***	-0.4563***	-0.2610***	-0.2162***
	(0.042)	(0.040)	(0.039)	(0.035)	(0.034)	(0.033)
Geographic distance		-0.6266***	-0.5694***		-0.6168***	-0.5720***
		(0.035)	(0.037)		(0.035)	(0.035)
Common legal origins			0.1541***			0.0503
			(0.048)			(0.051)
Common language			0.4768***			0.5446***
			(0.079)			(0.077)
Colonial or dependency relationship			0.4135***			0.4052***
			(0.083)			(0.085)
Observations	320,025	320,025	320,025	320,025	320,025	320,025
Source country x year FE	Y	Y	Y	Y	Y	Y
Destination country x year FE	Y	Y	Y	Y	Y	Y

Sources: United Nations (Bailey et al. 2017), CEPII, fDi Markets, and IMF staff calculations.

Notes: Standard errors are clustered at the country-pair level. Period 2003-2021.

Online Annex Table 4.1.2. Robustness on Alternative Samples

	Dependent Variable: FDI (number of projects)				
	(1)	(2)	(3)	(4)	(5)
Ideal point distance, lagged	-0.1310***	-0.1157***	-0.1259***	-0.1229***	-0.1566***
	(0.034)	(0.043)	(0.038)	(0.039)	(0.041)
Geographic distance	-0.5102***	-0.6447***	-0.5368***	-0.5931***	-0.6135***
	(0.037)	(0.039)	(0.035)	(0.040)	(0.039)
Common legal origins	0.1389***	0.1537***	0.1652***	0.1590***	0.1578***
	(0.048)	(0.046)	(0.047)	(0.052)	(0.043)
Common language	0.3911***	0.5482***	0.4296***	0.4665***	0.4667***
	(0.078)	(0.080)	(0.076)	(0.084)	(0.081)
Colonial or dependency relationship	0.2805***	0.5056***	0.3950***	0.4266***	0.4196***
	(0.074)	(0.090)	(0.080)	(0.087)	(0.088)
Observations	229,262	269,436	115,659	291,547	312,830
Source country x year FE	Y	Y	Y	Y	Y
Destination country x year FE	Y	Y	Y	Y	Y
Sample	Manufacturing	Services	Restricted	No fin. centers	Drop China
	Dependent Variable: FDI (USD million)				
Ideal point distance, lagged	-0.1999***	-0.2352***	-0.2346***	-0.2106***	-0.2192***
	(0.032)	(0.038)	(0.032)	(0.033)	(0.036)
Geographic distance	-0.5743***	-0.5941***	-0.5331***	-0.6023***	-0.6105***
	(0.036)	(0.034)	(0.033)	(0.038)	(0.039)
Common legal origins	0.0478	0.1195**	0.0727	0.0643	0.0745
	(0.056)	(0.048)	(0.050)	(0.055)	(0.050)
Common language	0.5039***	0.6108***	0.4795***	0.5400***	0.5353***
	(0.084)	(0.076)	(0.075)	(0.079)	(0.081)
Colonial or dependency relationship	0.3320***	0.4889***	0.3845***	0.4160***	0.4030***
	(0.085)	(0.094)	(0.082)	(0.090)	(0.089)
Observations	229,262	269,436	115,659	291,547	312,830
Source country x year FE	Y	Y	Y	Y	Y
Destination country x year FE	Y	Y	Y	Y	Y
Sample	Manufacturing	Services	Restricted	No fin. centers	Drop China

Sources: United Nations (Bailey et al. 2017), CEPII, fDi Markets, and IMF staff calculations.
Notes: Standard errors are clustered at the country-pair level. Period 2003-2021.

Online Annex Table 4.1.3. Robustness to alternative measures of geopolitical distance and additional controls

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable: FDI (number of projects)							
Ideal point distance, lagged				-0.1028**	-0.1182***	-0.1151***	0.0075
				(0.041)	(0.038)	(0.039)	(0.028)
Geographic distance	-0.5661***	-0.5747***	-0.5530***	-0.5604***	-0.3565***	-0.5680***	
	(0.036)	(0.036)	(0.036)	(0.038)	(0.040)	(0.037)	
Common legal origins	0.1538***	0.1494***	0.1533***	0.1546***	0.1102**	0.1544***	
	(0.048)	(0.048)	(0.047)	(0.049)	(0.048)	(0.048)	
Common language	0.4760***	0.4823***	0.4736***	0.4795***	0.4262***	0.4749***	
	(0.079)	(0.079)	(0.079)	(0.080)	(0.076)	(0.079)	
Colonial or dependency relationship	0.4106***	0.4148***	0.4263***	0.3976***	0.3923***	0.4149***	
	(0.084)	(0.081)	(0.082)	(0.087)	(0.078)	(0.083)	
Ideal point distance rank, lagged	-0.3281***						
	(0.094)						
S measure of distance, lagged		-0.2946***					
		(0.113)					
Pi measure of distance, lagged			-0.2809***				
			(0.067)				
Trade barriers, starting				-0.0010			
				(0.003)			
Trade barriers, announced				0.0020			
				(0.004)			
Imports					0.2012***		
					(0.018)		
Exchange rate (yearly change)						-2.4574***	
						(0.933)	
Observations	320,025	319,987	319,987	252,172	257,077	317,770	115,637
Source country x year FE	Y	Y	Y	Y	Y	Y	Y
Destination country x year FE	Y	Y	Y	Y	Y	Y	Y
Country pair FE	N	N	N	N	N	N	Y
Dependent Variable: FDI (USD Million)							
Ideal point distance, lagged				-0.1854***	-0.2204***	-0.2157***	-0.1198**
				(0.035)	(0.032)	(0.033)	(0.055)
Geographic distance	-0.5717***	-0.5769***	-0.5478***	-0.5838***	-0.4082***	-0.5698***	
	(0.035)	(0.034)	(0.035)	(0.036)	(0.040)	(0.035)	
Common legal origins	0.0485	0.0405	0.0557	0.0648	0.0220	0.0501	
	(0.051)	(0.051)	(0.050)	(0.052)	(0.050)	(0.051)	
Common language	0.5508***	0.5500***	0.5389***	0.5176***	0.4989***	0.5434***	
	(0.078)	(0.078)	(0.076)	(0.079)	(0.074)	(0.077)	
Colonial or dependency relationship	0.3955***	0.4146***	0.4207***	0.3981***	0.3861***	0.4072***	
	(0.085)	(0.083)	(0.085)	(0.087)	(0.080)	(0.085)	
Ideal point distance rank, lagged	-0.5503***						
	(0.081)						
S measure of distance, lagged		-0.6239***					
		(0.099)					
Pi measure of distance, lagged			-0.4870***				
			(0.062)				
Trade barriers, starting				0.0012			
				(0.004)			
Trade barriers, announced				-0.0013			
				(0.004)			
Imports					0.1608***		
					(0.020)		
Exchange rate (yearly change)						-4.3679***	
						(1.076)	
Observations	320,025	319,987	319,987	252,172	257,077	317,770	115,637
Source country x year FE	Y	Y	Y	Y	Y	Y	Y
Destination country x year FE	Y	Y	Y	Y	Y	Y	Y
Country pair FE	N	N	N	N	N	N	Y

Sources: IMF *World Economic Outlook* , Global Trade Alert, Signorino and Ritter (1999), and Hage (2011).
Notes: Standard errors are clustered at the country-pair level. Period 2003-2021.

Online Annex Table 4.1.4. Robustness to Brownfield FDI (M&A) Measures

Dependent Variable:	**cross-border M&As (number of deals)**			**cross-border M&As (USD million)**		
	(1)	(2)	(3)	(4)	(5)	(6)
Ideal point distance, lagged	-0.5453***	-0.2660***	-0.1919***	-0.5087***	-0.3819***	-0.3270***
	(0.053)	(0.048)	(0.041)	(0.046)	(0.043)	(0.045)
Geographic distance		-0.8341***	-0.7798***		-0.5348***	-0.5058***
		(0.034)	(0.030)		(0.044)	(0.045)
Common legal origins			0.1924***			0.2568***
			(0.064)			(0.084)
Common language			0.5524***			0.1556
			(0.092)			(0.123)
Colonial or dependency relationship			0.2224**			0.1292
			(0.090)			(0.123)
Observations	150,811	150,811	150,811	150,811	150,811	150,811
Source country x year FE	Y	Y	Y	Y	Y	Y
Destination country x year FE	Y	Y	Y	Y	Y	Y
Country pair FE	N	N	N	N	N	N
Sample	All	All	All	All	All	All

Sources: United Nations (Bailey et al. 2017), CEPII, SDC Platinum database, and IMF staff calculations.

Notes: Standard errors are clustered at the country-pair level. Period 2003-2018.

Online Annex Table 4.1.5. List of strategic sectors and countries included in the main regression analysis

Strategic Sectors
As described in SEC 3 definitions: Manufacture of basic chemicals, fertilizers and nitrogen compounds, plastics and synthetic rubber in primary forms -- Manufacture of batteries and accumulators -- Manufacture of coke oven products -- Manufacture of consumer electronics -- Manufacture of domestic appliances -- Manufacture of electronic components and boards -- Manufacture of general-purpose machinery -- Manufacture of measuring, testing, navigating and control equipment; watches and clocks -- Manufacture of motor vehicles -- Manufacture of non-metallic mineral products n.e.c. -- Manufacture of pharmaceuticals, medicinal chemical and botanical products -- Mining of non-ferrous metal ores -- Support activities for petroleum and natural gas extraction. And following subsectors of ISIC code 20 (Manufacture of Chemicals and Chemical Products) for which there is not precise mapping into SEC classification: Biological products (except diagnostic) -- In-Vitro diagnostic substances -- Other (Biotechnology) -- Pesticide, fertilizers & other agricultural chemicals.
Source countries included in main regression:
Afghanistan; Albania; Algeria; Andorra; Angola; Antigua and Barbuda; Argentina; Armenia; Australia; Austria; Azerbaijan; Bahamas, The; Bahrain; Bangladesh; Barbados; Belarus; Belgium; Belize; Bhutan; Bolivia; Bosnia and Herzegovina; Botswana; Brazil; Brunei Darussalam; Bulgaria; Burkina Faso; Burundi; Cambodia; Cameroon; Canada; Chile; China; Colombia; Congo, Republic of; Costa Rica; Croatia; Cyprus; Czech Republic; Côte d'Ivoire; Democratic Republic of the Congo; Denmark; Djibouti; Dominican Republic; Ecuador; Egypt; El Salvador; Equatorial Guinea; Estonia; Ethiopia; Fiji; Finland; France; Gabon; Gambia, The; Georgia; Germany; Ghana; Greece; Guatemala; Guyana; Haiti; Honduras; Hungary; Iceland; India; Indonesia; Iran; Iraq; Ireland; Israel; Italy; Jamaica; Japan; Jordan; Kazakhstan; Kenya; Kiribati; Korea; Kuwait; Kyrgyz Republic; Lao P.D.R.; Latvia; Lebanon; Libya; Lithuania; Luxembourg; Madagascar; Malawi; Malaysia; Maldives; Mali; Malta; Mauritius; Mexico; Micronesia, Fed. States of; Moldova; Mongolia; Montenegro, Rep. of; Morocco; Mozambique; Myanmar; Namibia; Nepal; Netherlands; New Zealand; Nicaragua; Nigeria; North Macedonia; Norway; Oman; Pakistan; Panama; Papua New Guinea; Paraguay; Peru; Philippines; Poland; Portugal; Qatar; Romania; Russia; Rwanda; Samoa; San Marino; Saudi Arabia; Senegal; Seychelles; Sierra Leone; Singapore; Slovak Republic; Slovenia; Solomon Islands; South Africa; Spain; Sri Lanka; St. Kitts and Nevis; St. Lucia; Sudan; Sweden; Switzerland; Syria; Tajikistan; Tanzania; Thailand; Togo; Trinidad and Tobago; Tunisia; Türkiye; Turkmenistan; Uganda; Ukraine; United Arab Emirates; United Kingdom; United States; Uruguay; Uzbekistan; Vanuatu; Venezuela; Vietnam; Yemen; Zambia; and Zimbabwe.
Destination countries included in main regression:
Afghanistan; Albania; Algeria; Andorra; Angola; Antigua and Barbuda; Argentina; Armenia; Australia; Austria; Azerbaijan; Bahamas, The; Bahrain; Bangladesh; Barbados; Belarus; Belgium; Belize; Benin; Bhutan; Bolivia; Bosnia and Herzegovina; Botswana; Brazil; Brunei Darussalam; Bulgaria; Burkina Faso; Burundi; Cabo Verde; Cambodia; Cameroon; Canada; Central African Republic; Chad; Chile; China; Colombia; Comoros; Congo, Republic of; Costa Rica; Croatia; Cyprus; Czech Republic; Côte d'Ivoire; Democratic Republic of the Congo; Denmark; Djibouti; Dominica; Dominican Republic; Ecuador; Egypt; El Salvador; Equatorial Guinea; Eritrea; Estonia; Eswatini; Ethiopia; Fiji; Finland; France; Gabon; Gambia, The; Georgia; Germany; Ghana; Greece; Grenada; Guatemala; Guinea; Guinea-Bissau; Guyana; Haiti; Honduras; Hungary; Iceland; India; Indonesia; Iran; Iraq; Ireland; Israel; Italy; Jamaica; Japan; Jordan; Kazakhstan; Kenya; Kiribati; Korea; Kuwait; Kyrgyz Republic; Lao P.D.R.; Latvia; Lebanon; Lesotho; Liberia; Libya; Lithuania; Luxembourg; Madagascar; Malawi; Malaysia; Maldives; Mali; Malta; Mauritania; Mauritius; Mexico; Micronesia, Fed. States of; Moldova; Mongolia; Montenegro, Rep. of; Morocco; Mozambique; Myanmar; Namibia; Nepal; Netherlands; New Zealand; Nicaragua; Niger; Nigeria; North Macedonia; Norway; Oman; Pakistan; Panama; Papua New Guinea; Paraguay; Peru; Philippines; Poland; Portugal; Qatar; Romania; Russia; Rwanda; Samoa; Saudi Arabia; Senegal; Seychelles; Sierra Leone; Singapore; Slovak Republic; Slovenia; Solomon Islands; Somalia; South Africa; Spain; Sri Lanka; St. Kitts and Nevis; St. Lucia; St. Vincent and the Grenadines; Sudan; Suriname; Sweden; Switzerland; Syria; São Tomé and Príncipe; Tajikistan; Tanzania; Thailand; Togo; Trinidad and Tobago; Tunisia; Türkiye; Turkmenistan; Uganda; Ukraine; United Arab Emirates; United Kingdom; United States; Uruguay; Uzbekistan; Vanuatu; Venezuela; Vietnam; Yemen; Zambia; and Zimbabwe.

Online Annex 4.2. A Multidimensional Index of Vulnerability

This online annex describes the construction of the aggregate vulnerability index and the following three sub-indices.

1. Geopolitical index, which captures the idea that the vulnerability of an investment project to being relocated should increase with the geo-political distance between the host country and the source country. Therefore, a host country is more vulnerable the greater is the share of the FDI stock sourced from geo-politically distant countries. The index is defined as follows:

$$v_i^{geo} = \sum_j share_{ij}^{FDI} * \gamma^{geo}(i,j) \;, where\; \gamma^{geo}(i,j) = \frac{percentile\big(IPD(i,j)\big)}{100}$$

In the above, i denotes the host-country, j denotes the source-country, v_i^{geo} denotes the country-level geopolitical vulnerability measure, $share_{ij}^{FDI}$ denotes the estimated share of FDI stock in host-country i from source-country j, and function $\gamma^{geo}(i,j)$ is a measure of the geopolitical distance between the host and source. The index is bounded between 0 and 1, with higher values indicating greater vulnerability. The $share_{ij}^{FDI}$ is estimated by counting the number of greenfield FDI from j into i, after the GFC and before COVID (2010-2019), and dividing by the number of investments in country i over the same period from all source countries. The function $\gamma^{geo}(i,j)$ is the percentile of the bilateral IPD amongst all bilateral IPDs across all years. A lower percentile indicates closer geopolitical alignment between the source and host.

2. Market power index, which captures the idea that it may be harder to relocate projects out a sector in a host country if that host country is a major player in that sector. Therefore, host countries that have market power in many of the sectors where they host FDI are less vulnerable. The index is defined as follows:

$$v_i^{mkt} = \sum_s share_{i,s}^{FDI} * \gamma^{mkt}(i;s) \;, where\; \gamma^{mkt}(i;s) = \begin{cases} 0.5\; if\; country\; i\; is\; a\; top-10\; exporter\; in\; sector\; s \\ 1\; if\; otherwise \end{cases}$$

The $share_{i,s}^{FDI}$ denotes the estimated share of FDI stock in country i and sector s, from all source countries over the period 2010-2019. The function $\gamma^{mkt}(i;s)$ treats FDI in sector s, country i, as partly vulnerable if the country is amongst the top-10 exporters in that sector, and fully vulnerable if otherwise. A significant share of FDI in many host-countries are in non-tradeable sectors (e.g., retail, finance). These investments are treated as fully vulnerable in all countries in the baseline calculation. As robustness, an alternate calculation using tradeable sectors only yields similar results.

3. Strategic index, which captures the idea that source-countries may be particularly interested in re-locating investments in strategic sectors for national or economic security reasons. Both geo-politically close and distant host economies may be vulnerable along this dimension. The index is defined as follows:

$$v_i^{strat} = \sum_s share_{i,s}^{FDI} * \gamma^{strat}(s) \ , where\ \gamma^{strat}(s) = \begin{cases} 1\ if\ sector\ is\ strategic \\ 0\ if\ sector\ is\ non-strategic \end{cases}$$

Aggregate index. For each host country, an aggregate index of vulnerability is constructed by combining the three indices at the sector-source country level. The following equation defines the aggregate index:

$$v_i^{agg} = \frac{1}{2}\sum_j \sum_s share_{ij,s}^{FDI} * \left(\gamma^{geo}(i,j) * \gamma^{mkt}(i;s) + \gamma^{strat}(s)\right)$$

The $share_{ij,s}^{FDI}$ denotes the estimated share of FDI stock in country i – sector s and from source-country j, amongst the total FDI stock in that country. Market power in a sector is considered to ameliorate geopolitical vulnerability from the source country, and therefore $\gamma^{mkt}(i;s)$ and $\gamma^{geo}(i,j)$ are multiplied together. This market-power adjusted geopolitical vulnerability is added to $\gamma^{strat}(s)$, as the strategic dimension is considered to capture a separate aspect of GEF. The weighted average—summed across all sectors and source countries, is then divided by 2 so that the aggregate index is between 0 and 1.

Data. As elsewhere in the chapter, the distribution of FDI stocks in each host, by sector and by source, is proxied for by counting the number of greenfield investment projects—from fDi Markets—since the Global Financial Crisis, and prior to the outbreak of COVID-19 (2010-2019). Bilateral geopolitical distance is measured using the ideal point distance (Bailey et al. 2017). Alongside, export market shares are calculated based on bilateral exports flows from Trade Monitor Data for 2019.

Baseline assumptions. Hong Kong SAR and Macao SAR are merged with mainland China, while Taiwan Province of China is dropped. Financial centers are included.

Robustness. Several alternative thresholds and functional forms are considered to check the robustness of the indices. As well, the following alternate approaches are considered for calculating the index. The baseline index is broadly correlated with these alternate methods, and the findings of the chapter are robust to these alternate methods.

- Estimating FDI stocks starting from 2003 (first available year in fDi Markets) rather than 2010.
- Dropping mining sectors from strategic industries when calculating strategic vulnerability.
- Calculating each index using only sectors with non-zero exports.
- Estimating FDI stocks using value of projects, or the number of jobs created.
- Dropping Hong Kong and Macao SARs rather than merging with China.
- Dropping countries that are financial centers.

Online Annex 4.3. Empirical Evidence on FDI Spillovers to Host Countries

This online annex provides the details behind the country-level and firm-level evidence on FDI spillovers in host countries featured in the main text.

Country-level Evidence

Background

Not all FDI is alike and gains from FDI may differ by FDI types. To the extent that the composition of inward FDI types is also different across countries, the relationship between FDI and growth could vary across countries. A case in point is the distinctive nature of two major types of FDI: horizontal and vertical FDI. This has become more relevant as the degree of exposure to geoeconomic fragmentation risk is likely to vary across FDI types.[7]

Against the background, this section compares the relationship between FDI and growth across host countries classified into a group of horizontal or vertical countries.

Data and Methods

Previous studies proposed novel approaches to identifying horizontal and vertical FDI. Ramondo and others (2016) explore the U.S. BEA data that provide a detailed breakdown of sales by foreign subsidiaries into geographical and customer-type dimensions: inter-firm or intrafirm local sales; inter-firm or intra-firm exports to other countries. The idea is that, since horizontal (vertical) FDI firms tend to sell their products mainly to local unaffiliated (affiliated) customers, subsidiaries with a high share of local inter-firm sales (total intra-firm sales) in total sales can be classified as horizontal (vertical) FDI firms.

Alternatively, Alfaro and Charlton (2009) propose to use information on parent and subsidiary firms' sector affiliations to distinguish different types of FDI. Specifically, a parent and subsidiary pair that belongs to the same sector is likely to be horizontal FDI, while a pair that belongs to different sectors is likely to be vertical FDI.

Following these approaches, the chapter constructs two different country-level proxy measures on the prevalence of horizontal FDI as opposed to vertical FDI. First, aggregating respective sales data in a given country by Korean foreign subsidiaries, a country with more than 50 percent of local unaffiliated sales in total sales is classified as a horizontal FDI country, while the other countries are classified as vertical FDI countries.[8] A limitation of this approach is that it is strictly based on Korean MNCs' perspectives.

Hence, the chapter also consider an alternative approach, by exploring the ownership structure information in the Orbis database employed in Ando and Wang (2020). A case in which a

[7] Vertical FDI is likely to be more exposed to risks from rising protectionism as higher tariffs, for example, would make horizontal FDI more attractive while making vertical FDI less attractive. Moreover, a risk of geoeconomic fragmentation, particularly in the current form of tech wars, is expected to hurt vertical FDI more as it is centered around advanced technology embodied in input production where vertical FDI tends to prevail.

[8] Foreign subsidiary-level data from the Export-Import Bank of Korea are comparable to the U.S. BEA data. See Ahn and Park (2022) for more details.

subsidiary belongs to the same 2-digit industry as the parent firm is identified as horizontal FDI, while a case in which a subsidiary belongs to a different 2-digit sector from their parents' is categorized as a vertical FDI. Aggregating up the total number of horizontal and vertical FDI firms, if a country's share of horizontal FDI firms in total foreign owned firms is above 20 percent is classified as a horizontal FDI country, while a country below the same threshold value is classified as a vertical FDI country. One limitation of this proxy variable is that, in several countries, the coverage of foreign owned firms in the Orbis database is limited.

The relationship between FDI and growth is then assessed in a parsimonious specification, with a particular focus on the difference between horizontal and vertical FDI countries, as defined above:

$$Y_{it} = \beta_1 FDI_{it-1} + \gamma X_{it} + \epsilon_{it},$$

where Y_{it} is real GDP growth in country *i* at time *t*, FDI_{it-1} is lagged FDI over GDP and the controls in X_{it} include lagged log-GDP, all of which are taken from the IMF World Economic Outlook database. Country and time fixed effects are also included, and standard errors are clustered at the country level. The baseline sample covers 160 countries between 1981 and 2021.

Estimation Results

Columns 1-3 in Online Annex Table 4.3.1 summarize the baseline estimation results on the full set of countries, regardless their horizontal/vertical FDI classification. There is a strong positive correlation between FDI and growth, especially strong among EMDEs.

Employing the first country-level proxy variable, based on subsidiary-level sales information, column 1 in Online Annex Table 4.3.2 reports the estimation results for all horizontal FDI countries, which are further broken down into AEs and EMDEs (columns 2 and 3). Similarly, columns 4-6 show estimation results for all vertical FDI countries, AE vertical FDI countries, and EMDE vertical FDI countries, respectively. Overall, there is a strong positive correlation between FDI and growth for vertical FDI countries,

Online Annex Table 4.3.1 Country-Level Estimation Results: Baseline

By income levels	All	AEs	EMDEs
By FDI types	All	All	All
	(1)	(2)	(3)
		coefficients	
Lagged FDI over GDP	0.165***	0.0291**	0.233***
	(0.0595)	(0.0129)	(0.0820)
Lagged Log of real GDP	-4.679***	-5.051***	-4.589***
	(0.603)	(0.682)	(0.683)
		standardized coefficients	
Lagged FDI over GDP	0.159***	0.067**	0.180***
	(0.0595)	(0.0129)	(0.0820)
Lagged Log of real GDP	-0.985***	-0.575***	-0.763***
	(0.603)	(0.682)	(0.683)
Observations	5274	1103	4171
Adj-R2	0.253	0.602	0.239

Source: IMF staff calcualtions.
Note: All specifications include country and year fixed effects. Columns (1)-(3) consider all countries, advanced economies, emerging and developing market economies, respectively. Standard errors are clustered at the country level.
***p<0.01, **p<0.05, *p<0.1.

but this relationship does not hold for horizontal FDI countries. Looking at the results by income levels makes it clear that the strong positive correlation among vertical FDI countries is driven entirely by EMDEs. Online Annex Table 4.3.3 confirms these findings relying on the proxy variable based on sector affiliation information. Qualitative results are very close, except that a positive relationship between FDI and growth is also found for horizontal FDI in AEs.

These findings reflect the distinctive nature of horizontal and vertical FDI; horizontal FDI are more frequent among final goods producers that tend to bring simple (and labor intensive) assembly technology to host countries. By contrast, vertical FDI tends to be concentrated among intermediate goods producers, which are more likely to employ more sophisticated (and skill intensive) technology.

Online Annex Table 4.3.2 Country-Level Estimation Results: Sales Information-Based Classification

By income levels	All	AEs	EMDEs	All	AEs	EMDEs
By FDI types	Horizontal	Horizontal	Horizontal	Vertical	Vertical	Vertical
	(1)	(2)	(3)	(4)	(5)	(6)
			coefficients			
Lagged FDI over GDP	-0.0302	0.0116	-0.0535	0.0840**	0.0152	0.186***
	(0.0235)	(0.0132)	(0.164)	(0.0408)	(0.0215)	(0.0666)
Lagged Log of real GDP	-4.230***	-7.570***	-4.575***	-3.008***	-3.715**	-3.489***
	(1.488)	(1.981)	(1.409)	(0.794)	(1.647)	(0.995)
			standardized coefficients			
Lagged FDI over GDP	-0.040	0.033	-0.028	0.109**	0.037	0.138***
	(0.0235)	(0.0132)	(0.164)	(0.0408)	(0.0215)	(0.0666)
Lagged Log of real GDP	-1.203***	-0.976***	-0.997***	-0.795***	-0.391**	-0.680***
	(1.488)	(1.981)	(1.409)	(0.794)	(1.647)	(0.995)
Observations	948	410	538	1475	491	984
Adj-R2	0.344	0.678	0.282	0.425	0.589	0.417

Source: IMF staff calcualtions.

Note: All specifications include country and year fixed effects. Columns (1)-(3) consider horizontal FDI countries only. Columns (4)-(6) consider vertical FDI countries only. Standard errors are clustered at the country level. ***p<0.01, **p<0.05, *p<0.1.

Online Annex Table 4.3.3 Country-Level Estimation Results: Industry Information-Based Classification

By income levels	All	AEs	EMDEs	All	AEs	EMDEs
By FDI types	Horizontal	Horizontal	Horizontal	Vertical	Vertical	Vertical
	(1)	(2)	(3)	(4)	(5)	(6)
			coefficients			
Lagged FDI over GDP	0.0946	0.172***	0.0774	0.112**	0.00639	0.218***
	(0.0615)	(0.0199)	(0.0857)	(0.0455)	(0.0118)	(0.0797)
Lagged Log of real GDP	-3.847***	-5.683***	-3.172***	-4.312***	-2.387	-4.869***
	(0.938)	(0.431)	(0.838)	(0.869)	(2.302)	(0.980)
			standardized coefficients			
Lagged FDI over GDP	0.063	0.174***	0.047	0.146**	0.017	0.197***
	(0.0615)	(0.0199)	(0.0857)	(0.0455)	(0.0118)	(0.0797)
Lagged Log of real GDP	-0.951***	-0.701***	-0.702***	-1.019***	-0.255	-0.861***
	(0.938)	(0.431)	(0.838)	(0.869)	(2.302)	(0.980)
Observations	1554	244	1310	2651	859	1792
Adj-R2	0.315	0.685	0.305	0.288	0.589	0.260

Source: IMF staff calcualtions.

Note: All specifications include country and year fixed effects. Columns (1)-(3) consider horizontal FDI countries only. Columns (4)-(6) consider vertical FDI countries only. Standard errors are clustered at the country level. ***p<0.01, **p<0.05, *p<0.1.

Firm-level Evidence

Background

Foreign entry may have different impacts depending on whether it mostly affects intra-industry domestic competitor firms as opposed to inter-industry domestic suppliers/buyers.[9] Previous firm-level studies focusing on one country find mixed evidence on this.[10] To better understand potential costs of FDI deterred by geo-economic fragmentation, it is important to identify specific sources of spillover effects from inward FDI in host countries. This part of the analysis evaluates firm-level FDI spillovers by exploring cross-country sector-level variation in FDI.[11]

Data and Methods

The fDi Markets Database is matched with the World Bank Enterprise Surveys (WBES), which provide a rich set of standardized firm-level information in a repeated cross-sectional design

[9] In a nutshell, intra-industry spillover refers to the case in which FDI in any given sector potentially benefit sales and innovation by local firms in the same sector. Backward (forward) linkages refer to the case in which an upstream (downstream) domestic firm could benefit from FDI in downstream (upstream) sectors.

[10] For intra-industry spillover effects, Aitken and Harrison (1999) find a negative spillover effect in Venezuela, which is attributed to the market-stealing effect caused by entering foreign firms, whereas Haskel and others (2007) and Keller and Yeaple (2009) report positive spillover effects in the United Kingdom and United States, respectively. By contrast, inter-industry spillover effects tend to be found mostly positive for backward linkages (Harrison and Rodriguez-Clare, 2010). Javorcik (2004) explore Lithuanian firm-level data to separately estimate intra-industry and inter-industry spillover effects where the latter is further broken down into backward and forward linkages. The estimation results support the strong presence of backward linkages: positive productivity spillovers from FDI take place mostly through contacts between foreign firms and their local suppliers in upstream sectors. Blalock and Gertler (2008) confirm technological spillovers from FDI via backward linkages among Indonesian firms. Jiang and others (2018) find both backward and intra-industry spillover effects from international joint ventures in China. Jude (2016) and Newman and others (2015) confirm positive backward spillover effects and negative forward spillover effects in Romania and Vietnam, respectively.

[11] In line with the literature, this chapter only considers spillovers from manufacturing sector FDI.

(with different countries surveyed in different years) for more than 180,000 firms in over 150 countries between 2006 and 2022. Firm-level performance measures in the standardized WBES dataset includes employment, sales, investment, and R&D expenditures. The current analysis aims to separately estimate inter-industry and intra-industry spillover effects on firm-level labor productivity, and thus is close to the approach taken in Mercer-Blackman and others (2021).

To measure inter-industry linkages, the global input-output matrix from the EORA database is used to construct the weighted sum of FDIs across input or output sectors for a given country-sector, where weights are calculated from a share of input from (or output to) respective sector in total inputs (or outputs). Specifically, these are expressed as:

$$FDI_{cjt}^{user} = \sum\nolimits_{s \neq abroad} \left[\left(\frac{\alpha_{cjs}}{\sum_s \alpha_{cjs}} \right) \times FDI_{cst} \right]$$

for forward linkages to domestic users in downstream sectors, and:

$$FDI_{cjt}^{supplier} = \sum\nolimits_{u \neq abroad} \left[\left(\frac{\alpha_{cuj}}{\sum_u \alpha_{cuj}} \right) \times FDI_{cut} \right]$$

for backward linkages to domestic suppliers in upstream sectors. In the definitions of the forward and backward linkages, α_{cus} is total input supplied by sector *s* to produce output in sector *u*, taken from the EORA database for each country *c*; FDI_{cj} is country-sector level inward FDI measured as the number of new greenfield FDI in the fDi Markets database, which effectively serves as a measure for intra-industry spillover effects and thus is also denoted as FDI_{cj}^{within}.[12]

The baseline regression is specified as:

$$\Delta \ln LP_{icjt} = \beta_1 \ln\left(FDI_{cjt-3}^{within}\right) + \beta_2 \ln\left(FDI_{cjt-3}^{supplier}\right) + \beta_3 \ln\left(FDI_{cjt-3}^{user}\right) + FE_{cj} + FE_{ct} + FE_{jt} + \varepsilon_{icjt}$$

for estimating both intra-industry and inter-industry spillover effects at the same time, where $\Delta \ln LP_{icjt}$ denotes a firm *i*'s labor productivity growth over the previous three years.[13] Using the lagged values of FDI and including fixed effects FE_{cj}, FE_{ct}, and FE_{jt} that captures country-sector, country-year, and sector-year fixed effects, respectively, might partly mitigate the concerns for the most obvious sources of endogeneity. Standard errors are clustered in multiple dimensions at the country-sector and country-year level.

Estimation Results

Columns 1-3 in Online Annex Table 4.3.4 summarize the baseline estimation results from the analysis of both inter-industry and intra-industry spillover effects when FDI from all source countries is considered. Intra-industry spillover effects are positive and statistically significant only for AEs. Backward spillover effects are positive and statistically significant, particularly in EMDEs. Forward spillover effects are negative, but not statistically significant.

[12] 1 is added to FDI measures to include observations in those country-sectors without new FDI in given year.

[13] The questionnaire includes total sales and number of workers in the last fiscal year and three fiscal years ago so that labor productivity growth over the period can be calculated.

Online Annex Table 4.3.4 Firm-Level Estimation Results

Sample (host country)	All	AEs	EMDEs	All	AEs	EMDEs	All	AEs	EMDEs
Source country	All	All	All	AEs	AEs	AEs	EMDEs	EMDEs	EMDEs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					coefficients				
Intra-industry spillover	0.159*	0.890**	0.141	0.139	0.768*	0.125	0.0909	1.009	0.0776
	(0.0899)	(0.394)	(0.0922)	(0.100)	(0.438)	(0.103)	(0.192)	(1.007)	(0.196)
Backward spillover	0.340**	0.759	0.372**	0.293*	0.758	0.285*	0.256	0.527	0.451*
	(0.144)	(0.931)	(0.148)	(0.149)	(1.124)	(0.151)	(0.240)	(1.529)	(0.251)
Forward spillover	-0.277	-1.298	-0.288	-0.285*	-0.734	-0.273	-0.185	-1.663	-0.339
	(0.181)	(0.999)	(0.181)	(0.168)	(1.015)	(0.171)	(0.320)	(1.989)	(0.329)
					standardized coefficients				
Intra-industry spillover	0.028*	0.217**	0.025	0.024	0.177*	0.021	0.005	0.084	0.004
	(0.0899)	(0.394)	(0.0922)	(0.100)	(0.438)	(0.103)	(0.192)	(1.007)	(0.196)
Backward spillover	0.107**	0.349	0.114**	0.091*	0.333	0.086*	0.027	0.103	0.044*
	(0.144)	(0.931)	(0.148)	(0.149)	(1.124)	(0.151)	(0.240)	(1.529)	(0.251)
Forward spillover	-0.085	-0.557	-0.086	-0.085*	-0.299	-0.080	-0.020	-0.296	-0.035
	(0.181)	(0.999)	(0.181)	(0.168)	(1.015)	(0.171)	(0.320)	(1.989)	(0.329)
Observations	129557	16316	113114	129557	16316	113114	129557	16316	113114
Adj-R2	0.178	0.159	0.178	0.178	0.159	0.177	0.178	0.159	0.177

Source: IMF staff calcualtions.

Note: All specifications include country-sector, country-year and sector-year fixed effects. Columns (1)-(3) consider FDI from all source countries; Columns (4)-(6) consider FDI from AEs only. Columns (7)-(9) consider FDI from EMDEs only. Standard errors are clustered at the country-sector and country-year level. ***p<0.01, **p<0.05, *p<0.1.

These results are consistent with the previous literature that finds that pro-competitive effects and market stealing effects operate within an industry in the opposite direction; the former may dominate in AEs, while the latter may prevail in EMDEs (e.g., Aitken and Harrison, 1999). As for inter-industry spillovers, positive productivity spillovers from FDI take place mainly through contacts between foreign affiliates and local suppliers in upstream sectors rather than through contacts between foreign affiliates and local buyers in downstream sectors (e.g., Javorcik 2004).

Columns 4-6 and columns 7-9 in Online Annex Table 4.3.4. report extended results, breaking down FDI source countries into AEs and EMDEs, respectively. The results are consistent with the notion that FDI from AEs tend to embody more advanced technology than FDI from EMDEs: positive intra-industry spillover effects in AEs are driven mainly by FDI from AEs. Moreover, positive backward spillover effects in EMDEs stem from FDI originating in both AEs and EMDEs, while standardized coefficients suggest that FDI from AEs yields two times stronger effects than FDI from EMDEs.

Online Annex 4.4. Modeling FDI Fragmentation

This online annex provides a summary of key elements of the IMF's Global Integrated Monetary and Fiscal model (GIMF) and its calibration; the assignment of regions into geo-political blocs; and the calibration of productivity losses for EMDE regions; a scenario where only China and the U.S. impose barriers on one another; and different assumptions around uncertainty for the non-aligned regions.

Description of The Global Integrated Monetary and Fiscal Model (GIMF)

Summary of the Model Structure

The IMF's GIMF is an annual, multi-region, micro-founded dynamic stochastic general equilibrium model (DSGE) of the global economy. In this chapter, GIMF comprises 8 regions: the United States, EU+, other advanced economies, China, Southeast Asia, India and Indonesia, Latin America and the Caribbean, and the rest of the world.[14] Alongside the standard elements, a tradable sector related to global value chains (GVC) was added for this chapter, referred to hereafter as "the GVC sector." More detailed expositions of the model can be found in Kumhof and others (2010) and Anderson and others (2013).

Some households are modeled as non-Ricardian, finitely lived, overlapping generations, as found, for example, in Blanchard (1985). These saving households choose consumption, savings, and labor supply. The remaining households are liquidity constrained, consume all their income every period and set their labor supply proportional to that of the saving households and reinforce the short-term non-Ricardian properties of the model.

Profit-maximizing firms (owned by households) operate in monopolistically competitive markets, and produce goods in non-tradable, tradable, and the GVC sectors. These three types of goods are based on sectors from the OECD Inter-Country Input-Output Database (OECD 2021; presented in Online Annex Table 4.4.1).

Firms in every sector choose investment to maximize their net present value. Investment requires inputs sourced both domestically and from foreign regions. Inputs sourced from various regions are not perfectly substitutable. The analysis in the chapter puts barriers on the

[14] Specifically, the regions comprise the following countries: United States is alone; EU+ is the European Union and Switzerland; other advanced economies is Australia, Canada, Iceland, Israel, Japan, Korea, New Zealand, Norway, and the United Kingdom; China refers to Mainland China and Hong Kong SAR; Southeast Asia is Brunei, Cambodia, Lao PDR, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam; Latin America is Argentina, Brazil, Chile, Colombia, Costa Rica, Mexico, and Peru; India and Indonesia are a region; and the rest of the world includes Russia, South Africa, and Türkiye plus the regions of Africa, the Caribbean, Central Asia, other Latin America, the Middle East, and Oceania, and any other EMDEs not accounted for elsewhere.

Online Annex Table 4.4.1. Definition of GIMF's Production Sectors

Nontradables		Tradables		GVC goods	
Code	**Sector Name**	**Code**	**Sector Name**	**Code**	**Sector Name**
D35	Electricity and natural gas	D01T02	Agriculture, hunting, forestry	D05T06	Mining (energy)
D36T39	Water	D03	Fishing	D07T08	Mining (non-energy)
D41T43	Construction	D09	Mining (support)	D13T15	Textiles, leather and footwear
D45T47	Wholesale and retail trade	D10T12	Food	D16	Wood and wood products
D53	Postal services	D23	Other non-metallic products	D17T18	Paper products and printing
D61	Telecommunications	D49	Land transport	D19	Coke and refined oil products
D68	Real estate	D52	Warehousing	D20	Chemicals
D77T82	Administration	D55T56	Hotels and restaurants	D21	Pharmaceutical products
D84	Public administration	D58T60	Publishing and broadcasting	D22	Rubber and plastics
D85	Education	D64T66	Finance and insurance	D24	Basic metals
D86T88	Health			D25	Fabricated metal products
D90T93	Arts			D26	Computers and electronics
D94T96	Other services			D27	Electrical equipment
D97T98	Households as employers			D28	Other machinery
				D29	Motor vehicles
				D30	Other transport equipment
				D31T33	Repair
				D50	Water transport
				D51	Air transport
				D62T63	Information Technology
				D69T75	Professional

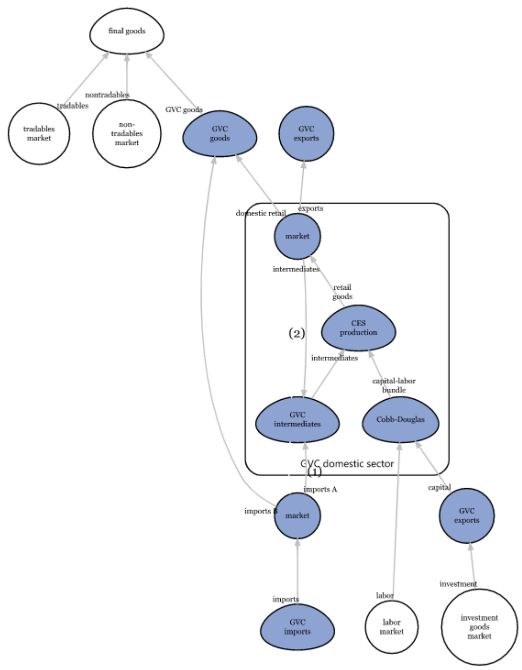
Sources: OECD (2021); and IMF staff calculations.

import of these inputs from opposing bloc regions. The GVC sector is added to the model, as FDI can play an important role in developing country's links to global value chains, though FDI contributes to productive capacity in other sectors as well.

Non-tradable goods and domestically produced tradable goods are produced using some combination of labor and capital.

The GVC sector is more complex than the other two sectors, as seen in Online Annex Figure 4.4.1, as GVC goods are used both in final goods and as inputs in the production of other GVC goods. The sector is intended to represent industries such as semiconductors, with chips going into the production of computers sold to consumers (a final good), or as inputs into automobile-parts (another GVC good). Production in the GVC sector combines capital and labor (bundled using a Cobb-Douglas function) with already produced GVC goods, which are both imported (labeled (1)) and domestically sourced (labeled (2)). The produced output is then split between inputs into final goods or cycled back as inputs into the production of other GVC goods, both domestically and abroad.

Online Annex Figure 4.4.1 The Global Value Chain Sector in GIMF



Regions trade final goods (consumption and investment), and tradable and GVC intermediate goods. The flows of these goods are tracked bilaterally. Trade flows react to demand, supply and pricing (i.e., the terms of trade and bilateral real exchange rates) conditions.

The model captures barriers to trade using "non-tariff barriers" (NTBs), which affects the model's importers and exporters in ways similar to tariffs but does not generate fiscal revenues. NTBs in GIMF can take two forms, and they have identical economic impacts. The more standard first form is where country A imposes an NTB on imports from country B, which country B's exporters partially pass on to country A's importers through higher prices. The second form is where country B imposes the NTB on its exports to country A. This also results in country B's exporters passing on the cost as much as possible to country A's importers. This second form of NTB is used in the chapter, reflecting that source countries are trying to restrict flows of investment inputs to destinations in the opposing bloc.

Monetary and fiscal policies are set to passively respond to shocks according to inflation forecast-based targeting and debt-GDP ratio targeting rules respectively.

Summary of the Calibration

Each region's economy is calibrated using the OECD Inter-Country Input-Output Database for 2018 (OECD 2021), drawing on its national accounts and fiscal ratios. National accounts ratios are summarized in Online Annex Table 4.4.2. The size of the various sectors works in tandem with more specific parameterizations in the various sectors, such as consumption and international trade, discussed below.

For consumption, the intertemporal elasticity of substitution is common across regions at 0.2. The share of liquidity constrained households varies based on level of financial market development, and is set at 25 percent for the United States, EU+, the other advanced economies, and China, and at 50 percent for the remaining regions. Regions with high shares of liquidity constrained households have more volatility in GDP, as they are less able to smooth their consumption under temporary shocks or implement gradual adjustments under permanent shocks.

Online Annex Table 4.4.2. Domestic Sector Calibration
(percent of region's GDP, unless noted otherwise)

	United States	EU+	Other Advanced Economies	China	South-east Asia	Rest of the World	India and Indonesia	Latin America
Share of Global GDP (%, US$)	24.4	18.9	16.5	16.7	2.3	11.6	4.5	5.1
Domestic Demand								
Household Consumption	65.4	54.9	56.3	51.7	58.8	58.7	56.4	63.0
Private Investment	17.1	32.2	17.5	22.5	24.3	22.2	27.7	16.0
Trade								
Aggregate Exports	11.5	20.1	23.5	17.4	61.7	24.9	19.9	21.0
Consumption	*3.5*	*6.4*	*5.4*	*5.0*	*20.9*	*6.0*	*6.3*	*5.5*
Investment	*1.6*	*3.2*	*3.6*	*3.1*	*6.9*	*0.9*	*2.8*	*2.3*
Intermediate	*2.5*	*3.5*	*3.9*	*1.8*	*10.8*	*3.4*	*2.7*	*4.0*
GVC	*3.8*	*7.1*	*10.5*	*7.5*	*23.2*	*14.6*	*8.2*	*9.3*
Goods Imports	11.5	20.1	23.5	17.4	61.7	24.9	19.9	21.0
Investment	*1.4*	*2.8*	*2.4*	*1.6*	*8.7*	*5.6*	*2.4*	*2.6*
Intermediate	*1.7*	*3.8*	*4.1*	*2.6*	*11.3*	*3.2*	*2.9*	*3.2*
GVC	*5.4*	*7.0*	*9.8*	*9.2*	*29.5*	*7.3*	*11.7*	*9.2*

Sources: OECD (2021); and IMF staff calculations.

Region size and openness to trade also differentiate the role of regions in the global economy. Regions with smaller shares of global GDP will have less impact on the global neutral interest rate. A region's degree of openness determines how activity in the rest of the world will spill over onto it, and how that region influences the rest of the world.

Many of the elasticities in GIMF are calibrated the same across regions, including for trade and the combination of various goods to produce final goods. However, each region has a unique set of related bias parameters, which, given the elasticities, are computed based on the calibration of key steady-state ratios based on OECD (2021). For this chapter, the most important elasticities are related to trade and combining imports and domestically-produced goods to produce intermediate and final goods (Online Annex Table 4.4.3). A key parameter is the elasticity of substitution for investment inputs sourced from different foreign regions, which influences the role of diversion of investment input flows in a fragmented world. The benchmark elasticity of 1.5 and a higher value of 3 are considered. Demand for goods in the GVC sector are assumed to be relatively inelastic (all well under 1), compared to other elasticities of demand and trade, which are usually elastic at around 1.5. Final goods are a combination of nontradable goods and a tradable goods bundle, with an elasticity of 0.5. The tradable goods bundle is assembled from tradable intermediate goods and GVC goods with an elasticity of 0.95.

Online Annex Table 4.4.3. Calibration of Key Production and Trade Elasticities, All Regions

Elasticity between =>	***Capital-Labor / GVC***	***Domestic / Imported***	***Different Regions***
Consumption	-	1.5	1.5
Investment	-	1.5	1.5*
Tradables	-	1.5	1.5
GVC Goods	0.3	0.6^	0.5

Source: IMF staff calculations.
* Alternative value of 3.0 used when exploring trade diversion.
^ Elasticity between domestic and imported when using GVC goods in the production of final goods or of other GVC goods.

Construction of Geo-Political Blocs

This section outlines the assignment of model regions into geo-political blocs, based on the bilateral IPD scores averaged over 2017-2021. First, every country is ranked based on its closeness to the two pole countries: China and the US. These rankings are used to calculate six statistics for each country, equal 1 if true for that country and 0 if otherwise. The six statistics are (i) is relatively closer to China than the US; (ii) is relatively closer to the US than China; (iii) in the closest quartile to China; (iv) in the closest quartile to the US; (v) in the closest quartile to neither; and (vi) in the closest quartile to both.

Second, the six statistics for countries are aggregated up to the regional level, with countries weighted by GDP in PPP terms. Online Annex Table 4.4.4 summarizes the regional averages.

Third, the relative leans towards China and the US, based on statistics (i) and (ii), are used to sort regions into a group closer to China (Southeast Asia, India and Indonesia, rest of the world) and a group closer to the US (EU+, other AEs, Latin America and the Caribbean). From each group, the region with the least intense affiliation, as measured by statistic (v)—in the closest quartile to neither China nor the US, are assigned as non-aligned regions in the baseline fragmentation scenario. The remaining regions in each group form the two geopolitical blocs.

Online Annex Table 4.4.4. Geopolitical Alignment Statistics by Region

Region	Closer to China	Closer to U.S.	Closest quartile of China	Closest quartile of U.S.	Closest quartile of neither	Closest quartile of both
1.United States	0.0%	100.0%	0.0%	100.0%	0.0%	0.0%
2. China	100.0%	0.0%	100.0%	0.0%	0.0%	0.0%
3. EU+	0.0%	100.0%	0.0%	99.8%	0.2%	0.0%
4. Other AEs	0.0%	100.0%	0.0%	65.1%	34.9%	0.0%
5. India and Indonesia	100.0%	0.0%	0.0%	0.0%	100.0%	0.0%
6. Southeast Asia	100.0%	0.0%	54.3%	0.0%	45.7%	0.0%
7. LAC	12.2%	87.8%	5.8%	0.0%	94.2%	0.0%
8. ROW	83.5%	16.5%	42.5%	3.2%	54.4%	0.0%

Sources: Bailey and others (2017); IMF *World Economic Outlook*.
Note: IMF staff calculations.

Calibrating Productivity Losses Associated with Lower FDI Flows

The conditional correlation between FDI inflows-to-GDP and labor productivity is estimated using the following equation separately for EMDE and AE recipients, using a cross-country panel between 1980-2021.

$$logLP_{i,t} = \beta_0 + \beta_1 logLP_{i,t-1} + \beta_2 \left(\frac{FDI}{GDP}\right)_{i,t-1} + \delta_t + \gamma_i + \epsilon_{i,t} \quad (1)$$

In equation (1), $(logLP_{i,t})$ denotes the logarithm of labor productivity, $(logLP_{i,t-1})$ is the lagged value of the logarithm of labor productivity, and $\left(\frac{FDI}{GDP}\right)_{i,t-1}$ is the lagged ratio of FDI inflows to GDP. Time and country fixed effects are included. The estimates, reported in Online Annex Table 4.4.5, suggest an economically and statistically significant conditional correlation between lagged FDI to GDP and log labor productivity in EMDEs. The coefficient of 0.147 implies that a 10 percentage point increase in FDI inflows to GDP is associated 1.47 percent increase in labor productivity levels. The corresponding coefficient is small and insignificant for AEs.

To map these estimates into the model, first define (i) $\left\{\left(\widetilde{\frac{FDI}{GDP}}\right)_{i,t-j+1}\right\}_{j=0}^{\infty}$ as the sequence of FDI inflows to GDP in region *i* in a fragmentation scenario, with barriers rising starting in year *t*, and define (ii) $\left\{\left(\widehat{\frac{FDI}{GDP}}\right)_{i,t-j+1}\right\}_{j=0}^{\infty}$ as the corresponding sequence in the no-fragmentation scenario.

The permanent nature of the shock leads to permanent differences between sequences (i) and (ii), with the differences in labor productivity levels between the fragmentation and no-fragmentation economies cumulating over time. Equation (1) is used to obtain the difference in labor productivity between the two economies, s periods after the beginning of the shock, as shown in equation (2).

$$\left[\log(\widetilde{LP})_{i,t+s} - \log(\widehat{LP})_{i,t+s}\right] = \beta_2 \textstyle\sum_{j=0}^{s} \beta_1 \left[\left(\widetilde{\frac{FDI}{GDP}}\right)_{i,t+j-1} - \left(\widehat{\frac{FDI}{GDP}}\right)_{i,t+j-1}\right] \qquad (2)$$

As the model does not have a variable mapping directly to FDI, the import of investment inputs is used as a proxy on the right-hand side of equation (2).

Online Annex Table 4.4.5 Estimated Conditional Correlations between FDI/GDP and Labor Productivity

	Dependent Variable: Labor Productivity	
	(1)	(2)
Lagged FDI over GDP	-0.00399	0.147**
	(0.00801)	(0.0586)
Labor prductivity (lagged)	0.960***	0.963***
	(0.00521)	(0.00678)
Constant	0.464***	0.366***
	(0.0586)	(0.0647)
Observations	1262	4313
Rsquared	0.997	0.998
Period	1980-2021	1980-2021
Sample	AEs	EMDEs

Source: IMF staff calculations.

First, the model is run to obtain the sequence of each EMDE regions' import of investment inputs from AE regions, in the no-fragmentation and fragmentation scenarios. These are then used to calculate labor productivity changes for EMDE regions using equation (2), with s = 10 (i.e., losses cumulated for ten years). Second, these estimated labor productivity losses are fed back into the model to obtain the overall impact of fragmentation.

Losses mainly arise for EMDE regions in the China bloc, while non-aligned or US bloc EMDE regions may see some increase in flows due to diversion. The labor productivity changes are cumulated for ten years rather than indefinitely, to capture the idea that China itself is becoming a technological leader in many areas and can partly substitute as a source of knowledge transfer for its bloc members over time.

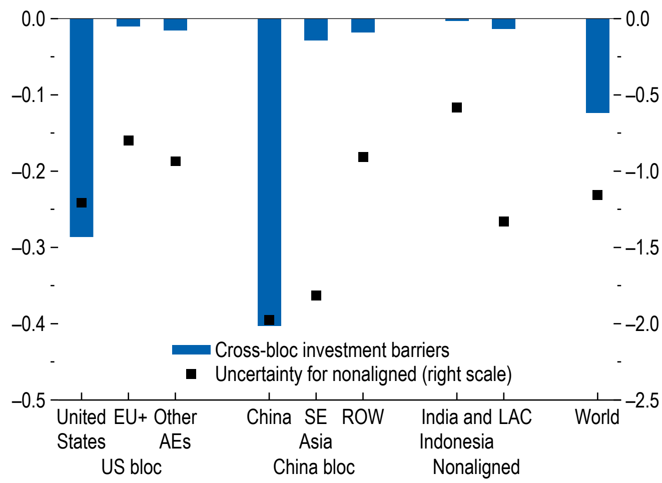
Fragmentation Scenario with Barriers Between the U.S. and China Only

A scenario in which the US and China impose barriers on each other, while the six other regions all remain non-aligned, is considered. In line with the results presented in the main text, regions can significantly mitigate their losses if they are able to remain non-aligned, with no barriers to investment flows with either bloc, and do so with certainty (Online Annex Figure 4.4.2). Under the benchmark elasticity of substitution between investment inputs sourced from different regions (1.5), any gains from the diversion of investment flows to non-aligned regions is dominated by the negative impact of reduced external demand, such that the non-aligned experience small output losses.

Alternative Assumptions for Policy Uncertainty

Regions can be in one of three policy regimes in a fragmented world: part of the US bloc, part of the China bloc, or non-aligned (i.e., non-aligned regions). This chapter considers two possibilities regarding investors' expectations about the future alignment of non-aligned regions: investors either expect the regions will remain non-aligned permanently (certainty case), or that there is some positive probability of these regions joining one bloc or the other (uncertainty case). This type of policy uncertainty can persist indefinitely, and as discussed in the literature, significantly weigh on trade and investment. Policy uncertainty can effectively raise the bar for market entry or investment, affecting economic decisions similarly to formal barriers (Handley and Limao, 2022). The analysis of uncertainty in this chapter exploits this relationship, imposing partial barriers to capture the implied impact on investment flows from uncertainty.

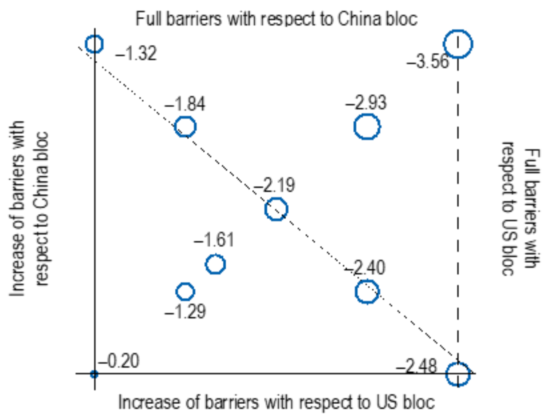
Online Annex Figure 4.4.2. Long-Term GDP Losses, Barriers between China and the United States Only
(Percent deviation from no-fragmentation scenario)



Source: IMF staff calculations.
Note: Scenario reflects explicit barriers to reduce investment input flows by 50 percent between China and the United States only, while all other regions remain nonaligned. AEs = advanced economies; EU+ = European Union and Switzerland; LAC = Latin America and the Caribbean; ROW = rest of the world; SE Asia = Southeast Asia.

As investors' perceived expectations regarding non-aligned regions in a hypothetical fragmentation scenario are impossible to pin down, the main text considers an illustrative case where such uncertainty translates into implicit barriers equal to half those faced by regions in the two blocs. Online Annex Figure 4.4.3 presents several other possibilities, using alternate combinations than the 50-50 scenario in the main text.

Online Annex Figure 4.4.3. Impact on Nonaligned GDP, Various Uncertainty Assumptions
(Percent deviation from no-fragmentation scenario)



Source: IMF staff calculations.
Note: Nonaligned regions are India and Indonesia, and Latin America and the Caribbean. Full barriers refer to nonaligned regions facing same level of investment input import barriers as regions in the opposing bloc. Bubble size represents the level of losses in each scenario.

The bottom-left corner corresponds to the non-aligned with certainty scenario as discussed in the main text, while the top-left and top-right corners correspond to the non-aligned joining the US bloc and the China bloc respectively. Smaller degrees of uncertainty (e.g., 25 percent implied barriers with either bloc) is associated with smaller losses. Facing smaller barriers with respect to the US bloc leads to smaller losses in general, given the relative importance of that bloc as a source of investment flows.

Online Annex 4.5. Balance Sheet Exposure to Fragmentation Risk

This online annex complements Box 2 on “Balance Sheet Exposure to Fragmentation Risk” by providing further details about the data and methodology. Robustness checks as well as additional results not reported in the box are also provided.

Data Sources and Methodology

Bilateral cross-border financial linkages across countries are constructed using (1) bilateral portfolio equity and debt investments taken from the IMF Coordinated Portfolio Investments Statistics Survey (CPIS) and (2) bilateral cross-border loans to non-banks, taken from the BIS International Locational Banking Statistics and reported on a residency basis. The total stock of non-FDI assets and liabilities for each country vis-a-vis the rest of the world is the sum of both components and captures the amount of capital invested in (and borrowed from) each partner country (in US dollars).

Small adjustments to the latest vintage of BIS data were made to ensure maximum country coverage. For India and Indonesia, BIS cross-border bank loans to non-banks were imputed after 2015 and 2016, respectively, assuming that (i) the bilateral distribution of bank loans to non-banks remained constant and (ii) loan volumes grew in line with the total amount of cross border loans (to both bank and non-bank borrowers) reported by the BIS for each country. For Germany and Japan, BIS cross-border bank loans to non-banks were estimated assuming they were in line with the bilateral distribution of total cross-border bank investments (both loans and debt securities) reported by the BIS. For China, estimates of cross-border bank loans were taken directly from Horn and others (2021). For Argentina, Russia and Saudi Arabia, BIS data on cross-border bank loans were not available and no substitute could be found in the literature. As a result, the stock of non-FDI assets and liabilities for these countries only captures CPIS portfolio investment data and exposures should be interpreted as a lower bound on the “true” exposure.

Since a large share of portfolio investments are booked in financial centers which are simply conduits for other countries’ investments, CPIS positions are first reallocated to their parent country using matrices based on fund holdings from Coppola and others (2021) and transformed into a nationality-based bilateral position. The reallocation matrices used are available from 2007-2021. Between 2001 and 2007, positions are reallocated using the 2007 reallocation matrix.

Political proximity data is taken from Bailey and others (2017). For every country, the Ideal Point Distance (IPD) variable is averaged between 2002 and 2021 and then normalized into a political proximity index, γ, with values ranging from [0,1] where a value of 0 (1) represents the most (least) politically distant country. All IPDs are rebased to ensure that the average IPD across countries when the destination is the US equals the average IPD across all destinations excluding the US. This is done to avoid unduly inflating exposures, as the IPD suggests the US is very politically distant from all countries and positions vis-à-vis the US are very large.

The (gross) balance sheet exposure to fragmentation risk for country i at time t is defined as:

$$fragmentation\_exposure_{i,t} = \frac{\sum_j (p_{i,j,t} - \gamma_{i,j} p_{i,j,t})}{X_{i,t}}$$

where $p_{i,j,t}$ is the bilateral non-FDI cross-border position (assets plus liabilities) for country i and counterpart country j at time t; $\gamma_{i,j} p_{i,j,t}$ is the politically-weighted version of the same position, and $X_{i,t}$ represents a country specific variable used to normalize exposures and express it as a share. This share captures the percentage of assets and liabilities at risk in a fragmentation scenario. In the main text, both nominal Gross Domestic Product in US dollars ($GDP_{i,t}$) and total cross-border positions for country i ($\sum_j p_{i,j,t}$) are used. GDP data is taken from the WEO database.

Online Annex Table 4.5.1 Composition of Country Groups in the Sample

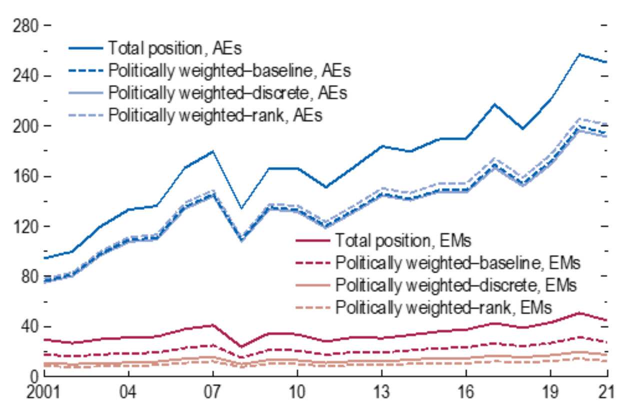
Advanced economies		Emerging Economies
Australia	Portugal	Argentina
Austria	Singapore	Bahrain
Belgium	South Korea	The Bahamas
Canada	Spain	Brazil
Cyprus	Sweden	Chile
Denmark	Switzerland	China
Finland	United Kingdom	India
France	United States	Indonesia
Germany		Mexico
Greece		Panama
Ireland		Philippines
Italy		Russia
Japan		Saudi Arabia
Luxembourg		Türkiye
Netherlands		South Africa

The final sample covers 38 countries (23 AE and 15 EM) accounting for 86 percent of world GDP. Online Annex Table 4.5.1 shows the composition of each country group. Compared to International Investment Position data from Lane and Milesi-Ferretti (2018), cross-border positions constructed in this Appendix represent 70.8% of total external assets and 59.3% of total external liabilities among the countries in the sample.

Robustness Exercises

Key findings presented in the box are robust to (i) alternative normalizations of the IPD variable and (ii) using an alternative measure of political proximity. Online Annex Figure 4.5.1 shows how gross exposures vary with two alternative transformations of the IPD variable, namely (i) a discrete measure, where countries with a proximity index below the first quartile are all assigned a weight of 0, those between the first and third quartiles are assigned a weight of 0.5, and those above the third quartile are all assigned a weight of 1; (ii) a continuous "rank" measure, which computes the ranking of each country based on the IPD and is normalized to be

Online Annex Figure 4.5.1. Gross Exposures, Assets and Liabilities, 2001–21
(Percent of GDP)



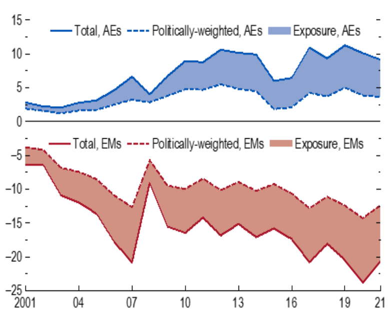
Sources: Bailey, Strezhnev, and Voeten (2017); Bank for International Settlements; IMF Coordinated Portfolio Investments Statistics Survey; and IMF staff calculations.
Note: The figure shows total and politically weighted positions based on 1) the baseline; 2) a discrete version of the ideal point distance variable; and 3) a continuous (rank) version of the ideal point distance variable for both AEs and EMs. AEs = advanced economies; EMs = emerging market economies.

expressed in a range of [0,1]. Online Annex Figure 4.5.1 shows that the baseline measure of political proximity delivers more conservative results (i.e., less exposures to fragmentation risks). Similarly, using a political proximity measure based on Häge (2011)—as done in Chapter 3 of the April 2023 *Global Financial Stability Report*—generates qualitatively similar results, but tends to increase estimated exposures relative to those presented in the box by a factor of 1.5 for AE and roughly 2 for EM in 2021. Overall, those results suggest that exposures presented in the box should be interpreted as conservative estimates.

Additional Results

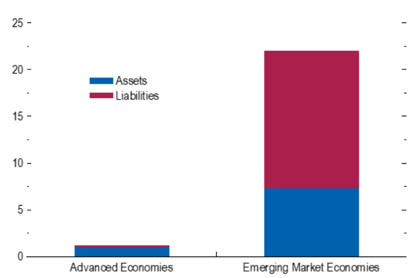
Online Annex Figure 4.5.2 reports a net measure (asset minus liabilities) of exposures to fragmentation by country group. Over the last 20 years, AE have accumulated a large and positive net exposure to fragmentation risks (6 percent of GDP in 2021), whereas EM have become increasingly liable to politically distant creditors (-8 percent of GDP). A concentration analysis also reveals that emerging markets are more exposed to concentration risks, especially on the liability side: Online Annex Figure 4.5.3 shows that the 5 percent most politically distant countries in EM currently account for 20 percent of their gross mismatch (against 1 percent for AE). Finally, as of 2021, assets exposures represented 9 percent of the financial system's total assets in G20 countries (on average), while liabilities exposures accounted for 8% of the total credit going to the non-financial sector (Online Annex Figure 4.5.4).

Online Annex Figure 4.5.2. Net Exposures, 2001–21
(Percent of GDP)



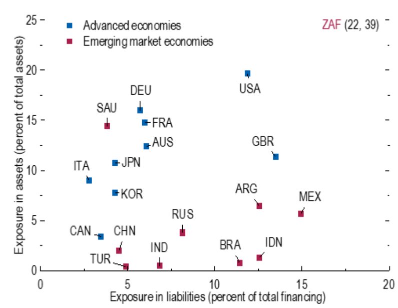
Sources: Bailey, Strezhnev, and Voeten (2017); Bank for International Settlements; IMF Coordinated Portfolio Investments Statistics Survey; and IMF staff calculations.
Note: Shaded areas represent the net exposure to fragmentation as the difference between total assets-liabilities and politically weighted assets-liabilities as percent of GDP. AEs = advanced economies; EMs = emerging market economies.

Online Annex Figure 4.5.3. Contribution of the Bottom Fifth Percentile of Political Proximity Countries to Gross Exposures, 2021
(Percent of Gross Exposure)



Sources: Bailey, Strezhnev, and Voeten (2017); Bank for International Settlements; IMF, Coordinated Portfolio Investments Statistics Survey; and IMF staff calculations.
Note: The plot shows the share of gross exposures accounted for by the 5-percent most politically distant countries, by assets and liabilities.

Online Annex Figure 4.5.4. G20 Assets and Liabilities Exposures, 2021



Sources: Bank of International Settlement; Central Bank of Argentina; IMF, Monetary and Financial Statistics; Organisation for Economic Co-operation and Development; Saudi Central Bank; and IMF staff calculations.
Note: Y-axis shows the gross exposures on the asset side as a ratio of the total assets of the financial system. X-axis shows the gross exposure on the liability side as a ratio of the total credit of the non-financial sector.

REFERENCES

Ahn, JaeBin and Jee-Hyeong Park. 2022. "Watch What They Do, Not What They Say or Look Like." *Economics Letters*, 213: 110346.

Aitken, Brian J. and Ann E. Harrison. 1999. "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela." *American Economic Review*, 89(3): 601-618.

Alfaro, Laura and Andrew Charlton. 2009. "Intra-Industry Foreign Direct Investment." *American Economic Review*, 99(5): 2096-2119.

Anderson, Derek, Ben Hunt, Mika Kortelainen, Michael Kumhof, Douglas Laxton, Dirk Muir, Susanna Mursula, and Stephen Snudden. 2013. "Getting to Know GIMF: The Simulation Properties of the Global Integrated Monetary and Fiscal Model." IMF Working Paper 2013/055, International Monetary Fund, Washington, DC.

Ando, Sakai and Mengxue Wang. 2020. "Do FDI Firms Employ More Workers than Domestic Firms for Each Dollar of Assets?" IMF Working Paper No. 2020/056.

Antràs, Pol and Elhanan Helpman. 2004. "Global Sourcing." *Journal of Political Economy*, 112(3): 552-580.

Bailey, Michael A., Anton Strezhnev and Erik Voeten. 2017. "Estimating dynamic state preferences from United Nations voting data." *Journal of Conflict Resolution*, 61(2): 430-56.

Barba-Navaretti, Giorgio and Anthony Venables. 2004. *Multinational Firms in the World Economy*, Princeton University Press.

Blalock, Garrick and Paul J. Gertler. 2009. "How Firm Capabilities Affect Who Benefits from Foreign Technology." *Journal of Development Economics*, 90(2): 192-197.

Blanchard, Olivier. 1985. "Debts, Deficits and Finite Horizons." *Journal of Political Economy* 93(21): 223-47.

Brainard, Lael. 1997. "An Empirical Assessment of the Proximity-Concentration Trade-off Between Multinational Sales and Trade." *American Economic Review*, 87(4): 520-544.

Coppola, Antonio, Mattero Maggiori, Brent Neiman, and Jesse Schreger. (2021). "Redrawing the Map of Global Capital Flows: The Role of Cross-Border Financing and Tax Havens." *The Quarterly Journal of Economics*, 136 (3): 1499–1556.

Damgaard, Jannick, Thomas Elkjaer, and Niels Johannesen. 2019. "What Is Real and What Is Not in the Global FDI Network?" IMF Working Paper No. 19/273. International Monetary Fund, Washington, DC.

Häge, Frank M. (2011). "Choice or Circumstance? Adjusting Measures of Foreign Policy Similarity for Chance Agreement." *Political Analysis*, 19(3): 287-305.

Handley, Kyle, and Nuno Limao. 2022. "Trade Policy Uncertainty." *Annual Review of Economics*, 14: 363-95.

Harrison, Ann and Andres Rodriguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy for Developing Countries." In Rodrik, Dani and Mark Rosenzweig (eds.) *Handbook of Development Economics*, Vol 5, chapter 63: 4039-4214.

Haskel, Jonathan E., Sonia C. Pereira, and Matthew J. Slaughter. 2007. "Does Inward Foreign Direct Investment Boost the Productivity of Domestic Firms?" *The Review of Economics and Statistics*, 89(3): 482–496.

Helpman, Elhanan, Marc Melitz, and Stephen Yeaple. 2004. "Export versus FDI with Heterogeneous Firms." *American Economic Review*, 94(1): 300-316.

Horn, Sebastian, Carmen M. Reinhart, and Christoph Trebesch. (2021). "China's overseas lending." *Journal of International Economics*, 133: 103539.

Javorcik, Beata. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages." *American Economic Review*, 94(3): 605-27.

Jiang, Kun, Wolfgang Keller, Larry D. Qiu, and William Ridley. 2018. "International Joint Ventures and Internal vs. External Technology Transfer: Evidence from China." NBER Working Paper No.24455.

Jude, Cristina. 2016. "Technology Spillovers from FDI: Evidence on the Intensity of Different Spillover Channels." *The World Economy*, 39(2): 1947-1973.

Keller, Wolfgang and Stephen R. Yeaple. 2009. "Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States." *The Review of Economics and Statistics*, 91(4): 821-831.

Kumhof, Michael, Douglas Laxton, Dirk Muir, and Susanna Mursula. 2010. "The Global Integrated Monetary and Fiscal Model (GIMF) – Theoretical Structure." International Monetary Fund, IMF Working Paper 10/34. Washington, DC.

Lane, Philip R., and Gian Maria Milesi-Ferretti. (2018). "The External Wealth of Nations Revisited: International Financial Integration in the Aftermath of the Global Financial Crisis." *IMF Economic Review*, 66: 189–222.

Mercer-Blackman, Valerie, Wei Xiang, and Fahad Khan. 2021. "Understanding FDI Spillovers in the Presence of GVCs." Policy Research Working Paper No. 9645, The World Bank, Washington DC.

Newman, Carol, John Rand, Theodore Talbot, and Finn Tarp. 2015. "Technology Transfers, Foreign Investment and Productivity Spillovers." *European Economic Review*, 76: 168-187.

Organization for Economic Cooperation and Development (OECD). 2021. "OECD Inter-Country Input-Output Database." Organization for Economic Cooperation and Development. Paris. http://oe.cd/icio

Ramondo, Natalia, Veronica Rappoport, and Kim J. Ruhl. 2016. "Intrafirm Trade and Vertical Fragmentation in U.S. Multinational Corporations." *Journal of International Economics*, 98: 51-59.

Santos Silva, J.M.C. and Silvana Tenreyro. 2006. "The Log of Gravity." *The Review of Economics and Statistics*, 88(4): 641–58.

Signorino, Curtis S., and Jeffrey R. Ritter. 1999. "Tau-b or Not Tau-b: Measuring the Similarity of Foreign Policy Positions." *International Studies Quarterly*, 43(1): 115-44.

Toews, Gerhard and Pierre-Louis Vezina. 2022. "Resource discoveries, FDI bonanzas, and local multipliers: Evidence from Mozambique." *The Review of Economics and Statistics*, 104(5): 1046-1058.