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Heterogeneous Impact of Geopolitical Risk on Foreign Direct Investment*

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Abstract

This study investigates how rising geopolitical tensions reshape global foreign direct investment (FDI) using greenfield FDI data, focusing on near-shoring and political and economic friend-shoring. We find substantial heterogeneity across industries and FDI types. Political friend-shoring has intensified in recent years, particularly after Russia's invasion of Ukraine, but its impact varies by sector: it is significant in chemicals yet insignificant in electrical equipment and semiconductors. Near-shoring is mainly observed in low-tech industries. By contrast, firms in electrical equipment and semiconductors increasingly depend on geographically distant partners, potentially incurring economic costs and production risks. Although economic friend-shoring is weak at the aggregate level, it becomes significant when China is excluded and in selected high-tech industries. Overall, the results underscore pronounced industry-level differences and suggest that strengthening regional trade agreement networks may improve supply chain resilience amid geopolitical uncertainty.

Keywords: Geopolitical risk, FDI, Gravity model
JEL Classification Codes: F13; F14; F23

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1. Introduction

Global foreign direct investment (FDI) has significantly declined in recent years. According to the IMF World Economic Outlook (2023), global FDI inflows decreased from approximately 3.3% of global GDP in the early 2000s to approximately 1.3% from 2018 to 2022. This sharp shift in FDI coincides with heightened geopolitical tensions, most notably the escalation of U.S.–China trade conflicts and Russia's invasion of Ukraine.

These developments have raised concerns about the fragmentation of the global economy. Scholars and policymakers have particularly highlighted the risks of geopolitical fragmentation, the emergence of regional blocs, and the broader phenomenon of "slowbalization," characterized by a deceleration in the expansion of global economic integration. In this context, an expanding body of literature finds that firms are actively adjusting their international sourcing and investment strategies in response to rising geopolitical risks.

Recent studies have emphasized three major trends in sourcing strategies. First, near-shoring refers to firms' increasing reliance on geographically proximate countries as production or investment destinations. Second, political friend-shoring refers to the tendency to source from or invest in countries that share geopolitical preferences. Third, economic friend-shoring denotes sourcing and investment patterns that favor countries with close economic ties, often proxied by participation in regional trade agreements (RTAs). These strategic adjustments have been documented in Alfaro and Chor (2023), Freund et al. (2024), and Ando et al. (2026), which found that geopolitical considerations are increasingly central to firms' global value chain decisions.

This study examines whether and to what extent near-shoring and political and economic friend-shoring are reflected in global FDI patterns. Focusing on greenfield FDI flows, which entail high sunk costs and long-term commitments, the analysis assesses whether recent changes are temporary responses to geopolitical shocks or reflect a more permanent structural transformation of global production networks. Unlike trade flows, which can adjust quickly to short-run shocks, FDI involves long-term strategic location choices by multinational firms and directly reflects the geographical reallocation of production activities within global value chains.

A growing body of literature has examined how rising geopolitical tensions are reshaping global trade and investment patterns. Alfaro and Chor (2023) documented the declines in U.S. FDI in China. In contrast, U.S. investment in Mexico has increased, indicating a reallocation of production locations in response to geopolitical and trade policy shocks. Xue's (2024) analysis of the effects of U.S. tariff hikes found that higher tariffs redirect FDI away from China toward third countries. Using a multicountry general equilibrium model incorporating FDI, Xue (2024) also evaluated the welfare implications of trade wars for both the U.S. and China.

More recent studies identify geopolitical alignment as a key determinant of international investment. Aiyar et al. (2024) and Gopinath et al. (2025) introduced an indicator of bilateral political distance. Their studies of the role of political alignment in shaping the geopolitical footprint of bilateral international trade and FDI flows suggest that multinational firms are altering their investment patterns to promote political friend-shoring. Similarly, Ando et al. (2026) examined whether firms prioritize near-shoring or economic and political friend-shoring when shifting procurement patterns amid rising geopolitical tensions. Using international trade data, they show that procurement increased from politically friendly countries during rising geopolitical risks but not from economically friendly (proxied by an RTA dummy) or neighboring countries.[1]

Building on this body of research, this study examines how global FDI patterns have evolved alongside rising geopolitical tensions using comprehensive global greenfield FDI

[1] Similar to Ando et al. (2026), Freund et al. (2024) also examined the shift in U.S. sourcing patterns stemming from the 2018 tariff increases on China, focusing on political, economic, and geographical distance. They report that while sourcing from bordering or distant countries increased in the high-tech sector and from countries with lower per capita labor costs in the low-tech sector, sourcing from politically friendly countries or countries with RTAs did not increase.

flow data. Although our study does not establish the direction of causality, it extends the literature in the following two ways. First, we explore the heterogeneity in FDI responses across sectors, regions, and FDI types. We distinguish between different types of FDI, including North–South and South–South investment flows. Second, while much of the existing literature focuses primarily on the effects of political friend-shoring, we provide a more comprehensive perspective by jointly examining near-shoring and both political and economic friend-shoring in the context of FDI.

The rest of the study is organized as follows. Section 2 presents the data we used, and Section 3 presents the empirical specification. After providing the estimation results in Section 4, Section 5 concludes this study.

2. Data

This study uses the fDi Markets database compiled by the Financial Times, which provides project-level information on global greenfield FDI for more than 200 countries.[2] The data include source and destination countries, industry classifications, and estimated capital investment. A key advantage of fDi Markets over aggregate datasets, such as

[2] The fDi Markets database is widely used in academic literature to evaluate the effects of policy shifts—such as Brexit or international trade restrictions (Breinlich et al., 2020; Jungmittag and Marschinski, 2023). It has also been employed to assess the implications of FDI on both home and host countries' outcomes, including employment generation and economic growth (Desbordes, 2022; Crescenzi et al., 2022).

UNCTAD, is that bilateral FDI flows can be decomposed by industry, allowing a detailed analysis of sectoral and geographical reallocation in response to geopolitical tensions.

For the empirical analysis, we used aggregated data on greenfield FDI at the origin–destination–industry level from 2014 to 2024. FDI destination countries include Japan, China, Korea, Taiwan, the 10 ASEAN member states, the top 30 FDI recipients in the UNCTAD World Investment Report 2023, the UK, Ireland, and the Netherlands.[3] Our main outcome variables are the number of greenfield FDI projects and the estimated capital expenditures associated with these projects. Given that FDI flows exhibit substantial year-to-year volatility, we avoid short-run fluctuations by using cumulative values over time to capture medium- to long-run investment patterns.

We distinguish between high- and low-tech sectors using classifications in the related literature. Chemical products, automobiles, machinery, and electronic machinery are considered high-tech sectors, while other manufacturing industries are classified as low-tech. This allows us to examine heterogeneity in FDI reallocation across technological characteristics.

3. Empirical specification

[3] The list of destinations, origin countries, and industries is presented in Appendix Tables A1 and A2.

Building on recent research on the effects of the U.S.–China trade war and rising geopolitical risks on international investment patterns (e.g., Aiyar et al., 2024; Ando et al., 2026), we estimate a gravity model of bilateral greenfield FDI flows. The gravity framework provides a natural setting for analyzing how bilateral relationships shape firms' location choices across countries.

Bilateral greenfield FDI flows from origin country *i* to destination country *j* in sector *s* and year *t* are modeled as a function of bilateral relationship variables, denoted by Z_{ijt}, and a set of standard control variables, X_{ij}. The bilateral relationship variables capture dimensions of geopolitical and economic proximity, which are key to our analysis of near-shoring and political and economic friend-shoring.

$$FDI_{ijst} = \exp\left(\alpha + \beta_1 Z_{ijt-1} + \beta_2 Z_{ijt-1} \times D^{2018} + \beta_3 Z_{ijt-1} \times D^{2022} + \beta_4 X_{ij} + FE_{it} + FE_{jt} + \epsilon_{ijst}\right) \quad . \tag{1}$$

The control variables include commonly used gravity covariates, including indicators for a common language (*Common lang off*), common legal origin (*Com Legal origin*), and historical colonial or dependency relationships between country pairs (*Colonial dependency*). To account for multilateral resistance terms and time-varying country-specific factors, we include origin-country-year fixed effects and destination-country-year fixed effects. These fixed effects absorb all time-varying country-level characteristics, including macroeconomic conditions, policy changes, and aggregate investment attractiveness. The model is estimated using the Poisson pseudo-maximum likelihood estimator.

We capture changes in bilateral relationships associated with near-shoring and friend-shoring by including three key variables in Z_{ijt}. The first variable is ideal-point distance (*IP Dist*), which proxies for political friend-shoring. This measure is based on the ideal point estimates developed by Bailey et al. (2017) and reflects similarities in United Nations General Assembly voting patterns. A smaller ideal-point distance indicates closer geopolitical alignment between countries i and j, whereas a larger distance indicates greater divergence in their geopolitical preferences. This measure enables us to quantify the influence of political alignment in shaping bilateral FDI flows.

The second variable, geographical distance (*Dist*), captures near-shoring behavior. Data on bilateral geographical distance are obtained from the CEPII database. An increase in the sensitivity of FDI flows to geographic distance over time is considered evidence of near-shoring, as firms place greater weight on proximity when selecting investment locations.

The third variable is an RTA dummy, which proxies for economic friend-shoring.

The RTA indicator, taken from the updated dataset constructed by Egger and Larch (2008), equals 1 if an RTA in a given year connects a pair of countries.

We examine how the effects of these bilateral relationship variables evolve by interacting them with year dummy variables. We include a dummy variable D^{2018} (post-2018 dummy), which equals 1 for 2018 onward and captures the period following the escalation of the U.S.–China trade war, and a dummy variable D^{2022} (post-2022 dummy), which equals 1 for 2022 onward and captures the period following Russia's invasion of Ukraine. These interaction terms enable us to determine assess whether geopolitical shocks have altered the importance of political alignment, geographical proximity, and economic ties in shaping global FDI patterns.

4. Results

4.1 Baseline results

Table 1 presents the baseline estimation results from the gravity model of bilateral greenfield FDI flows.[4] Columns (1)–(2) use estimated capital expenditures as the dependent variable, while columns (3)–(4) use the number of FDI projects. Although the coefficient of *IP Dist* itself is insignificant, its interaction term with the post-2022 dummy is negative and statistically significant. This result suggests that, after 2022, investment

[4] Summary statistics and correlation matrix are presented in Appendix Tables A3 and A4.

increasingly shifted toward politically aligned partners, indicating strengthened political friend-shoring following Russia's invasion of Ukraine. In contrast to Ando et al. (2026), who find that the effects of political distance became visible in international trade data around 2018, the response of FDI appears to be more gradual. This slower adjustment is consistent with the presence of substantial fixed costs associated with FDI, which may delay the emergence of such effects. We also find evidence of near-shoring. The interaction between geographical distance and the post-2018 dummy is positive and significant when capital expenditures are used, indicating that after the escalation of the U.S.–China trade war, FDI became more sensitive to distance and shifted toward geographically closer destinations.

We conducted several robustness checks. Columns (2) and (4) include origin–destination country fixed effects. We confirmed the estimated coefficients remain largely unchanged. Next, instead of the post-2018 and 2022 dummies, we include time dummies interacted with the bilateral relationships variable to examine other effects, such as the 2020 pandemic. In Figure 1, we plot a series of event-study style coefficients. We see that the *IP dist* becomes negative and significant around 2021 and 2023 and thereafter, whereas geographical distance and RTA do not.[5] As an additional robustness check, we

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[5] While Aiyar et al. (2024) found that IP distance has a generally negative impact on

exclude the years 2020 and 2021 to account for potential distortions caused by the COVID-19 pandemic. As shown in Appendix Table A5, the major results do not change much.

Table 2 presents sector-specific estimation results, allowing us to explore heterogeneity in FDI responses to geopolitical tensions across industries, with Columns (1) and (2) focusing on low-tech sectors and Columns (3) and (4) reporting results for high-tech sectors. While *IP Dist* becomes significant when interacting with the post-2022 dummy for both the low- and high-tech sectors, it is greater in the high-tech sectors, suggesting they are more sensitive to political tensions after 2022.

In contrast, the interaction between geographical distance and the post-2018 dummy becomes statistically significant only for low-tech sectors. The coefficient is negative and significant, indicating that near-shoring behavior is primarily observed in low-tech industries after the U.S.–China trade war escalated. Columns (5)–(8) further disaggregate the sample by examining specific manufacturing industries. We examine the chemical and machinery sectors, including automotive, electronics, and semiconductor industries.

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greenfield FDI, the negative and significant effects are found only in the year 2021 and afterward in our results. When estimating the model using only the interaction term between IP distance and time dummy variables, the coefficient of the cross-term became larger and more significant around 2019. The coefficient plot is shown in Appendix Figure A1.

We find that the impact of political distance is heterogeneous across industries: FDI in the chemical industry becomes sensitive to political distance after 2022, whereas that in machinery-related sectors does not. The interaction between the RTA dummy and the post-2018 dummy is positive and statistically significant in the electronics and semiconductor sectors, suggesting that economic friend-shoring has intensified in these industries following the start of the U.S.–China trade war.

In these industries, the coefficient for the interaction between geographic distance and the post-2022 dummy variable is also positive and significant, which aligns with Freund et al. (2024) and Ando et al. (2026). This result may reflect the increasing geographic concentration of global production in the electrical and semiconductor sectors. Suppliers in these industries, particularly the semiconductor sector, are concentrated in South Korea, Japan, China, the European Union (EU), and the U.S. Consequently, firms may invest in geographically remote yet technologically specialized locations amid heightened geopolitical risks.

4.2 Heterogeneity with respect to the type of FDI and destination regions

To further explore heterogeneity in FDI reallocation patterns across regions, we extend the baseline specification by introducing additional dummy variables $\boldsymbol{R_{ij}}$ that captures both the type of FDI and the destination region.

$$FDI_{ijst} = \exp\,(\alpha + \beta_1\, Z_{ijt-1} + \beta_2 Z_{ijt-1} \times D2018 \times \boldsymbol{R_{ij}}$$

$$+\beta_3 Z_{ijt-1} \times D2022 \times \boldsymbol{R_{ij}} + \beta_4\, X_{ij} + FE_{it} + FE_{jt} + \epsilon_{ijst}) \quad . \qquad (2)$$

Regarding the type of FDI, we treat OECD member countries as the North and distinguish North–South FDI and South–South FDI from other types of FDI. Regarding the destination-region dummy, we include it for the EU and Asia. Using these region-specific indicators, we can assess whether near-shoring and friend-shoring dynamics vary systematically across destination markets with different institutional and economic characteristics. As an additional analysis, we estimate the model excluding FDI flows to or from China. Given China's central role in global production networks and its involvement in recent geopolitical tensions, excluding China allows us to examine whether China-related dynamics primarily drive the observed patterns.

Table 3 (a) presents the estimation results with the additional dummy variables for North–South (*NS*) and South–South (*SS*) FDI. The triple interaction between ideal location distance, the 2018 dummy variable, and the *NS FDI* dummy is negative and significant, indicating that political friend-shoring emerged after 2018 alongside the U.S.–China trade war for *NS FDI*. In contrast, the effect for South–South FDI becomes significant only after 2022, following Russia's invasion of Ukraine. These results suggest that political friend-shoring emerged earlier in North–South than in South–South FDI. As shown in the results for Column (2), excluding China-related FDI, the coefficient for *IP Dist* became significant for both *NS* and *SS FDI* only after 2022, indicating that the Column (1) results for *NS FDI* regarding *IP Dist* are attributable to China-related FDI.

In the results excluding China-related FDI in Column (2), both the RTA × post-2022 interaction term and the RTA × post-2018 × *SS FDI* interaction term are positive and statistically significant. Additionally, the coefficient on the triple interaction is larger than that on the RTA × post-2022 term. These findings suggest that economic friend-shoring, as proxied by RTAs, has intensified outside China, emerging earlier and exhibiting particularly strong effects for South–South FDI.

Tables 3 (b) and 3 (c) present the results of examining FDI differences by type, further broken down by sector into low- and high-tech industries. For *NS FDI*, the interaction between *IP Dist* and the post-2018 dummy is negative and statistically significant only for low-tech sectors, indicating that political friend-shoring in *NS FDI* is especially pronounced in low-tech industries and emerged already after 2018. By contrast, for *SS FDI*, the interaction between *IP Dist* and the post-2022 dummy is negative and statistically significant in both the low- and high-tech sectors, suggesting that political friend-shoring in *SS FDI* strengthened after 2022 across sectors. The finding that only the *IP Dist* × post-2022 × *SS FDI* interaction term is significant in the high-tech sector suggests that geopolitical linkages are more important in investment flows between developing countries than in those from developed countries within the high-tech industry.

Overall, the results in Table 3 (b) and (c) highlight significant heterogeneity across both FDI types and sectors. Political friend-shoring in *NS FDI* is concentrated in low-tech sectors and emerges earlier, whereas in *SS FDI*, it becomes salient after 2022 across sectors. These findings indicate that the interplay among geopolitical risks, sector characteristics, and host countries' development levels is crucial in shaping the global reallocation of FDI.

Table 4 examines FDI outside China and examines heterogeneity in FDI reallocation patterns across destination regions and sectors by introducing interaction terms with region-specific dummy variables, with a particular focus on Asia and the European Union (*Asia des* and *EU des*).[6] This specification enables us to assess whether near-shoring and friend-shoring dynamics vary systematically across regions.

For Asia-bound FDI, the *IP Dist* × post-2022 × *Asia des* interaction term becomes negative and statistically significant, implying that political friend-shoring emerged after 2022 once China is excluded from the sample. In the high-tech industry, the interaction between the RTA and the post-2018 dummy variables had a statistically significant

[6] Estimation results, including FDI to/from China, are presented in Appendix Table A7.

positive effect across regions. In contrast, the coefficient on the cross-term with the Asia-bound FDI dummy was negative, indicating that the RTA effect is weaker for Asia-bound FDI. Thus, in this region, the effect of economic friend-shoring through formal trade agreements is less than political coordination and regional production structures. In the case of EU-bound FDI, the results reveal strong evidence of near-shoring in high-tech sectors. The *Dist* × post-2018 × *EU des* interaction term is negative and statistically significant in high-tech industries, indicating that EU high-tech sectors increasingly attract investment from geographically proximate countries. These findings underscore the importance of regional and sectoral heterogeneity in analyzing the impact of geopolitical risks on global investment patterns.

5. Conclusion

This study examines the heterogeneous influence of increasing geopolitical tensions on global FDI patterns using global greenfield FDI data, with a particular focus on near-shoring and political and economic friend-shoring. The results yield several important findings. First, political friend-shoring has intensified in recent years, especially after Russia invaded Ukraine. However, its effects are heterogeneous across industries, with a statistically significant effect in some sectors, such as the chemical industry, yet a statistically insignificant effect in others, including electrical equipment and semiconductors. Second, we find that near-shoring is observed in low-tech industries, whereas firms in sectors such as electrical equipment and semiconductors increasingly rely on distant suppliers. The latter pattern may incur economic costs, including potential production losses. Third, we find evidence of economic friend-shoring in specific cases. While the aggregate effect of RTA is not statistically significant, it becomes significant when China is excluded from the sample or when focusing on specific sectors, particularly high-tech industries. These results indicate that strengthened RTA networks improve supply chain resilience. In addition, we also show that there is substantial regional and sectoral heterogeneity in FDI reallocation as a response to heightened geopolitical risks.

Geopolitical risks are not static but continue to evolve. Taken together, our results highlight that the fragmentation of global FDI networks is likely to be uneven and sector-specific rather than uniform. Monitoring future policy shifts—including potential changes in U.S. trade policy—will therefore be crucial for understanding the evolving architecture of global production networks.

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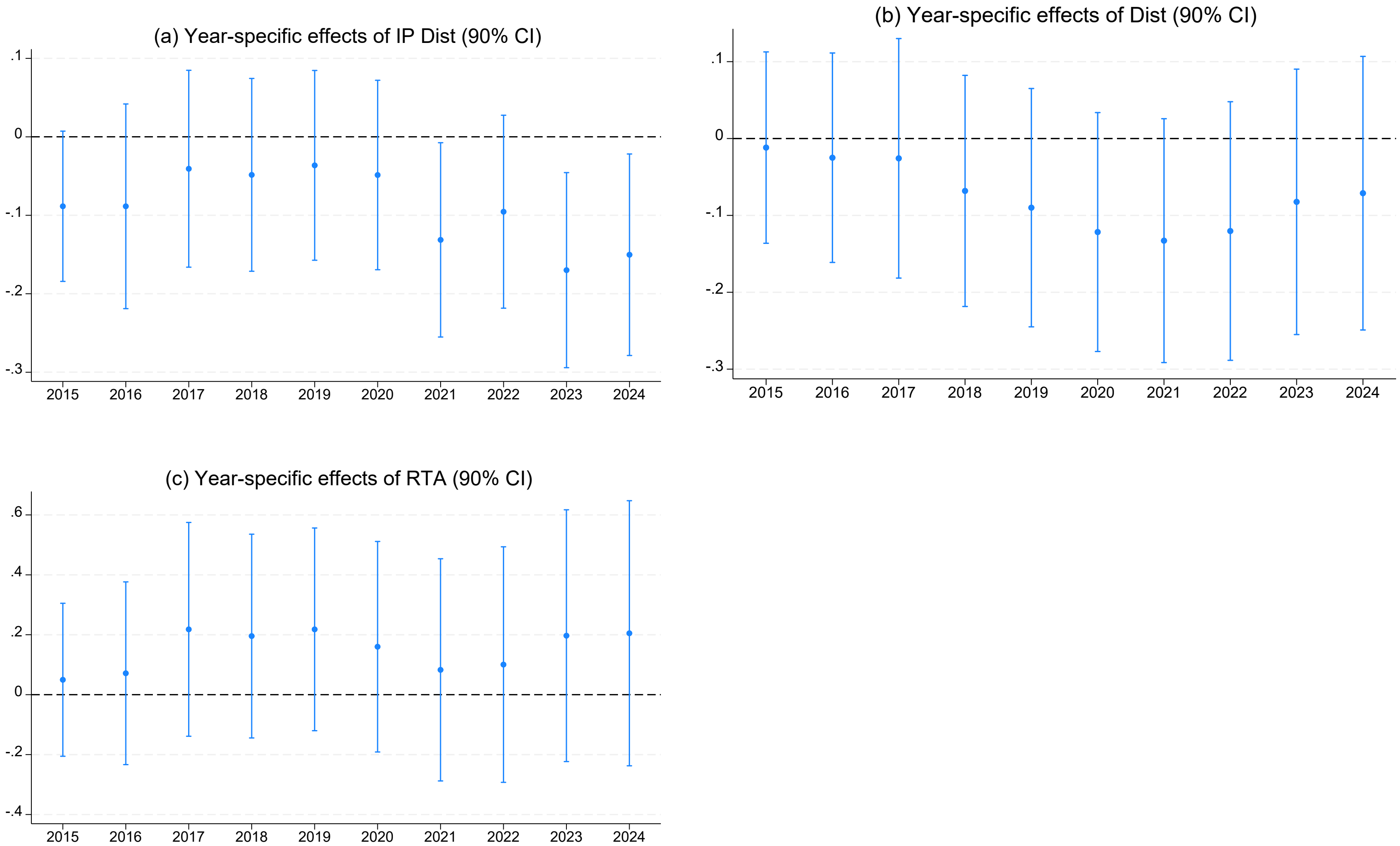
Figure 1 Coefficients of time dummies interacted with bilateral relationship variables



Tables

Table 1 Baseline results

	(1)	(2)	(3)	(4)
VARIABLES	Capital expenditure		# of projects	
IP Dist	0.0255	0.0386	0.0394	0.00517
	(0.0384)	(0.0363)	(0.0278)	(0.00974)
IP Dist × D2018	-0.0112	-0.0124	0.0115	0.00201
	(0.0313)	(0.0280)	(0.0159)	(0.00833)
IP Dist × D2022	-0.0693**	-0.0549**	-0.0212**	-0.0129**
	(0.0278)	(0.0258)	(0.0101)	(0.00586)
Dist	-0.207***		-0.239***	
	(0.0649)		(0.0383)	
Dist × D2018	-0.0902**	-0.0635*	-0.0128	0.00139
	(0.0389)	(0.0382)	(0.0191)	(0.0130)
Dist × D2022	0.0216	0.0518	-0.00685	-0.00192
	(0.0377)	(0.0376)	(0.00858)	(0.00676)
RTA	0.208	0.0175	0.0477	0.0168
	(0.139)	(0.136)	(0.0798)	(0.0419)
RTA × D2018	0.0277	0.0712	-0.0451	-0.000888
	(0.0888)	(0.0804)	(0.0433)	(0.0262)
RTA × D2022	0.0242	0.0451	-0.0160	0.0197
	(0.109)	(0.0986)	(0.0356)	(0.0226)
comlang_off	0.0788		0.105	
	(0.113)		(0.0721)	
comleg_pretrans	0.123		0.188***	
	(0.0908)		(0.0499)	
colony	0.222*		0.217***	
	(0.123)		(0.0682)	
FE_{it}, FE_{jt}	Yes	Yes	Yes	Yes
FEij	No	Yes	No	Yes
Observations	92,463	92,716	92,463	92,716
Pseudo-R2	0.344	0.439	0.367	0.415

Note: Figures in parentheses are standard errors clustered by origin and country. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively.

Table 2 Estimation results by sector

	(1) Low Tech	(2) High Tech	(3) Chemical	(4) Automobile	(5) Electric	(6) Semi-conductor
IP Dist	0.00127	0.0943	0.260***	0.0272	0.0396	0.745***
	(0.0461)	(0.0577)	(0.0887)	(0.0867)	(0.116)	(0.219)
IP Dist × D2018	-0.0439	0.0441	0.0663	-0.00946	0.0600	-0.114
	(0.0358)	(0.0529)	(0.0954)	(0.0573)	(0.0943)	(0.177)
IP Dist × D2022	-0.0557*	-0.123**	-0.186***	-0.0640	-0.116	-0.289
	(0.0319)	(0.0480)	(0.0533)	(0.0539)	(0.0746)	(0.222)
Dist	-0.217***	-0.150	-0.214*	0.161	-0.290***	-0.677***
	(0.0763)	(0.0917)	(0.119)	(0.154)	(0.0809)	(0.155)
Dist × D2018	-0.0899**	-0.0831	-0.116	-0.0934	0.0129	0.227
	(0.0450)	(0.0576)	(0.0898)	(0.0995)	(0.0848)	(0.172)
Dist × D2022	-0.00371	0.0493	0.0240	-0.0610	0.126*	0.375**
	(0.0375)	(0.0528)	(0.0407)	(0.0522)	(0.0699)	(0.180)
RTA	0.421**	-0.0984	0.0636	0.402	-0.358*	-0.849*
	(0.176)	(0.180)	(0.195)	(0.361)	(0.214)	(0.440)
RTA × D2018	-0.0357	0.167	-0.00931	-0.0297	0.603***	0.905*
	(0.0998)	(0.128)	(0.181)	(0.239)	(0.217)	(0.520)
RTA × D2022	-0.0226	0.0202	-0.150	-0.0458	0.0853	-0.135
	(0.101)	(0.150)	(0.0951)	(0.141)	(0.236)	(0.429)
Observations	61,078	31,059	9,546	6,169	11,878	1,638
Pseudo-R2	0.343	0.491	0.601	0.728	0.575	0.803

Note: Figures in parentheses are standard errors clustered by origin and country. ***, **, and * indicate statistical significance at the 1, 5, and 10% levels, respectively. Origin country-year and destination country fixed effects and dyadic controls (common official language, contiguity, and colony) are included.

Table 3 (a) Estimation results by type of FDI

	(1)		(2)	
			Excluding China	
	Coef	S.E.	Coef	S.E.
IP Dist	-0.0113	(0.0579)	-0.0670	(0.0533)
IP Dist × D2018	-0.00284	(0.0448)	0.0190	(0.0418)
IP Dist × D2022	-0.00638	(0.0339)	0.0301	(0.0310)
IP Dist × NS	0.213	(0.175)	0.247	(0.220)
IP Dist × D2018 × NS	-0.303***	(0.110)	-0.231	(0.142)
IP Dist × D2022 × NS	-0.0654	(0.0888)	-0.179*	(0.0958)
IP Dist × SS	0.115	(0.113)	0.372**	(0.179)
IP Dist × D2018 × SS	-0.0335	(0.0800)	-0.127	(0.153)
IP Dist × D2022 × SS	-0.202***	(0.0755)	-0.369***	(0.0857)
Dist	-0.312***	(0.104)	-0.345***	(0.106)
Dist × D2018	-0.0288	(0.0741)	-0.0234	(0.0758)
Dist × D2022	0.00386	(0.0476)	0.0192	(0.0466)
Dist × NS	0.213	(0.178)	-0.0315	(0.224)
Dist × D2018 × NS	-0.0853	(0.102)	0.0827	(0.118)
Dist × D2022 × NS	0.0123	(0.0710)	0.0879	(0.0980)
Dist × SS	0.259	(0.178)	0.0139	(0.234)
Dist × D2018 × SS	-0.142	(0.100)	0.0101	(0.122)
Dist × D2022 × SS	-0.0172	(0.0698)	0.0526	(0.0921)
RTA	-0.0734	(0.213)	-0.211	(0.224)
RTA × D2018	0.0109	(0.186)	0.0304	(0.201)
RTA × D2022	0.269	(0.175)	0.359**	(0.178)
RTA × NS	0.630**	(0.304)	0.711*	(0.391)
RTA × D2018 × NS	-0.436*	(0.253)	-0.425	(0.364)
RTA × D2022 × NS	-0.304	(0.237)	-0.357	(0.299)
RTA × SS	0.237	(0.281)	0.143	(0.336)
RTA × D2018 × SS	0.371	(0.235)	0.648*	(0.342)
RTA × D2022 × SS	-0.359*	(0.212)	-0.333	(0.265)
Observations	92,463		82,800	
Pseudo-R2	0.345		0.342	

Note: See notes in Table 2.

Table 3 (b) Estimation results by type of FDI: Low-tech sectors

	(1)		(2)	
			Excluding China	
	Coef	S.E.	Coef	S.E.
IP Dist	-0.0781	(0.0617)	-0.145**	(0.0568)
IP Dist × D2018	0.0177	(0.0450)	0.0558	(0.0453)
IP Dist × D2022	-0.00277	(0.0365)	0.0304	(0.0367)
IP Dist × NS	0.353*	(0.195)	0.454*	(0.262)
IP Dist × D2018 × NS	-0.320***	(0.120)	-0.354**	(0.161)
IP Dist × D2022 × NS	-0.0936	(0.103)	-0.200*	(0.118)
IP Dist × SS	0.211*	(0.117)	0.420**	(0.177)
IP Dist × D2018 × SS	-0.100	(0.0860)	-0.119	(0.145)
IP Dist × D2022 × SS	-0.178**	(0.0869)	-0.386***	(0.102)
Dist	-0.181*	(0.107)	-0.182	(0.112)
Dist × D2018	-0.121	(0.0788)	-0.135	(0.0836)
Dist × D2022	-0.000746	(0.0566)	0.0166	(0.0569)
Dist × NS	-0.0304	(0.180)	-0.164	(0.223)
Dist × D2018 × NS	0.0693	(0.108)	0.124	(0.117)
Dist × D2022 × NS	-0.000988	(0.0845)	0.0761	(0.100)
Dist × SS	0.0758	(0.180)	-0.0476	(0.233)
Dist × D2018 × SS	0.0105	(0.109)	0.0564	(0.116)
Dist × D2022 × SS	-0.0301	(0.0818)	0.0353	(0.0948)
RTA	0.206	(0.231)	0.167	(0.247)
RTA × D2018	-0.185	(0.189)	-0.269	(0.212)
RTA × D2022	0.157	(0.154)	0.245	(0.162)
RTA × NS	0.725***	(0.280)	0.647*	(0.365)
RTA × D2018 × NS	-0.503*	(0.278)	-0.534	(0.358)
RTA × D2022 × NS	-0.149	(0.228)	-0.0916	(0.293)
RTA × SS	0.00526	(0.342)	-0.102	(0.429)
RTA × D2018 × SS	0.530**	(0.248)	0.701*	(0.361)
RTA × D2022 × SS	-0.215	(0.236)	-0.159	(0.314)
Observations	61,078		55,143	
Pseudo-R2	0.345		0.349	

Note: See notes in Table 2.

Table 3 (c) Estimation results by type of FDI: High-tech sectors

	(1)		(2)	
			Excluding China	
	Coef	S.E.	Coef	S.E.
IP Dist	0.129	(0.0941)	0.0696	(0.0877)
IP Dist × D2018	-0.0447	(0.0793)	0.00139	(0.0726)
IP Dist × D2022	-0.0219	(0.0506)	0.0342	(0.0479)
IP Dist × NS	-0.146	(0.225)	-0.102	(0.216)
IP Dist × D2018 × NS	-0.194	(0.185)	-0.0594	(0.210)
IP Dist × D2022 × NS	0.0689	(0.108)	-0.113	(0.103)
IP Dist × SS	-0.00418	(0.172)	0.661**	(0.309)
IP Dist × D2018 × SS	0.105	(0.141)	-0.312	(0.243)
IP Dist × D2022 × SS	-0.278**	(0.112)	-0.383**	(0.170)
Dist	-0.530***	(0.127)	-0.594***	(0.129)
Dist × D2018	0.119	(0.102)	0.124	(0.100)
Dist × D2022	-0.0107	(0.0612)	-0.0304	(0.0590)
Dist × NS	0.679***	(0.224)	-0.0212	(0.284)
Dist × D2018 × NS	-0.301**	(0.141)	0.109	(0.233)
Dist × D2022 × NS	0.0351	(0.0870)	0.222	(0.190)
Dist × SS	0.657***	(0.223)	-0.0239	(0.263)
Dist × D2018 × SS	-0.345**	(0.138)	0.0467	(0.222)
Dist × D2022 × SS	0.0121	(0.0841)	0.177	(0.173)
RTA	-0.607**	(0.252)	-0.807***	(0.268)
RTA × D2018	0.299	(0.220)	0.368*	(0.216)
RTA × D2022	0.313*	(0.183)	0.375*	(0.194)
RTA × NS	0.454	(0.509)	0.804	(0.876)
RTA × D2018 × NS	-0.268	(0.409)	0.00768	(0.726)
RTA × D2022 × NS	-0.398	(0.313)	-0.803**	(0.383)
RTA × SS	0.685**	(0.319)	0.151	(0.469)
RTA × D2018 × SS	0.141	(0.283)	0.669	(0.436)
RTA × D2022 × SS	-0.443**	(0.210)	-0.263	(0.322)
Observations	31,059		27,323	
Pseudo-R2	0.496		0.490	

Note: See notes in Table 2.

Table 4 Estimation results with destination region dummy (excl. FDI to/from China)

	(1)		(2)		(3)	
	Coef	S.E.	Coef	S.E.	Coef	S.E.
IP Dist	-0.0915	(0.0631)	-0.198***	(0.0639)	0.132	(0.116)
IP Dist × D2018	0.0242	(0.0528)	0.0328	(0.0742)	0.0432	(0.0929)
IP Dist × D2022	-0.0284	(0.0502)	-0.00575	(0.0619)	-0.0257	(0.0726)
IP Dist × EU_des	0.0852	(0.0914)	0.149	(0.104)	-0.0907	(0.156)
IP Dist × D2018 × EU_des	-0.0591	(0.0768)	-0.0493	(0.100)	-0.0490	(0.129)
IP Dist × D2022 × EU_des	0.0440	(0.0634)	-0.00131	(0.0762)	0.108	(0.102)
IP Dist × Asia_des	0.294*	(0.163)	0.369**	(0.174)	0.219	(0.247)
IP Dist × D2018 × Asia_des	0.0178	(0.120)	0.0228	(0.136)	-0.0790	(0.223)
IP Dist × D2022 × Asia_des	-0.252**	(0.0981)	-0.292**	(0.122)	-0.224	(0.138)
Dist	-0.221*	(0.124)	-0.0599	(0.125)	-0.443***	(0.140)
Dist × D2018	-0.0726	(0.0832)	-0.196**	(0.0801)	0.214**	(0.107)
Dist × D2022	0.0422	(0.0594)	0.0102	(0.0657)	0.0831	(0.0773)
Dist × EU_des	-0.410**	(0.162)	-0.670***	(0.211)	-0.189	(0.156)
Dist × D2018 × EU_des	0.293**	(0.118)	0.514***	(0.156)	-0.0401	(0.127)
Dist × D2022 × EU_des	-0.126*	(0.0722)	-0.0507	(0.102)	-0.212***	(0.0691)
Dist × Asia_des	-0.179	(0.204)	-0.362*	(0.218)	0.123	(0.337)
Dist × D2018 × Asia_des	0.0359	(0.130)	0.0888	(0.137)	-0.215	(0.262)
Dist × D2022 × Asia_des	0.176*	(0.106)	0.166	(0.121)	0.0818	(0.201)
RTA	-0.0274	(0.303)	0.492	(0.334)	-0.976***	(0.269)
RTA × D2018	-0.00139	(0.215)	-0.238	(0.201)	0.453**	(0.226)
RTA × D2022	0.274	(0.198)	0.140	(0.186)	0.405**	(0.188)
RTA × EU_des	-0.636	(0.420)	-1.398***	(0.511)	0.489	(0.435)
RTA × D2018 × EU_des	0.488	(0.330)	1.068***	(0.405)	-0.293	(0.341)
RTA × D2022 × EU_des	-0.338	(0.388)	-0.348	(0.551)	-0.306	(0.295)
RTA × Asia_des	0.303	(0.348)	0.129	(0.444)	0.894***	(0.333)
RTA × D2018 × Asia_des	0.152	(0.239)	0.0779	(0.252)	0.122	(0.245)
RTA × D2022 × Asia_des	-0.416*	(0.230)	-0.216	(0.249)	-0.716***	(0.259)
Sectors	All		Low-tech		High-tech	
Observations	82,800		55,143		27,323	
Pseudo-R2	0.342		0.348		0.491	

Note: See notes in Table 2.

Appendix A Table A1 List of countries

Destination countries	Origin countries		
ARG	AND	GHA	NGA
BEL	ARE	GRC	NLD
BRA	ARG	GRL	NOR
BRN	AUS	HND	NPL
CAN	AUT	HRV	NZL
CHE	AZE	HUN	OMN
CHL	BEL	IDN	PAK
CHN	BGD	IND	PAN
DEU	BGR	IRL	PER
DNK	BHR	IRN	PHL
ESP	BIH	ISL	POL
FRA	BLR	ISR	PRT
GBR	BMU	ITA	QAT
IDN	BOL	JOR	ROU
IND	BRA	JPN	RUS
IRL	CAN	KEN	SAU
ITA	CHE	KOR	SGP
JPN	CHL	KWT	SRB
KHM	CHN	LBN	SVK
KOR	COL	LBY	SVN
MEX	CUB	LIE	SWE
MMR	CYM	LKA	SYC
MYS	CYP	LTU	THA
PHL	CZE	LUX	TUN
POL	DEU	LVA	TUR
RUS	DNK	MAC	UKR
SGP	EGY	MAR	URY
SWE	ESP	MCO	USA
THA	EST	MEX	VEN
TUR	FIN	MLT	VNM
USA	FRA	MNG	WSM
VNM	GBR	MUS	ZAF
	GEO	MYS	

Table A2 List of Industries

Food & Beverages
Textiles
Wood products
Paper, printing & packaging
Chemicals
Pharmaceuticals
Plastics
Rubber
Ceramics & glass
Building materials
Metals
Business machines & equipment
Engines & turbines
Industrial equipment
Medical devices
Consumer electronics
Electronic components
Semiconductors
Automotive OEM
Automotive components
Non-automotive transport OEM
Aerospace
Consumer products
Renewable energy

Table A3 Summary statistics

	N	Mean	SD	p10	p90
FDI(# of projects)	92463	172.77	894.75	0.00	287.70
FDI(Capital)	92463	2.92	7.47	0.00	7.00
IP Dist (logged)	92463	-0.58	1.26	-2.23	0.63
Dist (logged)	92463	8.25	1.09	6.66	9.32
RTA	92463	0.59	0.49	0.00	1.00
Common lang off	92463	0.14	0.34	0.00	1.00
Com Legal origin	92463	0.26	0.44	0.00	1.00
Colonial dependency	92463	0.07	0.25	0.00	0.00

Table A4 Correlation matrix

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
[1]	*FDI(# of projects)*	1.000							
[2]	*FDI(Capital)*	0.412	1.000						
[3]	*IP Dist (logged)*	0.044	0.063	1.000					
[4]	*Dist (logged)*	0.011	-0.022	0.454	1.000				
[5]	*RTA*	-0.010	-0.021	-0.446	-0.508	1.000			
[6]	*Common lang off*	0.000	0.033	-0.037	-0.078	0.083	1.000		
[7]	*Com Legal origin*	-0.011	-0.002	-0.075	-0.047	0.060	0.414	1.000	
[8]	*Colonial dependency*	0.023	0.051	0.026	0.003	-0.074	0.367	0.276	1.000

Table A5 Robustness check: Excluding year in 2020 and 2021

	(1)	(2)	(3)	(4)
VARIABLES	Capital expenditure		# of projects	
IP Dist	0.0249	0.0407	0.0393	0.00894
	(0.0384)	(0.0393)	(0.0278)	(0.0104)
IP Dist × *D2018*	0.0173	0.0131	0.0207	0.00663
	(0.0281)	(0.0240)	(0.0131)	(0.00765)
IP Dist × *D2022*	-0.0982***	-0.0837***	-0.0305***	-0.0179**
	(0.0333)	(0.0317)	(0.0118)	(0.00811)
Dist	-0.208***		-0.239***	
	(0.0650)		(0.0384)	
Dist × *D2018*	-0.0593*	-0.0533	0.000484	0.00414
	(0.0334)	(0.0333)	(0.0148)	(0.0109)
Dist × *D2022*	-0.00855	0.0397	-0.0200	-0.00393
	(0.0492)	(0.0480)	(0.0150)	(0.0105)
RTA	0.205	0.0313	0.0472	0.0130
	(0.139)	(0.150)	(0.0798)	(0.0459)
RTA × *D2018*	0.0868	0.0852	-0.00447	-0.00129
	(0.0753)	(0.0658)	(0.0319)	(0.0225)
RTA × *D2022*	-0.0349	0.0137	-0.0565	0.0211
	(0.141)	(0.123)	(0.0565)	(0.0308)
comlang_off	0.0903		0.106	
	(0.115)		(0.0721)	
comleg_pretrans	0.116		0.187***	
	(0.0919)		(0.0500)	
colony	0.206		0.216***	
	(0.126)		(0.0683)	
FE_{it}, FE_{jt}	Yes	Yes	Yes	Yes
FEij	No	Yes	No	Yes
Observations	75,623	75,830	75,623	75,830
Pseudo-R2	0.355	0.449	0.378	0.425

Note: See notes in Table 2.

Table A6 Robustness check: event-study type estimation

	coef	se
IP Dist	0.0859	(0.0723)
IP Dist × y2015	-0.0885	(0.0582)
IP Dist × y2016	-0.0886	(0.0793)
IP Dist × y2017	-0.0407	(0.0763)
IP Dist × y2018	-0.0485	(0.0747)
IP Dist × y2019	-0.0364	(0.0735)
IP Dist × y2020	-0.0486	(0.0734)
IP Dist × y2021	-0.131*	(0.0753)
IP Dist × y2022	-0.0954	(0.0748)
IP Dist × y2023	-0.170**	(0.0756)
IP Dist × y2024	-0.150*	(0.0781)
Dist	-0.187*	(0.106)
Dist × y2015	-0.0118	(0.0757)
Dist × y2016	-0.0250	(0.0828)
Dist × y2017	-0.0258	(0.0947)
Dist × y2018	-0.0682	(0.0914)
Dist × y2019	-0.0899	(0.0942)
Dist × y2020	-0.122	(0.0945)
Dist × y2021	-0.133	(0.0964)
Dist × y2022	-0.120	(0.102)
Dist × y2023	-0.0824	(0.105)
Dist × y2024	-0.0711	(0.108)
RTA	0.0879	(0.220)
RTA × y2015	0.0498	(0.155)
RTA × y2016	0.0715	(0.185)
RTA × y2017	0.218	(0.217)
RTA × y2018	0.196	(0.207)
RTA × y2019	0.218	(0.206)
RTA × y2020	0.160	(0.214)
RTA × y2021	0.0829	(0.225)
RTA × y2022	0.101	(0.239)
RTA × y2023	0.197	(0.255)
RTA × y2024	0.205	(0.269)
comlang_off	0.0800	(0.113)

comleg_pretrans	0.121	(0.0906)
colony	0.226*	(0.124)
Observations	92,463	
Pseudo-R2	0.344	

Note: See notes in Table 2.

Table A7 Estimation results with destination region dummy (incl. FDI to/from China)

	(1)		(2)		(3)	
	Coef	S.E.	Coef	S.E.	Coef	S.E.
IP Dist	-0.0247	(0.0526)	-0.0463	(0.0654)	0.0495	(0.102)
IP Dist × D2018	-0.0167	(0.0426)	-0.0421	(0.0585)	0.0296	(0.0792)
IP Dist × D2022	-0.0918*	(0.0471)	-0.0988*	(0.0579)	-0.110*	(0.0659)
IP Dist × EU_des	-0.00468	(0.0820)	-0.0269	(0.103)	0.0131	(0.136)
IP Dist × D2018 × EU_des	0.0110	(0.0704)	0.0430	(0.0872)	-0.00666	(0.121)
IP Dist × D2022 × EU_des	0.105*	(0.0621)	0.0900	(0.0723)	0.165*	(0.0922)
IP Dist × Asia_des	0.109	(0.0976)	0.108	(0.107)	0.149	(0.167)
IP Dist × D2018 × Asia_des	0.00841	(0.0686)	0.00585	(0.0824)	-0.0294	(0.117)
IP Dist × D2022 × Asia_des	-0.0474	(0.0730)	0.00144	(0.0890)	-0.150	(0.106)
Dist	-0.159	(0.124)	-0.0690	(0.121)	-0.262	(0.179)
Dist × D2018	-0.0878	(0.0831)	-0.157*	(0.0825)	0.0817	(0.132)
Dist × D2022	0.0198	(0.0597)	-0.00828	(0.0628)	0.118	(0.0786)
Dist × EU_des	-0.444***	(0.163)	-0.662***	(0.209)	-0.283	(0.179)
Dist × D2018 × EU_des	0.317***	(0.119)	0.504***	(0.156)	0.0338	(0.145)
Dist × D2022 × EU_des	-0.115	(0.0743)	-0.0435	(0.102)	-0.243***	(0.0742)
Dist × Asia_des	-0.0127	(0.198)	-0.222	(0.205)	0.385	(0.294)
Dist × D2018 × Asia_des	-0.0583	(0.126)	0.0496	(0.140)	-0.286	(0.184)
Dist × D2022 × Asia_des	0.0795	(0.0845)	0.0541	(0.101)	-0.0501	(0.120)
RTA	0.141	(0.279)	0.524*	(0.301)	-0.614**	(0.296)
RTA × D2018	-0.0322	(0.197)	-0.131	(0.189)	0.215	(0.257)
RTA × D2022	0.191	(0.199)	0.0460	(0.174)	0.372**	(0.187)
RTA × EU_des	-0.707*	(0.409)	-1.237**	(0.495)	0.199	(0.446)
RTA × D2018 × EU_des	0.409	(0.331)	0.862**	(0.393)	-0.125	(0.389)
RTA × D2022 × EU_des	-0.252	(0.282)	-0.249	(0.396)	-0.325	(0.239)
RTA × Asia_des	0.195	(0.310)	0.0421	(0.382)	0.741**	(0.312)
RTA × D2018 × Asia_des	0.136	(0.231)	0.0823	(0.231)	0.0815	(0.282)
RTA × D2022 × Asia_des	-0.367*	(0.215)	-0.159	(0.208)	-0.651***	(0.211)
Sectors	All		Low-tech		Hihg-tech	
Observations	92,463		61,078		31,059	
Pseudo-R2	0.345		0.344		0.496	

Note: See notes in Table 2.

Figure A1 A coefficient plot for the model only with the interaction term between time dummies and IP distance