Industry Linkages, Uncertainty, and Cross-border Mergers*

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Abstract

Multinational firms are strategically changing their organizations in response to escalating geopolitical risks. This paper investigates the role of mergers and acquisitions (M&A) in restructuring firm organizations in a time of uncertainty. Our initial step quantifies the relative distance between acquiring and target firms within a production value chain. Regression analysis shows that heightened economic policy uncertainty correlates with a greater likelihood of cross-border acquisitions occurring at more distant production stages. We present a conceptual model grounded in the hypothesis that firms integrate farther along global value chains during times of uncertainty. The implications of our model align consistently with the empirical findings, highlighting the trade-off between synergies and exposure to unexpected shocks in vertical integration decisions along the global production network.

Keywords: Global value chains, Cross-border mergers and acquisitions, foreign direct investment, upstreamness.

JEL Classification: F1, F2

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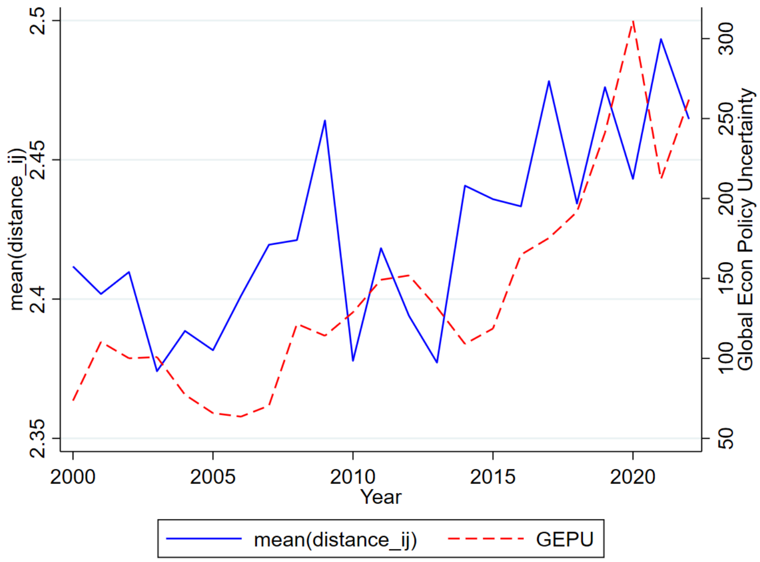
1 Introduction

Global value chains face unprecedented challenges following the COVID-19 pandemic, rising US-China trade tensions, and other geopolitical shocks (Alfaro and Chor, 2023; Aiyar et al., 2023). In this uncertain environment, multinational firms are attempting to reorganize their production across borders. Integration of production stages located in different countries often takes place through cross-border mergers and acquisitions (M&A). For example, as a response to the US-China trade war, multinational firms are acquiring firms in Mexico as a means to relocate their manufacturing operations out of China (Reuters, 2023).

The subject of organizing production across borders or global value chains remains a vital topic of study in the trade literature. However, the role played by cross-border M&As in the organization of global value chains has received relatively little attention. This includes understanding how M&A influences a firm's decisions regarding expanding its boundaries and broader organizational choices. This paper aims to address this gap by being the first to examine the role of cross-border M&As in the vertical integration of production stages across borders in a time of uncertainty. In particular, we document that when economic policy uncertainty intensifies, more distant production stages in the value chain become more likely to be acquired.

We explore the relationship between acquiring and target firms along a value chain using cross-border M&A deals from 2000 to 2022 and the US Input-Output (I-O) tables. First, we classify these deals into different types of foreign direct investment (FDI), as outlined by Alfaro and Charlton (2009). For analytical simplicity, FDI is usually classified as horizontal or vertical. Firms engage in horizontal FDI when they replicate a subset of their activities or processes in another country, in other words, when production is duplicated in an offshore venue (Markusen, 1984; Markusen and Venables, 2000). Firms engage in vertical FDI when they fragment production by function, that is, when often motivated by cost considerations arising from factor cost differences, they break up the value-added chain (Helpman, 1984). Combining sector-level information and the I-O tables to distinguish horizontal from vertical FDI, we classify a horizontal FDI as a target in the same sector code as the acquirer and a vertical FDI as a target that produces in sectors that input to the acquirer's product. Our

Figure 1: Industry Distance of Cross-border M&A and Global Economic Policy Uncertainty



Notes: This figure shows the time trends of the average industry distance (the relative distance between merging firms in a value chain) and the global economic policy uncertainty index (Baker et al., 2016). The industry distance is calculated using cross-border M&A deals, and the year periods are based on announcement dates.

analysis shows that the majority of cross-border M&A deals involve vertical integration, in the sense that acquiring and target firms are linked through input-output relationships. This finding motivates us to develop a precise measure of the degree of vertical integration between acquirers and targets in M&A transactions and to examine how it evolves over time.

To assess the nature of the input-output relationships between firms engaged in cross-border M&As, we measure the distance between acquirer and target industries along a value chain using the *upstreamness* (Antràs et al., 2012; Alfaro et al., 2019). The upstreamness measure represents a weighted average of how many stages are removed from output j to the use of input i, indicating the relative distance between the output and the input in a value chain.

This measure allows us to characterize the degree of vertical integration with greater precision. We first focus on the industry linkage between acquirer and target pairs and show that, in general, firms located closer along a value chain are more likely to merge. This finding is supported by the literature considering that M&A allows firms to exploit complementarities in assets between an acquirer and a target (Nocke and Yeaple, 2007; Nocke and Yeaple, 2008;

Takayama, 2024). We further show how input contractibility—the extent to which inputs can be specified and enforced through contracts—shapes firms' integration choices. Higher input contractibility reduces the likelihood of integration at a given value-chain distance, consistent with efficient arm's-length contracting. At the same time, contractibility attenuates the negative effect of value-chain distance on M&A, indicating that well-functioning contracts mitigate the coordination frictions that integration would otherwise address.

Second, we relate time variation in industry distance between acquirers and targets in production value chains with economic uncertainty. Notably, industry distance and the level of global economic policy uncertainty, measured by Baker et al. (2016), exhibit strikingly parallel trends (Figure 1). The average distance between an acquirer and a target in a value chain becomes larger during the global financial crisis and experiences an even more pronounced increase after 2014, aligning with higher economic uncertainty due to political turmoil. Consistent with these patterns, our regression results suggest a positive and statistically significant relationship between industry distance and economic policy uncertainty: firms are more likely to acquire targets located farther along the value chain during periods of heightened uncertainty. These findings are robust to alternative measures of industry distance that incorporate secondary industry codes.

We propose a model to rationalize our empirical findings. Our model emphasizes the trade-off between merger synergies and exposure to unexpected shocks in firms' vertical integration decisions. On the one hand, M&A transactions tend to occur between proximate industries because firms can realize greater productivity gains from merging. This distance penalty is attenuated when the output industry exhibits higher contractibility. On the other hand, firms face industry-specific disruption shocks, and the likelihood and heterogeneity of experiencing such shocks increase during periods of heightened economic uncertainty, as industry-level outcomes become more dispersed—a feature documented in Bloom (2014).

We conjecture that merging with a more distant firm reduces the probability that both the acquirer and the target experience simultaneous shocks, enhancing the survival prospects of the merged entity during economically turbulent times. Consequently, heightened economic uncertainty shifts firms' integration choices toward more distant partners along the value chain, consistent with our empirical findings. Our comparative statics indicate that economic uncertainty has a stronger effect on the distance between acquirers and targets along the production value chain with higher input contractibility. When contracting frictions are lower, firms can more easily respond to uncertainty by integrating with more distant stages of production. These mechanisms generate testable implications that are consistent with our empirical results.

Our study relates to the finance literature concerning cross-border M&A.[1] The extensive body of literature explores the financial factors incentivizing firms to engage in cross-border M&A, such as cheap financial capital through acquirer-country valuations (Baker et al., 2008; Bergant et al., 2023) and undervalued assets in target countries (Chari et al., 2010). However, a significant fraction of cross-border M&A involves industry diversification, contributing to the integration of a production process across borders (Chari, 2021). To the best of our knowledge, we provide the first study on the role of M&A in industry diversification, particularly focusing on the sequential nature of production and the influence of policy uncertainty.

Our work is also related to the two strands of literature on international trade and foreign direct investment. The first strand of literature examines the role of FDI, particularly the impact of M&A on firms' performance. Complementary assets between a foreign acquirer and a domestic target determine a new affiliate's performance (Arnold and Javorcik, 2009; Guadalupe et al., 2012; Blonigen et al., 2014). For instance, unlike greenfield investment, a firm can improve its productivity by acquiring additional assets from its M&A partner, such as firm-specific capability (Nocke and Yeaple, 2007; Nocke and Yeaple, 2008; Takayama, 2024). In contrast to this literature, our study focuses on the relationship between acquirer and target industries and how that industry relationship and a firm's motivation toward M&A change over time, particularly during times of uncertainty.

The second strand of trade literature focuses on firms' integration and outsourcing choices, including Grossman and Hart (1986), Grossman and Helpman (2002), Grossman and Helpman (2005), Antràs (2003), Antràs and Helpman (2004), Antràs and Helpman (2008), Acemoglu et al. (2007), Johnson and Noguera (2012), and Antràs and Chor (2013).[2]

[1]Chari (2021) and Erel et al. (2024) provide an extensive review of the finance literature on cross-border M&A.

[2]There are other relevant studies, including, but not limited to Antràs et al. (2012), Baldwin and Venables

As noted in previous work, challenges remain in taking models of global value chains to the data. We adopt the methodology developed by Alfaro et al. (2019) to measure the relative distance between M&A partners in a value chain and analyze the relationship with economic policy uncertainty.

Finally, there is a growing literature regarding the economic effect of policy uncertainty on international trade (Handley and Limão, 2017; Crowley et al., 2018; Steinberg, 2019) and on cross-border M&A(Bonaime et al., 2018; Cao et al., 2019).[3] For example, Bonaime et al. (2018) show that political uncertainty decreases aggregate M&A deal values and the probability of merging. In contrast to their study, we focus on how the boundaries of firms change across borders through M&A. Specifically, our empirical analysis reveals that heightened economic policy uncertainty correlates with a greater likelihood of cross-border acquisitions occurring at more distant production stages. These findings further add to the ongoing discussions in academia and policy circles regarding the influence of FDI. Despite concerns regarding the adverse effects of FDI due to volatility, particularly during crises compared to domestic investments, our results suggest that production and financial links between foreign subsidiaries and parent firms have the potential to mitigate and lessen the negative effects of economic downturns.

The remainder of the paper is organized as follows. We introduce our data in Section 2 and discuss the industry diversification through cross-border M&A in Section 3. We present our empirical results in Section 4 and propose the model in Section 5. Section 6 concludes.

2 Data

In this section, we describe the datasets used in our analysis. We combine detailed information on M&A deals with input-output production linkages and measures of economic policy uncertainty. These data sources allow us to characterize the value-chain relationships

(2013),Costinot et al. (2013), Koopman et al. (2014), Antràs and Chor (2018), and Johnson (2018). For surveys of the global value chains literature, see Antràs and Yeaple (2014) and Antràs and Chor (2022).

[3] Alfaro and Chen (2012) show that vertical and financial linkages enhance the resilience of foreign subsidiaries during crisis periods, highlighting the role of multinational organizational structures in mitigating negative shocks. Related work examines the impact of trade restrictions on trade flows and global supply chains (Fajgelbaum et al., 2020; Grossman et al., 2023; Freund et al., 2024; Handley et al., 2025).

between acquirer and target industries and to examine how industry distance varies with economic conditions.

2.1 Cross-border M&A Deals

We use cross-border M&A deals completed from 2000 to 2022. Our M&A data comes from Zephyr, an extensive database of global M&A transactions led by Bureau van Dijk. For each deal, we observe information such as the acquirer's and target's country and industry, acquisition share, and deal value.[4] The industry classification is in NAICS 2017, and some of the acquiring and target firms report multiple industry codes. We focus on the deals made by acquirers with their main industries in the manufacturing sector. Additionally, we restrict our data to deals involving more than 10% acquisitions, following the definition of FDI. The 10% cutoff is common in FDI studies to determine whether an acquiring firm has control over its target firm.[5] The final sample consists of 39,501 transactions across 119 source countries and 181 destination countries.[6]

2.2 US Input-Output (I-O) Tables

We identify the inter-industry relationship between acquirer's and target's industries using the 2012 US Benchmark I-O Tables from the Bureau of Economic Analysis (BEA). Following Antràs et al. (2012) and Alfaro et al. (2019), we use the detailed supplementary use table after redefinitions. We call an input industry i and an output industry j. The use table provides the direct requirements coefficient dr_{ij}, representing the value of input i used directly to produce a \$1 value of output j.[7] An input i can be used not only directly but also indirectly to produce output j. We compute the total requirements coefficient tr_{ij}, using

[4] Information on deal value is available for approximately 40% of the transactions.

[5] For example, the Bureau of Economic Analysis (BEA) defines foreign affiliates as overseas business entities that are established by US direct investment and in which US firms own or control 10% or more of the voting shares. The majority of acquirers obtain more than 10% ownership. Acquisitions with less than 10% ownership consist of only 4% of the total deals in our dataset.

[6] The majority of source countries include the US (20.14%), Germany (7.92%), UK (6.45%), and France (5.64%), and for destination countries, such as the US (14.97%), the UK (9.23%), Germany (8.46%), France (4.73%).

[7] We make the open-economy adjustment (Antràs et al., 2012) by dividing each ij industry cell by the sum of values in row i in the Use table (i.e., the value of gross output, Y_i, plus net export, $X_i - M_i$).

direct requirements coefficients dr_{ij}. The total requirements coefficients indicate the value of input i used directly and indirectly to produce a \$1 value of output j.[8] In the I-O tables, a unique 6-digit I-O industry code has been assigned to each industry. Using the BEA concordance, we map the 2012 I-O codes to 4-digit NAICS 2017 codes to merge the input-output relationship information with M&A deals data.[9]

2.3 Economic Policy Uncertainty Indexes

We use a news-based economic policy uncertainty index that covers our data period from 2000 to 2022. The indexes have a monthly frequency. The economic policy uncertainty (EPU) index is developed by Baker et al. (2016). This index is constructed by text search on major newspapers from different countries. Each national index shows the relative frequency of newspaper articles containing the terms related to economy (E), policy (P), and uncertainty (U).[10] Our main EPU index is the global economic policy uncertainty (GEPU) index, a GDP-weighted average of EPU indexes for 18 countries.[11]

2.4 Input Contractibility

We follow the approach of Nunn (2007) to measure the extent to which inputs are contractible. The key idea is that industries differ in their reliance on inputs whose quality or performance is more or less easily specified in contracts. Nunn (2007) uses the Rauch (1999) classification to distinguish products that are homogeneous, reference-priced, or differentiated. We first construct a contract-intensity measure, defined as the share of differentiated inputs used in the production of an output. We then define *contractibility* as one minus

[8]The total requirements coefficients are computed by $[I - D]^{-1}D$, where D is an $N \times N$ matrix with dr_{ij} in each ij industry-pair cell (N is the number of industries in the Use table).

[9]The concordance is not one-to-one because the number of input-output (I-O) industries exceeds that of NAICS industries. When a NAICS industry code is matched to multiple I-O codes, the direct and total requirements coefficients are allocated equally across the matched I-O codes.

[10]For example, the US EPU index shows the relative frequency of newspaper articles that contain at least one term from each group: (i) economy (E) group, "economic" or "economy"; (ii) policy (P) group, "congress", "legislation", "white house", "regulation", "Federal Reserve", or "deficit," and (iii) uncertainty (U) group, "uncertainty" or "uncertain."

[11]The source to the data is https://www.policyuncertainty.com/global_monthly.html. We use the index based on current-price GDP measures.

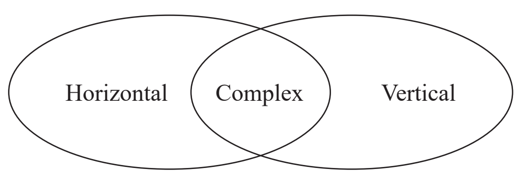
this contract-intensity measure (Alfaro et al., 2019). The contractibility measure is available only for output industries in the manufacturing sector.

3 Industry Relationships in Cross-border M&A

We examine the industry relationships between acquiring and target firms in this section. We first classify each deal into a type of FDI, which allows us to distinguish horizontal, vertical, and more complex forms of integration. We then introduce a measure of the proximity between acquirer and target industries along a production value chain. This measurement helps us to quantify how far a newly acquired stage is located from the acquirer's existing operations.

3.1 Integration Types on Cross-border M&A deals

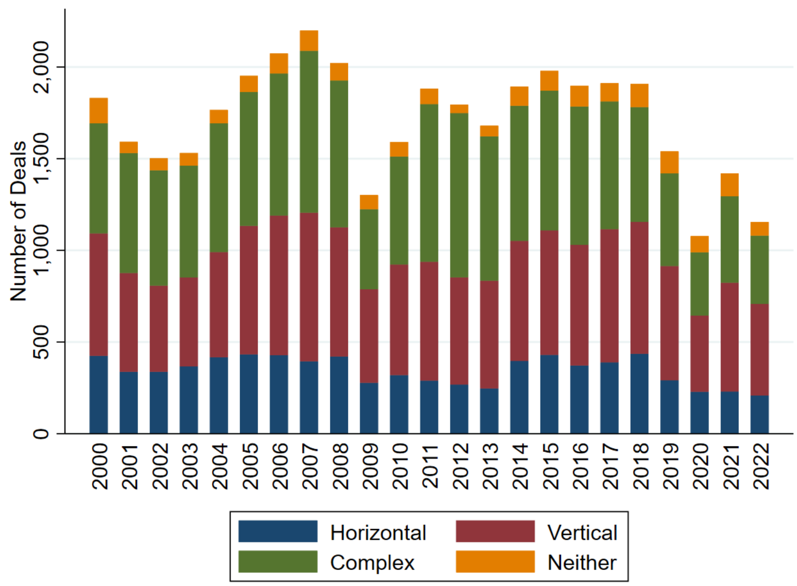
We explore the industry relationships between acquirer and target firms by classifying the M&A deals into different types of FDI. Following Alfaro and Charlton (2009), we propose four classifications of cross-border M&A deals:



(i) Horizontal: if an acquirer and a target share any industry codes or if the set of their industry codes is identical;
(ii) Vertical: if any industry of a target is an input to any industry of an acquirer, and the sets of their industry codes are not identical;
(iii) Complex: if an acquirer and a target share any industry, any industry of a target is an input to any industry of an acquirer, and the sets of their industry codes are not identical;
(iv) Neither: if none of these connections exists.

The complexity arises because both the acquiring and target firms have multiple industry codes. To define the input-output relationship between the two firms, we create all industry

Figure 2: Time Trend of FDI Types (Number of Transactions)



Source: Cross-border M&A data downloaded from Zephyr. Each M&A deal is classified into four types of FDI based on the rules outlined in this paper, and the year periods are based on their announcement dates.

pairs between acquirer and target industries, and match the total requirements coefficient, tr_{ij}, for each industry pair (here, we consider that a target industry as input i and an acquirer industry is output j, following Alfaro and Charlton (2009)). The target industry is an input to the acquiring industry if one of the total requirements coefficients, tr_{ij}, is larger than 0.0005.[12]

Among the total 39,501 M&A deals, 20% of the deals are horizontal (7,947 deals), 36% are vertical (14,220 deals), 39% are complex (15,226 deals), and 5% are in neither category (2,108 deals).[13] Only one-fifth of the total deals are horizontal M&A, which suggests that the majority of M&A deals are associated with industry diversification (i.e., M&A deals are either vertical or complex).

[12]We choose $tr_{ij} > 0.0005$ because this threshold yields a proportion of industry pairs with positive linkages comparable to the share implied by the direct requirements coefficients. While 59% of industry pairs have $dr_{ij} > 0$, using $tr_{ij} > 0.0005$ identifies 50% of industry pairs as connected. This ensures that the definition of vertical relatedness based on total requirements does not produce an unrealistically high or low number of linked pairs relative to the structure implied by direct requirements.

[13]We show the number of horizontal and vertical deals categorized by NAICS codes at different digit levels (four-digit, three-digit, two-digit, and one-digit). Consistent with the findings in Alfaro and Charlton (2009), we observe more horizontal deals than vertical deals at the one-digit level, while more M&A deals are classified as vertical than horizontal at the four-digit level (Table A.1).

More firms engage in cross-border M&A deals during a financial boom (Bergant et al., 2023). We plot the number of M&A deals with different FDI types during our data period. The year periods of this figure are based on the dates when deals are announced. Figure 2 shows the time trend with the total number of deals.[14] The number of deals increased from 2002 until the global financial crisis in 2007. The number remained stable after 2011, but it started decreasing in 2018 when the US-China trade war began.

3.2 Distance Between Acquirer and Target Industries

We measure the relative distance in a production value chain between output and input industries, i and j, using the I-O use table. Following Alfaro et al. (2019), we construct a distance measure (*upstreamness*), denoted by λ_{ij}.[15] The distance between input industry i and output industry j can be calculated by the following equation:

$$\lambda_{ij} = \frac{dr_{ij} + 2\sum_{k=1}^{N} dr_{ik}dr_{kj} + 3\sum_{k=1}^{N}\sum_{l=1}^{N} dr_{ik}dr_{kl}dr_{lj} + \ldots}{dr_{ij} + \sum_{k=1}^{N} dr_{ik}dr_{kj} + \sum_{k=1}^{N}\sum_{l=1}^{N} dr_{ik}dr_{kl}dr_{lj} + \ldots}, \tag{1}$$

where dr_{ij} is the direct requirements coefficient, and the number of industries in the I-O table is N.

The numerator of λ_{ij} is the weighted average of how many stages are removed from j the use of i is, using the direct requirements coefficient dr_{ij} as a weight. The first term of the numerator dr_{ij} represents the value of input i directly to produce a \$1 of output j, and the second term shows the value of input i to produce a \$1 of output j through producing the second stage of industry k. The denominator of λ_{ij} corresponds to the total requirements coefficient. The weighted average over the number of stages (in the numerator) using input i to produce j is scaled by the value of total input i used to produce output j (in the denominator). A higher level of λ_{ij} indicates the larger contribution of input i to the production of output j that is farther located from i on a value chain.

After we compute the industry distance, λ_{ij} using the I-O Use table for each ij industry pair, we take two steps to match the industry distance, λ_{ij} with each of the M&A deals.

[14] We plot the time trend using the number of deals instead of deal values because deal values are not reported for more than half (59%) of M&A. Figure A.1 shows the time trend in the values of transactions.

[15] The measure is also called an *average propagation length* (Dietzenbacher et al., 2005).

First, we map the I-O industry codes to NAICS 2017 using the concordance provided by the BEA. For a NAICS industry with multiple I-O industries, we take a simple mean over the matched I-O industry codes.[16] Second, to determine whether an acquirer or a target corresponds to the output industry j, we rely on direct input-output relationships at the three-digit I-O level. This aggregation is necessary because some fine-level input-output flows are suppressed for confidentiality in the Use table, while economically meaningful linkages are preserved at the three-digit level. Using this approach allows us to consistently assign input and output roles across industries. Note that the Use table does not report commodity flows to wholesalers, transportation, and warehousing in the I-O Use table. In practice, retailers should be considered as outputs, and thus, we assign the retail industries as the output industries. We delete observations with either a target or an acquirer in the wholesalers, transportation, and warehousing industries. These exclusions account for approximately 15% of all transactions.

One potential concern with the industry distance measure is its focus on the main industries of acquirers and targets. Firms involved in M&A, particularly acquirers, are often large and may have multiple industry codes. For instance, 58% (or 34%) of acquirers report more than two (or three) industry codes, while 33% (or 11%) of targets have more than two (or three) industry codes. To address the complexity of multiple industry codes, we also measure the industry distance in two ways. First, we make all possible combinations of acquirer and target industry codes and take the average. Second, we compute a measure that represents the degree to which newly acquired stages are positioned more upstream compared to stages that are not integrated before the merger. Appendix B.2 describes the details.

4 Empirical Facts on Value Chain Distance

We focus on the cross-border M&A deals where acquiring and target firms have vertical relationships (either vertical or complex types in the FDI classification introduced in Section 3.1) to run regressions. We also exclude the deals involving tax haven countries because firms

[16]We also compute the following alternative measures: the median value over the matched multiple I-O industry codes, the value picked randomly among the values over the matched I-O codes, and the weighted average using total requirements coefficients as weight.

Table 1: Descriptive Statistics

	Mean	Std Dev	Min	10th	Median	90th	Max	N
Upstreamness$_{ij}$, λ_{ij}	2.421	0.761	1.005	1.309	2.430	3.424	5.618	21,184
GEPU index	1.338	0.640	0.479	0.644	1.201	2.316	4.215	21,184
Input contractibility$_j$, θ_j	0.338	0.209	0.023	0.082	0.322	0.627	0.838	20,333

Notes: Industry distance, λ_{ij} is the mean of upstreamness$_{ij}$. The sample consists of 21,184 cross-border M&A deals with non-missing upstreamness$_{ij}$. The input contractibility measure is available only for manufacturing industries.

in tax havens frequently function as shell companies or special-purpose vehicles without real production activity. The list of tax haven countries is based on Hines and Rice (1994) and Tørsløv et al. (2023).[17] Table 1 shows the summary statistics for the variables we use in our regressions. The distance between acquirer and target industries in our cross-border M&A data ranges from 1 to 5.6.[18]

4.1 Industry Linkages and the Probability of M&A

First, we focus on industry variation and study whether the probability of an M&A transaction occurring between an industry pair depends on upstreamness. We aggregate M&A deals by input-output industry pairs ij and run the following linear probability regression:

$$\mathcal{I}[MA_{ij} = 1] = \beta_1 \log(\lambda_{ij}) + \beta_2\theta_j + \beta_3 \log(\lambda_{ij}) \times \theta_j + \alpha_i + \alpha_j + \epsilon_{ij},$$

where $\mathcal{I}[MA_{ij} = 1]$ is an indicator for whether M&A occurs in the particular industry pair.[19] The main regressor is the logarithm of the distance between acquirer and target industries, $\log(\lambda_{ij})$. We control for the regressions using input-industry fixed effects (FEs), α_i, and output-industry FEs, α_j. Standard errors are clustered by industry pairs. The coefficient of

[17] List of tax haven countries is in Appendix Table A.2. We do not exclude the Netherlands and Belgium in the sample as they host substantial real economic activity and together account for approximately 6% of cross-border M&A deals in our data.

[18] Figure A.2 shows the variation in λ_{ij}, by focusing on a particular industry: Computer and Peripheral Equipment Manufacturing (j = NAICS 3341).

[19] There are 265×265 industries in total (both in the manufacturing and service sectors). We exclude 179×179 industry pairs where both input and output industries are in the service sector. In our final sample, the upstreamness measure is missing for 2,070 industry pairs because their total requirements coefficients (denoted as the denominator in equation 1) are zeros.

Table 2: Probability of M&A and Industry Distance, λ_{ij}

	$\mathcal{I}[MA_{ij} = 1]$			
	(1)	(2)	(3)	(4)
upstreamness$_{ij}$ ($\log(\lambda_{ij})$)	-0.219^{***}	-0.274^{***}	-0.339^{***}	-0.367^{***}
	(0.008)	(0.013)	(0.021)	(0.021)
contractibility$_j$ (θ_j)		-0.110^{***}	-0.289^{***}	
		(0.009)	(0.046)	
$\log(\lambda_{ij}) \times \theta_j$			0.159^{***}	0.096^{**}
			(0.039)	(0.040)
Input industry FE	Yes	Yes	Yes	Yes
Output industry FE	Yes	No	No	Yes
N	36,113	20,655	20,655	20,655

Notes: Standard errors are clustered at the industry pair level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

interest is β_1 in this regression. The positive (or negative) sign of β_1 shows the positive (or negative) correlation between the probability that M&A occurs in an industry pair and the distance between industries in a production value chain. We also include output industry's input contractibility into the regression to analyze how contracting frictions in input sourcing affect the relationship between the probability of merging and industry distances.

Table 2 presents the results. Column 1 shows that the coefficient on $\log(\lambda_{ij})$ is negative and statistically significant, suggesting that firms that are closer to each other in a sequential production value chain are more likely to merge. The coefficient on contractibility θ_j is negative and significant, indicating that holding value-chain distance constant, higher contractibility reduces the probability of an M&A between industries. The result implies that if a firm in the output industry can source its inputs relatively more easily (i.e., higher input-contractibility), the firm is less likely to integrate through M&A because contracting at arms-length coordinates transactions efficiently. There is a positive and significant coefficient on the interaction term between industry distance and input contractibility (Column 3), indicating that the negative effect of distance on the probability of M&A is ameliorated in industries with high input contractibility. Contractibility mitigates coordination problems that integration would otherwise solve. These results remain robust to the inclusion of output industry fixed effects (Column 4). For robustness, we run additional regressions using alternative measures of distance. We consistently find the same sign and significance using different specifications (Appendix Table B.3).

4.2 The Time Variation in Value-Chain Distance and Economic Policy Uncertainty

Using M&A announcement dates, we examine time variation in industry distance between acquiring and target firms. We compute the annual weighted average distance, with weights given by the number of deals in each industry pair. Panel (a) of Figure 3 illustrates the annual trend in the weighted average distance between acquirer and target industries. The average distance increases during the global financial crisis, and further after 2014, with rising economic policy uncertainty.[20] We conjecture that the increasing trend in average upstreamness corresponds to significant economic events. To further explore this, we plot the annual trend with the GEPU index (Panel (b) of Figure 3). The figure shows a strong correlation between the average distance and GEPU, suggesting that firm pairs located farther apart along the production value chain tend to integrate when economic policy uncertainty is heightened.

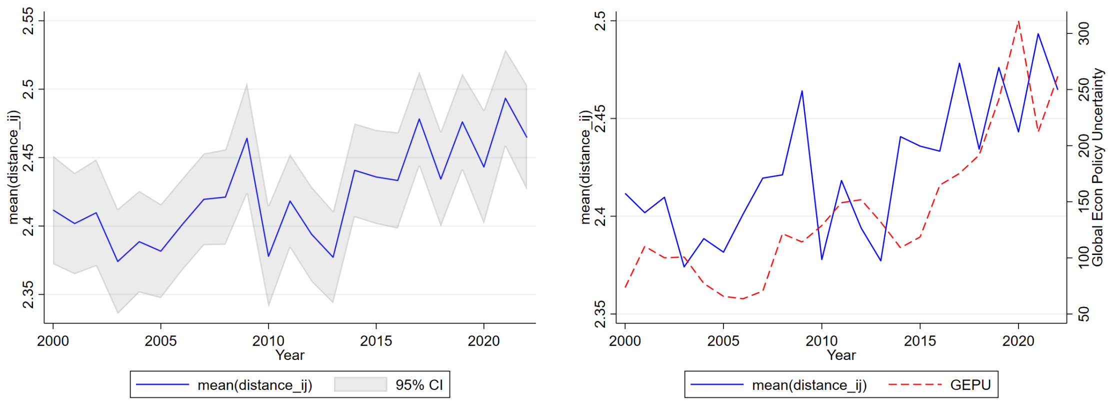
Using monthly data, we evaluate the statistical relationship between industry distance and economic policy uncertainty by estimating the following specification:

$$\log(\lambda_{ijt}) = \beta_1 \log(GEPU_{y(t)-1}) + \textit{country-pair-FEs} + \alpha_i + \alpha_j + \epsilon_{ijt},$$

where $\log(\lambda_{ijt})$ is the logarithm of the distance on a value chain between an acquirer and a target for each M&A transaction, and $\log(GEPU_{y(t)-1})$ is the log value of the GEPU index.

[20]The 2013 BEA revision capitalized R&D in national accounts, which affects the 2012 I-O table we used in this paper. Because of that revision, we less often observe the flows of NAICS 5417 (Scientific Research and Development Services) as inputs (i.e., the R&D industry can be a downstream output). For robustness, we present a corresponding figure, excluding deals in the R&D sector (Appendix Figure A.3). We observe a nearly identical trend.

Figure 3: Time Trend in Vertical Integration via M&A



(a) Average Industry Distance

(b) With the GEPU Index

Notes: Panel (a) shows the yearly weighted average industry distance, with weights given by the number of deals in each industry pair. Panel (b) plots the average industry distance together with the GEPU index.

Here, t indexes month–year and $y(t)$ denotes the calendar year associated with month t, so $\text{GEPU}_{y(t)-1}$ is the GEPU index in the previous calendar year. We use the one-year lag of GEPU to account for any time delays between changing economic conditions and M&A announcements. We include three sets of fixed effects: by country-pair, input-industry (α_i), and output-industry (α_j). Standard errors are clustered at the month-year and industry-pair levels.

Table 3 displays the results. The main specification (Column 3) includes all three fixed effects. The coefficient of $GEPU_{y(t)-1}$ is positive and statistically significant at the 5% level. Column 4 presents a more restrictive specification that additionally includes acquirer fixed effects. The coefficient on $GEPU_{y(t)-1}$ remains positive and statistically significant, indicating that even within the same acquirer over time, firms adjust their industry diversification strategies in response to economic uncertainty and are more likely to merge with targets located further along the production value chain during periods of heightened uncertainty.

We conduct two sets of robustness checks. First, we employ alternative measures of industry distance constructed using firms' main and secondary industry codes. Across these alternative specifications, the estimated coefficients remain positive and statistically significant in almost all cases (Appendix Table B.5). Second, we replace the GEPU index with the trade policy uncertainty (TPU) index developed by Caldara et al. (2020). The TPU

Table 3: Industry Distance and Global Economic Policy Uncertainty (GEPU) Index

	Industry distance, $\log(\lambda_{ijt})$			
	(1)	(2)	(3)	(4)
$\log(\text{GEPU}_{y(t)-1})$	0.023***	0.018***	0.006*	0.010**
	(0.006)	(0.005)	(0.003)	(0.004)
Country-pair FEs	No	Yes	Yes	Yes
Input industry FEs	No	No	Yes	Yes
Output industry FEs	No	No	Yes	Yes
Acquirer FEs	No	No	No	Yes
N	21,184	20,605	20,584	13,834

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the year-month period and industry pair level.

index is constructed using text searches of major US newspapers and focuses specifically on uncertainty related to trade policy, including tariffs, trade agreements, trade barriers, and (anti-)dumping measures. Using this alternative measure of uncertainty, we again find a positive and statistically significant effect of industry distance, λ_{ij}. Overall, these results indicate that heightened economic policy uncertainty—particularly trade policy uncertainty—shifts firms' cross-border M&A activity toward partners located farther along the production value chain.

5 Model

We propose a model to rationalize our empirical findings. We consider two identical countries, a source country s and a host country h. There are no transport costs or tariffs, and thus the price of each good is the same in both countries. The final demand is Y in each country.

5.1 Basic setup

5.1.1 Firms

There is a continuum of firms located in two countries. Firm i operates in country h, and firm j operates in country s. We assume that two firms are positioned along a value chain, where firm i operates in an upstream industry supplying an input to the downstream/output industry in which firm j operates.[21] Firms in the output industry procure inputs through contracts, and industries differ in the extent to which these input relationships are contractible. We denote the output industry's input contractibility by θ_j. Industries with higher θ_j can source and coordinate their inputs more easily through contractual arrangements.

Firms are indexed by industries (i.e., the industry of firm i is i, and the industry of firm j is j). Industries are uniformly distributed over the interval $[0, 1)$, which is mapped onto a circle of circumference 1. Industry locations are taken modulo 1, so 0 and 1 represent the same point on the circle.

The distance between two industries is denoted by λ_{ij}. It is defined as the shorter arc length between two industries on a circle, so $\lambda_{ij} \in [0, 1/2]$, and $\lambda_{ij} = \min\{|i-j|, 1-|i-j|\}$. For example, if $i = 0.1$ and $j = 0.5$, then $\lambda_{ij} = 0.4$, and if $i = 0.9$ and $j = 0.4$, then $\lambda_{ij} = 0.5$. Firms in the same industry produce differentiated brands in different countries (i.e., products in the same industry are imperfect substitutes).

Each firm has a different productivity level (or offers goods of different quality) ψ, and labor is the only factor of production. We assume that firm productivity ψ is independently distributed and orthogonal to industry characteristics (distance λ and input contractibility θ).

5.1.2 Preferences

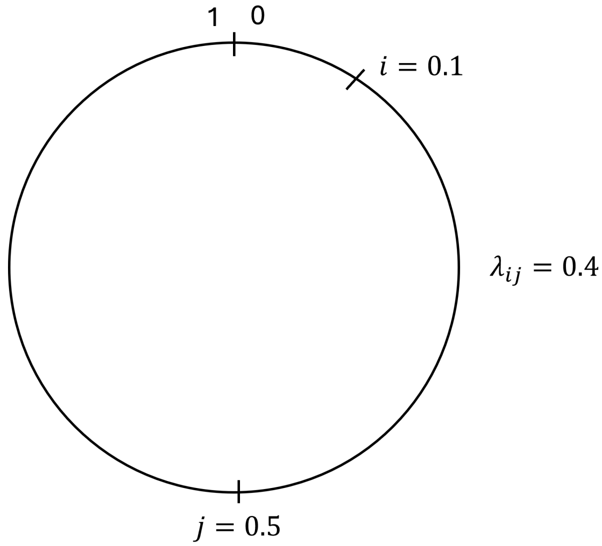
Representative consumers in both countries have identical CES preferences:

$$U = \left[\int_0^1 \sum_{k \in \{i,j\}} \psi_k^{\frac{1}{\sigma}} q_k^{\frac{\sigma-1}{\sigma}} dk \right]^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where q_k is consumption of good k, and $\psi_k > 0$ is the quality of that variety. Assume, for simplicity, that the elasticity of substitution $\sigma > 1$ between two firms in the same industry is the same as the elasticity of substitution across industries.

[21]For simplicity, we treat the downstream firm (the output industry) as the acquirer in the model. In the data, either the acquirer or the target may belong to the output industry.

Figure 4: Distance Between Two Industries



5.1.3 Merger

Firm j in the source country can offer to merge with firm i in the host country. The acquisition price is determined through the Nash bargaining between the acquirer and the target. After the merger, each merged party (i.e., acquirer j and target i) continues to operate and earns profits. The productivity of the integrated firm is higher the closer the industry distance between the two firms is. We define the post-merger productivity for each merged party as $v(\lambda_{ij}, \theta_j)\psi_k$ for $k \in \{i, j\}$, where $v(\lambda_{ij}, \theta_j)$ is a synergy amplification function.

The amplification function $v(\lambda_{ij}, \theta_j)$ reflects the empirical fact that M&A tends to occur between proximate industries, and that this distance penalty is attenuated when the output industry exhibits higher contractibility. We assume v is strictly decreasing in distance such that $v_\lambda(\lambda, \theta) < 0$ and $v_{\lambda\lambda}(\lambda, \theta) < 0$ (i.e., the decline is concave). Moreover, $v(0, \theta) > 1$ and $v(1/2, \theta) = 1$ so that merger synergy is maximized when the two firms operate in the same industry and disappears when industries are far apart. If the output firm operates in an industry with higher input contractibility θ_j, the merged entity faces lower integration frictions because production can be coordinated more effectively through contracts. Higher contractibility weakens the marginal loss from distance, so $v_{\lambda\theta}(\lambda, \theta) > 0$ and $v_{\lambda\lambda\theta}(\lambda, \theta) > 0$.[22]

[22] We do not set the equation of v explicitly here, but one possible form can be $v(\lambda, \theta) = 1 + \frac{a(1-4\lambda^2)}{1+b\theta}$,

5.1.4 Disruption Shocks

Economies face uncertainty, and industries are subject to disruption shocks. The likelihood of experiencing such shocks increases during periods of heightened economic uncertainty, as industry-level outcomes become more dispersed—a feature documented in Bloom (2014).[23] We assume that when an industry is hit by a disruption shock, all firms operating in that industry are affected. A firm that experiences a disruption shock must incur a recovery cost before it can resume normal production.

Suppose that the disruption shock occurs only in industries between $m \in [0, 1)$ and $m + r$ (more accurately, $m + r \mod 1$, that is, if $m + r \geq 1$, it is renamed as $m + r - 1$). Here, $r \in (0, 1/2)$ is a parameter that determines the length of the vulnerable segment. For instance, if $m = 0.2$ and $r = 0.1$, the disruption shock may occur only in industries $j \in [0.2, 0.3)$. If $m = 0.9$ and $r = 0.3$, the industries that may suffer are $j \in [0.9, 1) \cup [0, 0.2)$. We refer to these industries as "vulnerable industries." We assume that m is a uniformly distributed random variable, $m \sim U[0, 1)$, and thus the probability that any given industry is vulnerable is r. Conditional on being vulnerable, an industry is hit by the disruption shock with probability $\phi \in (0, 1)$. Therefore, the unconditional probability that an industry suffers from a disruption shock is $r\phi$.

This structure of the shock is meant to capture the idea that closer industries tend to receive correlated shocks. If $\lambda > r$, two industries are never vulnerable at the same time. If $\lambda \leq r$, the probability that both industries are vulnerable is $r - \lambda$ (again, recall that m follows $U[0, 1)$). The probability that one of the two industries is vulnerable and the other is not vulnerable is λ. Conditional on both industries being vulnerable, the probability that both are hit by the disruption shock is ϕ^2, the probability that exactly one is hit is $\phi(1 - \phi)$, and the probability that neither is hit is $(1 - \phi)^2$. Conditional on the event that exactly one industry is vulnerable, the probability that one of the two industries is hit by the disruption shock is ϕ.

When both firms' industries are hit by a disruption shock, the recovery cost is $c_H \psi_k$ for

where $a > 0$ and $b > 0$.

[23] Appendix Figure A.4 illustrates that periods of higher dispersion in US industry-level GDP are associated with elevated US economic policy uncertainty.

disrupted firms $k \in \{i, j\}$. When only one firm among the two merged firms is hit by the shock, the recovery cost is $c_L\psi_k$ for the disrupted firm $k \in \{i, j\}$, where $c_L < c_H$. The idea is that if only one part of the merged firm is hit by the shock, the other part is still intact, which makes it easier for the merged firm to recover. For stand-alone firms, by contrast, any disruption requires paying the full recovery cost $c_H\psi_k$. This reflects that a non-merged firm lacks internal redundancy: when it is hit by a shock, no unaffected unit exists to buffer operations. Hence, a stand-alone firm always incurs the full recovery cost when disrupted, whereas a merged entity bears this full cost only when both units are simultaneously affected and faces a lower recovery cost when the disruption hits only one unit.

5.2 Model Solution

5.2.1 Baseline Profits Under Monopolistic Competition

The CES demand function is derived from the consumer preference (2):

$$q_k = A\psi_k p_k^{-\sigma} \quad k \in \{i, j\},$$

where $A \equiv YP^{\sigma-1}$, and P is the price index $P = [\int_0^1 \sum_{k\in\{i,j\}} \psi_k p_k^{1-\sigma} dk]^{1/(1-\sigma)}$. Since the countries are symmetric, the price index is also the same in both countries.

Each firm behaves as a monopolist and maximizes its profit $\pi_k = (p_k - w)q_k$, where wage w is the unit cost of production. Countries are identical, so the wage in each country can be normalized to one. Under the CES demand and monopolistic competition, a firm sets a constant mark-up over the marginal cost: $p_k = \frac{\sigma}{\sigma-1}$. Given this price level, the price index becomes $P = \left(\frac{\sigma}{\sigma-1}\right) [\int_0^1 \sum_{k\in\{i,j\}} \psi_k dk]^{1/(1-\sigma)}$.

A firm's profit is

$$\pi_k = \Omega\psi_k, \tag{3}$$

where $\Omega \equiv A\left(\frac{1}{\sigma-1}\right)\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}$.

5.2.2 Merger Decisions

In what follows, we focus on the case in which the industry distance satisfies $\lambda_{ij} < r$, so that the two industries may be jointly vulnerable to disruption shocks. This ensures that the probabilities derived in the disruption-shock structure apply to the merger surplus.

When an acquirer j considers merging, the merged profits are given by:

$$E[\Pi_{ij}] = (\psi_i + \psi_j)[\Omega v(\lambda_{ij}, \theta_j) - (r - \lambda_{ij})(\phi^2 c_H + \phi(1-\phi)c_L) - \lambda_{ij}\phi c_L].$$

The first term is the profit after the merger (3), and the second term is the expected disruption cost.

If a firm $k \in \{i, j\}$ decides not to merge, it earns the expected stand-alone profit:

$$E[\pi_k] = \Omega\psi_k - r\phi c_H \psi_k.$$

Therefore, the expected merger surplus can be defined as:

$$\begin{aligned} E[V_{ij}] &= E[\Pi_{ij}] - E[\pi_i] - E[\pi_j] \\ &= (\psi_i + \psi_j)\Big[\Omega\big(v(\lambda_{ij}, \theta_j) - 1\big) - \phi(\phi - 1)(c_H - c_L)r + \phi^2(c_H - c_L)\lambda_{ij}\Big]. \end{aligned} \tag{4}$$

Because the amplification function of post-merger productivity $v(\lambda_{ij}, \theta_j)$ is decreasing in λ_{ij}, merging firm pairs with a smaller industry distance is more attractive. However, in terms of the risk from the disruption shock, merging firm pairs with a smaller λ_{ij} is unattractive because it is more likely that the merged firm will suffer from two shocks at the same time if λ_{ij} is small. The last term in (4), $\phi^2(c_H - c_L)\lambda_{ij}$, indicates that a larger λ_{ij} contributes positively to the expected merger surplus. With respect to the expected merger surplus (4), we assume an interior solution for the optimal distance, λ^*.

Maximizing the expected merger surplus leads to the first-order condition:[24]

$$-\Omega v_\lambda(\lambda^*, \theta_j) = \phi^2(c_H - c_L). \tag{5}$$

[24] Because firm productivity enters the surplus multiplicatively as $(\psi_i + \psi_j)$, it has no effect on the choice of merger distance. Thus, the model does not generate sorting on distance by productivity.

The left-hand side is positive (recall $v_\lambda(\lambda, \theta) < 0$) and increasing (recall $v_{\lambda\lambda}(\lambda, \theta) < 0$). The right-hand side is a constant (with respect to λ). We assume that parameter values ensure a positive surplus at the interior solution, $E[V_{ij}(\lambda^*)] > 0$, so that the proposed merger is accepted in equilibrium.[25] When merging, acquired firm i receives $(1 - \delta)E[V_{ij}] + E[\pi_i]$ as the acquisition price, where δ denotes the acquirer's bargaining power.

5.3 Comparative Statics

Consider the comparative statics of an increase in the probability of a disruption shock. The increase in global economic uncertainty can be viewed as a representation of an increase in ϕ. Applying the implicit function theorem to the first-order condition (5),

$$\frac{\partial \lambda^*}{\partial \phi} = -\frac{2\phi(c_H - c_L)}{\Omega v_{\lambda\lambda}(\lambda^*, \theta_j)}, \tag{6}$$

which is a positive number (note that $v_{\lambda\lambda}(\lambda, \theta) < 0$). This equation shows that the optimal distance λ^* increases with the level of economic uncertainty ϕ. The intuition is that the increased likelihood of a disruption shock makes it more costly to be vulnerable together. This risk can be mitigated by diversifying their industries via M&A. This model implication is in line with our empirical results discussed in Section 4.2.

We analyze the relationship between industry distance and the level of economic uncertainty, and how this is affected by the output industry's contractibility θ_j. Taking the derivative of (6) with respect to θ_j gives:

$$\frac{\partial \lambda^*}{\partial \phi \partial \theta_j} = \frac{2\phi(c_H - c_L)}{\Omega v_{\lambda\lambda}(\lambda^*, \theta_j)^2} \times v_{\lambda\lambda\theta}(\lambda^*, \theta_j).$$

Since higher contractibility weakens the marginal loss from distance ($v_{\lambda\lambda\theta}(\lambda, \theta) > 0$), it follows that $\frac{\partial \lambda^*}{\partial \phi \partial \theta_j} > 0$.[26] The industry distance between an acquirer and a target firm becomes larger as economic uncertainty increases, and higher contractibility enables firms

[25] On the circle, for a given i and given λ^*, there are typically two possible j (clockwise and counterclockwise). Since merger surplus depends only on industry distance and not on absolute location, the acquirer is indifferent between the two. We therefore select one deterministically (e.g., the clockwise firm) without loss of generality.

[26] For common functional forms of $v(\lambda, \theta)$, including the specification in Footnote 22, higher-order derivatives with respect to distance vanish, so no additional term $v_{\lambda\lambda\lambda}(\lambda^*, \theta_j)$ arises in the comparative statics.

Table 4: Input contractibility and the Sensitivity of Merger Distance to GEPU

	Industry distance $\log(\lambda_{ijt})$			
	(1)	(2)	(3)	(4)
$\log(\text{GEPU}_{y(t)-1})$	0.014***	−0.004	0.014***	0.005
	(0.005)	(0.011)	(0.005)	(0.007)
contractibility$_j$ (θ_j)	−0.162*	−0.169*		
	(0.095)	(0.096)		
$\log(\text{GEPU}_{y(t)-1}) \times \theta_j$		0.056**		
		(0.028)		
$\mathcal{I}[\text{high contractibility}_j = 1]$			−0.069	−0.073
			(0.052)	(0.052)
$\log(\text{GEPU}_{y(t)-1}) \times \mathcal{I}[\text{high contractibility}_j = 1]$				0.025**
				(0.011)
Country-pair FEs	Yes	Yes	Yes	Yes
N	19,757	19,757	19,757	19,757

Notes: The dependent variable is the log industry distance between acquirer and target industries. The key explanatory variable is the one-year lagged log Global Economic Policy Uncertainty index. Contractibility denotes the output industry's input contractibility (continuous measure), and high contractibility is an indicator for industries above the median. Input-industry fixed effects are excluded from this specification as the contractibility of the output industry's input bundle enters the construction. All regressions include country-pair fixed effects. Standard errors are clustered at the month-year period and industry-pair level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

to merge with targets located farther along the value chain.

We test this model implication by adding an input contractibility measure to the regressions in Table 3. The results are reported in Table 4. We use the output industry's input contractibility in columns 1 and 2. We also generate a dummy variable indicating whether the output industry is above the median in contractibility and use this measure in columns 3 and 4. We continue to observe a positive and significant coefficient on the lagged GEPU in columns 1 and 3. The coefficient on the output industry's input contractibility is negative and significant. Firms in industries with lower input contractibility utilize M&A as a substitute for missing contracts, which leads the firms to search farther and results in larger industry distance. The interaction term between lagged GEPU and input contractibility is positive and significant. This is consistent with the model implication (i.e., $\frac{\partial \lambda^*}{\partial \phi \partial \theta_j} > 0$). When economic uncertainty is high, input contractibility enables firms to merge with more distant partners in the value chain.

6 Conclusion

Multinationals have organized their global production systems to mitigate the risk of supply chain disruptions amid escalating economic policy uncertainty. In this paper, we examine the role of cross-border M&A in industry diversification. Firstly, we measure the distance between acquiring and acquired firms along the production value chain. Our results show that firms are more likely to merge with partners located closer along the value chain and that higher input contractibility facilitates integration. Our empirical analysis also indicates that a firm is more likely to merge with another firm located farther upstream in the value chain during times of heightened economic policy uncertainty.

Motivated by these two empirical facts, we build a model of vertical integration through mergers. In the model, a firm faces a trade-off: whether it gains a larger synergy by merging with another firm located closer along a value chain, or reduces the probability of getting an industry-specific shock by merging with another firm located farther along a value chain. The industry distance between merging firms will increase in times of economic uncertainty due to the higher expected likelihood of disruption shocks, which is consistent with our empirical findings. Our model links firms' vertical integration decisions via M&A to the levels of economic policy uncertainty.

There is a growing literature on the fragmentation of global value chains and its impacts on reallocation via trade. However, we highlight that significant reallocations are also taking place via cross-border M&A. An unanswered question is how the reconfiguration of the organization of production across borders takes place. For example, does a firm reorganize its production within or outside the boundaries of the firm? Addressing this question provides implications for diverse areas, including inflation, redistribution, reallocation, efficiency, and the environment. These topics open up interesting avenues of research, spanning different fields, such as finance, trade, development, and macroeconomics.

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Appendix A Additional Information of the Data

Table A.1: Patterns of Cross-border M&A Using Total Requirements Coefficients

	Four-digit	Three-digit	Two-digit	One-digit
Total	22,167	22,167	22,167	22,167
Horizontal	7,947	9,085	11,365	12,755
Vertical	14,220	13,082	10,802	9,412

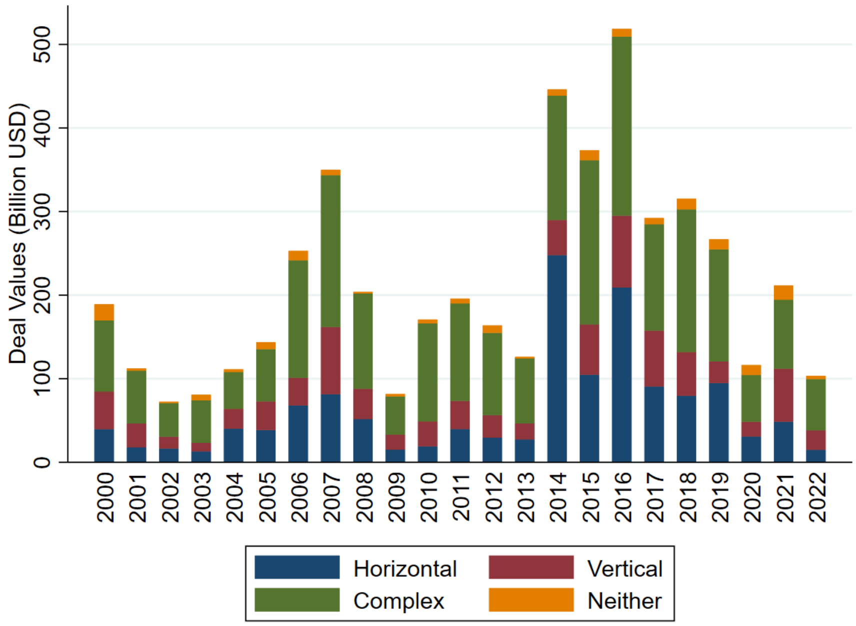
Notes: Authors' calculation using Zephyr data. Deals that are classified as Complex and Neither are excluded at the 4-digit level. Complex deals are included in Vertical FDI (and excluded from Horizontal FDI) at 3-digit, 2-digit, and 1-digit levels.

Table A.2: List of Tax Havens

Andorra, Anguilla, Antigua and Barbuda, Aruba, The Bahamas, Bahrain, Barbados, Belize, Bermuda, British Virgin Islands, Cayman Islands, Cook Islands, Curaçao, Cyprus, Dominica, Gibraltar, Grenada, Guernsey, Hong Kong, Ireland, Jordan, Lebanon, Liberia, Liechtenstein, Luxembourg, Macao, Maldives, Malta, Marshall Islands, Mauritius, Monaco, Netherlands Antilles, Panama, Puerto Rico, Samoa, Seychelles, Singapore, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Switzerland, Turks and Caicos Islands, and Vanuatu

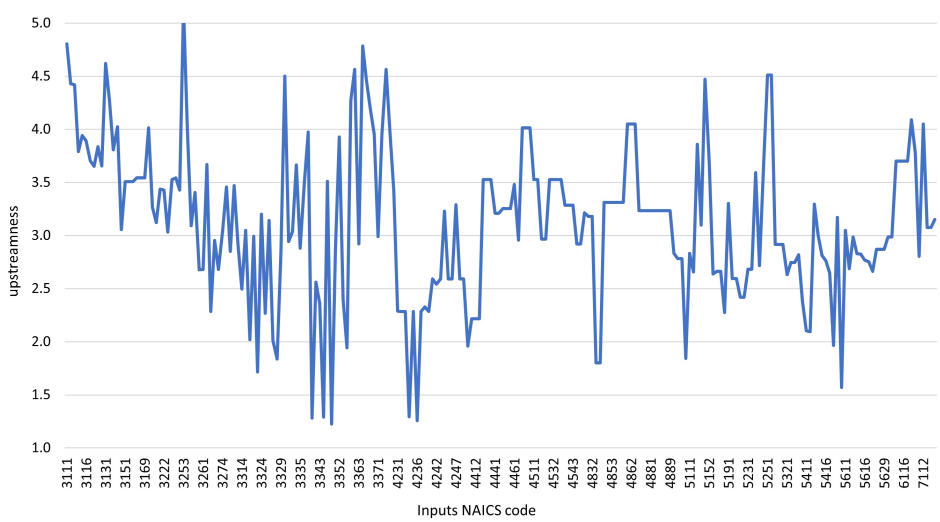
Notes: This table lists the tax-haven countries that appear in our cross-border M&A data. We retain the Netherlands and Belgium in the sample despite their classification as tax-haven jurisdictions in Tørsløv et al. (2023). Both countries have populations above 10 million and host substantial real economic activity. Together, they account for roughly 6% of cross-border M&A deals in our data, suggesting that their exclusion would remove a meaningful portion of production-related M&A activity.

Figure A.1: Time Trend of FDI Types (Value of Transactions)



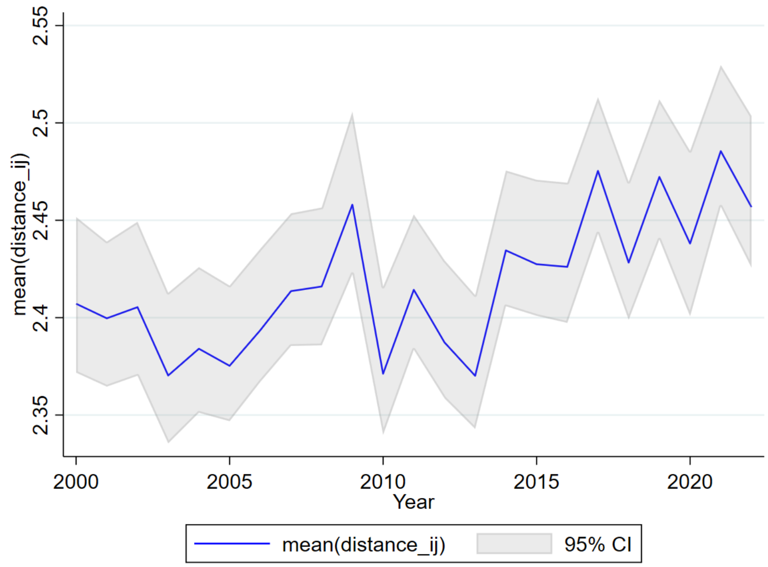
Source: Cross-border M&A data downloaded from Zephyr. Each M&A deal is classified into four types of FDI based on the rules outlined in this paper, and the year periods are based on their announcement dates.

Figure A.2: Industry Distance of Computer and Peripheral Equipment Manufacturing



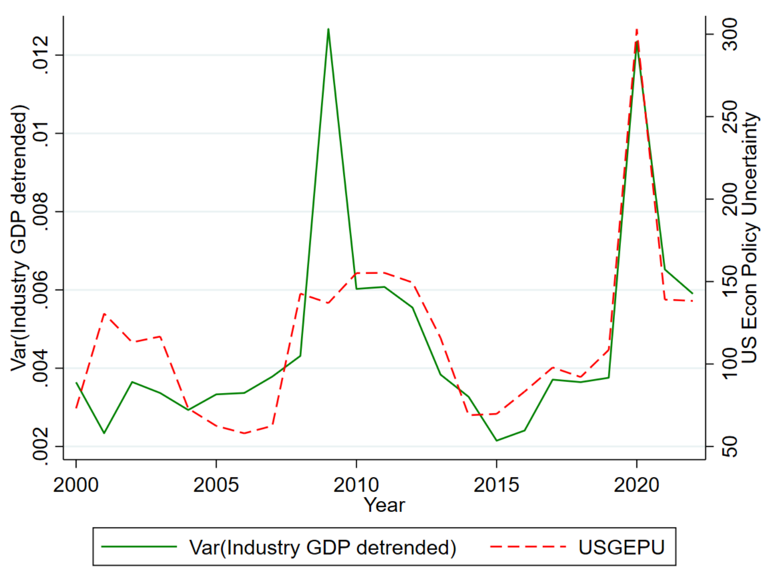
Notes: The figure displays the upstreamness of the computer and peripheral equipment manufacturing industry (NAICS 3341), calculated using the methods outlined in this paper.

Figure A.3: Average Distance (excluding R&D sector)



Notes: The figure shows the time trend of the average upstreamness, excluding the R&D sector.

Figure A.4: Variation across US Industry-Level GDP and US Economic Policy Uncertainty



Notes: This figure shows variation across US industry-level GDP and the US economic policy uncertainty (EPU) index. The two series are strongly correlated, with a correlation coefficient of 0.75. Industry-level GDP is measured using real gross output by industry from the Bureau of Economic Analysis. The sample includes 45 industries, of which 19 are manufacturing industries.

Appendix B Additional Regressions

B.1 Robustness: Section 4.1

Upstreamness$_{ij}$ measures are available at the I-O industry level, whereas industry codes in our M&A data are reported in NAICS. When a NAICS code maps to multiple I-O industry codes, we compute upstreamness$_{ij}$ as the simple mean across the corresponding I-O codes. Alfaro et al. (2019) propose alternative aggregation methods, including using the median value among the matched I-O codes, randomly selecting a single I-O code, and computing a weighted average using total requirements coefficients as weights. We obtain similar results under these alternative definitions. Table B.3 reports results based on upstreamness$_{ij}$ constructed using the median, denoted by $\tilde{\lambda}_{ij}$.

Table B.3: Probability of M&A and Alternative Upstreamness Measure, $\tilde{\lambda}_{ij}$

	$\mathcal{I}[MA_{ij} = 1]$			
	(1)	(2)	(3)	(4)
upstreamness$_{ij}$ ($\log(\tilde{\lambda}_{ij})$)	-0.110^{***}	-0.210^{***}	-0.262^{***}	-0.313^{***}
	(0.006)	(0.008)	(0.012)	(0.021)
contractibility$_j$ (θ_j)			-0.112^{***}	-0.255^{***}
			(0.009)	(0.046)
$\log(\tilde{\lambda}_{ij}) \times \theta_j$				0.127^{***}
				(0.039)
Input industry FE	No	Yes	Yes	Yes
Output industry FE	No	Yes	No	No
N	36,114	36,113	20,655	20,655

Notes: Standard errors are clustered at the industry pair level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2 Further Analysis for Section 4.2

We run two different types of robustness checks with (i) alternative measures of industry distance using the main and secondary industry codes, and (ii) the trade policy uncertainty (TPU) index, instead of the GEPU index.

B.2.1 Alternative Measures of Industry Distance

We measure the industry distance using the main and secondary industry codes of acquirers and targets. There are two alternative measures in addition to λ_{ij} that are calculated using only the main industry code. The first measure is the average of industry distance based on all possible combinations of acquirer and target industries. Table B.4 shows that the mean value of the average distance is similar to λ_{ij} where we use only the main industry code.

Another measure is called the level of integration, which shows how newly acquired stages are positioned more upstream compared to stages that are not integrated before the merger. We compute the level of integration for each of the M&A deals, d. With a unique input and output industry pair ij, we first identify the set of input industries i that have positive total requirements coefficients, tr_{ij}, $S(j) = \{i : tr_{ij} > 0\}$. Second, we define the group of inputs i that the downstream firm j has already integrated before the merger, as $I(j) \subseteq S(j)$, using the main and secondary industry codes of firm j. We define the remaining set of inputs i, that are not integrated by the firm j before the merger, as $NI(j) = S(j) \setminus I(j)$. In the set of non-integrated inputs, $NI(j)$, some of the inputs are newly integrated through the merger. The group of newly merged inputs is $M(j) \subseteq NI(j)$.

We are now ready to compute the level of integration:

$$\textit{Level-of-integration}_d = \frac{\Sigma_{i \in M(d)}\ \Phi_{ij}^{M(d)}\ \lambda_{ij}}{\Sigma_{i \in NI(d)}\ \Phi_{ij}^{NI(d)}\ \lambda_{ij}},$$

where $\Phi_{ij}^{M(d)} = \frac{tr_{ij}}{\Sigma_{i \in M(d)} tr_{ij}}$ and $\Phi_{ij}^{NI(d)} = \frac{tr_{ij}}{\Sigma_{i \in NI(d)} tr_{ij}}$. This indicator represents the weighted average distance of newly-merged inputs relative to that of pre-merger non-integrated inputs. A greater ratio indicates that relatively more upstream inputs are integrated through M&A, compared to the inputs that are not integrated before the M&A deal.

Table B.4: Appendix: Descriptive Statistics

	Mean	Std Dev	Min	10th	Median	90th	Max	N
Upstreamness$_{ij}$, λ_{ij}	2.421	0.761	1.005	1.309	2.430	3.424	5.618	21,184
Average upstreamness	2.481	0.558	1.005	1.789	2.474	3.178	5.594	21,184
Level of integration	1.074	0.299	0.394	0.658	1.079	1.460	2.450	14,669
TPU index	0.462	0.429	0.113	0.228	0.309	0.941	2.660	21,184

Notes: This table shows the summary statistics of alternative measures of industry distance using main and secondary industry codes. The table also shows the summary statistics of the trade policy uncertainty (TPU) index.

Table B.5 shows the regression results using alternative measures of industry distance using multiple industry codes. Results with average distance are very similar to the ones with the industry distance using only the main industry codes. The results with the level of integration measure are in columns 5-8. We observe the positive and significant coefficients except for the result with the most strict specification with acquirer FEs (column 8). When acquirer FEs are included in the regression using the level of integration measure, identification relies solely on within-acquirer changes in the relative upstreamness of newly integrated inputs. For large, serial acquirers that have already internalized a wide range of upstream inputs, the level-of-integration measure has little room to vary, substantially reducing detectable variation in this measure.

Table B.5: Regression Results with Industry Distance Using Multiple Industry Codes

	Average Upstreamness				Level of integration			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\log(GEPU_{y(t)-1})$	0.015***	0.012***	0.008***	0.006*	0.031***	0.025***	0.016***	0.004
	(0.004)	(0.004)	(0.003)	(0.003)	(0.007)	(0.006)	(0.005)	(0.010)
Country-pair	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Input ind	No	No	Yes	Yes	No	No	Yes	Yes
Output ind	No	No	Yes	Yes	No	No	Yes	Yes
Acquirer	No	No	No	Yes	No	No	No	Yes
N	21,184	20,605	20,584	13,834	14,669	14,145	14,125	8,510

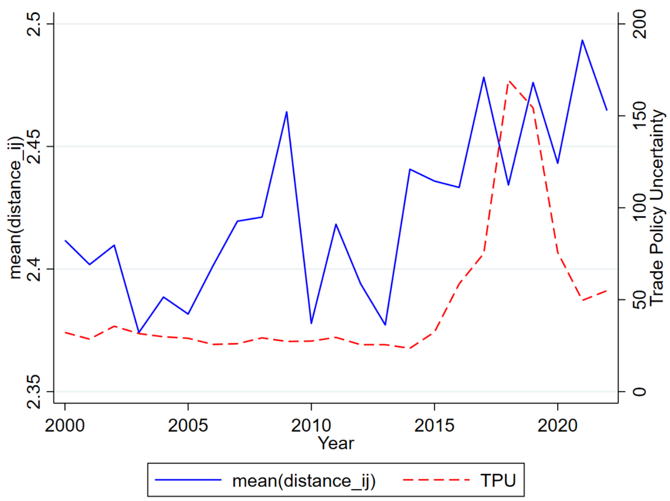
Notes: We take the log of both the average upstreamness and the level of integration measures. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the year-month period and industry pair level.

B.2.2 Trade Policy Uncertainty (TPU) Index

We examine the correlation between the industry distance of merging firms and the TPU index (Caldara et al., 2020). Baker et al. (2016) also provides an EPU index specifically for trade policy. Their measure is constructed by the text search for trade policy-related terms among the newspaper articles that contain each of the E, P, and U terms. We use the TPU index developed by (Caldara et al., 2020) since it covers more terms related to trade policy and a larger number of newspaper articles to search for trade policy-related terms.

The variation of the TPU index is different from the GEPU index. Specifically, the level of TPU has not changed until 2015 and increases sharply after 2015, reflecting the US-China trade war (Figure B.5). While the yearly trends of the industry distance and the TPU index are not the same in the figure, we still find the positive and significant coefficients of the TPU index with all specifications (Table B.6).

Figure B.5: Industry Distance and Trade Policy Uncertainty (TPU) Index



Notes: The figure shows the time trend of the average industry distance and the TPU index.

Table B.6: Industry Distance and Trade Policy Uncertainty (TPU) Index

	Upstreamness$_{ij}$, λ_{ij}			
	(1)	(2)	(3)	(4)
$\log(\text{TPU}_{y(t)-1})$	0.015***	0.010**	0.010***	0.006^{+}
	(0.005)	(0.005)	(0.003)	(0.004)
Country-pair FEs	No	Yes	Yes	Yes
Input ind FEs	No	No	Yes	Yes
Output ind FEs	No	No	Yes	Yes
Acquirer FEs	No	No	No	Yes
N	21,184	20,605	20,584	13,834

Notes: $^{+}p < 0.15$, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the year-month period and industry pair level.