Organizing Production Across Borders in a Time of Uncertainty*

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Abstract

Multinational firms are strategically reorganizing their production networks in response to escalating geopolitical risks. This paper investigates the impact of mergers and acquisitions (M&A) on restructuring production value chains across borders. 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 further along global value chains during times of uncertainty. The implications of our model align consistently with the empirical findings, shedding light on the dynamics of production network restructuring and firm boundaries expanding amid geopolitical uncertainty.

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

JEL Classification: F1, F2

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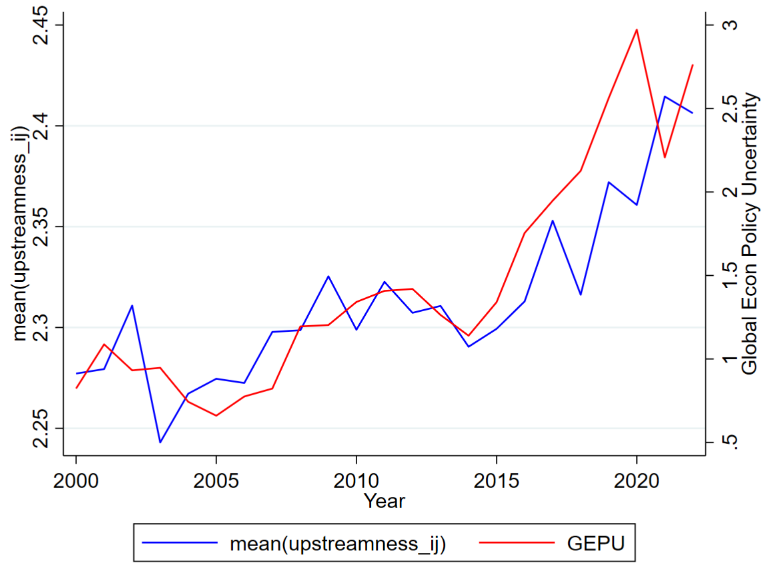
1 Introduction

Global value chains face unprecedented challenges following the US-China trade tensions, the COVID-19 pandemic, and geopolitical shocks (Alfaro and Chor, 2023; Aiyar et al., 2023). In response, multinational firms are facing an imperative to organize their production across borders. A frequently employed strategy involves the integration of production stages located in different countries through mergers and acquisitions (M&A), where multinational firms acquire ownership of targets across borders. For example, Mexico is attracting cross-border M&A investments as firms relocate their manufacturing operations out of China in response to the US-China trade war (Reuters, 2023).

The widespread division of production processes across the globe has been a critical topic in the trade literature. However, the impact of M&As on firm involvement in specific stages of production in the value chain has yet to be as extensively explored. 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 and contribute to the existing body of knowledge by being the first to examine the role of cross-border M&A in integrating production processes in a time of uncertainty. Notably, we document that farther production stages are more likely to be acquired when economic policy uncertainty intensifies.

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 four-digit sector-level information and input-output tables to distinguish horizontal from vertical FDI, we classify a horizontal FDI as a target in the same sector code as the

Figure 1: M&A Upstreamness and Global Economic Policy Uncertainty



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

acquirer and a vertical FDI as a target that produces in sectors that input to the acquirer's product. Our analysis shows that the majority of cross-border M&A deals involve vertical integration (i.e., an acquiring firm and a target firm have an input-output relationship). We also observe a time trend in the share of vertically integrated M&A deals. These findings motivate us to precisely measure the degree of vertical integration between acquiring and target firms through M&A and its evolution over time.

To assess the nature of the input-output relationships between firms engaged in cross-border M&As, we use a measure of the upstreamness of input i in the production of output j (Alfaro et al., 2019; Antràs et al., 2012). 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. Using this measure allows us to consider the relationship between the acquiring and target firms, and we show that firms located closer in the value chain are more likely to merge. However, we observe the relative distance between acquiring and target firms in a value chain varies over time, experiencing a significant increase after 2015.

We relate the time variation over distances between M&A partners in production value chains (i.e., the upstreamness) with economic uncertainty. Notably, the upstreamness and the level of global economic policy uncertainty (measured by Baker et al., 2016) exhibit strikingly parallel trends (Figure 1). The upstreamness increased during the global financial crisis and experienced even more significant growth after 2014, aligning with higher economic uncertainty due to political turmoil. This suggests that the relative distance between merging firms in a value chain becomes larger as economic uncertainty is heightened. Our regressions also show significant correlations between the upstreamness and the level of economic policy uncertainty. Specifically, we find that when the uncertainty reaches the level observed after the US-China trade war, the upstreamness increases by 1.4%. Our results are robust with fixed effects and other industry controls. We also obtain the same results with the trade policy uncertainty index developed by Caldara et al. (2020).

Finally, we rationalize our empirical findings with a model. Firms make relationship-specific investments to manage the risk of their supply chains being disrupted (Elliott et al., 2022; Grossman et al., 2023). We hypothesize that firms make such investments more when their economic risk is heightened. Building on Antàs and Helpman (2004) and Antàs and Chor (2013), we consider that a final-good producer engages in relationship-specific investments, such as managerial inputs, so that each input can be supplied. The intensity of this investment increases with higher economic uncertainty. The model implies that more stages are vertically integrated as a firm intensifies its relationship-specific investments, which is consistent with our empirical results.

Our work is related to the two strands of literature on international trade and foreign direct investment. The first focuses on firms' integration and outsourcing choices, including Grossman and Hart (1986), Grossman and Helpman (2002, 2005), Antràs (2003), Antràs and Helpman (2004, 2008), Acemoglu et al. (2007), Johnson and Noguera (2012), and Antràs and Chor (2013, 2022).[1] 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)

[1]There are other relevant studies, including, but not limited to Antràs et al. (2012) Baldwin and Venables (2013), Costinot et al. (2013), Koopman et al. (2014), Antràs and Chor (2018), Johnson (2018), and Borin and Mancini (2023). Antràs and Yeaple (2014) and Antràs and Chor (2022) provide extensive surveys of the literature concerning global value chains.

to measure the relative distance between M&A partners in a value chain and analyze the relationship with economic policy uncertainty.

The second strand of trade 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 country-specific capability (Nocke and Yeaple, 2007, 2008) and intangibles (Takayama, 2023). In contrast to this literature, our study focuses on a 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.

Our study also relates to the finance literature concerning cross-border M&A.[2] 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., 2009; 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.

Finally, there is a growing literature regarding the economic effect of policy uncertainty on international trade (Handley and Limao, 2017; Crowley et al., 2018; Steinberg, 2019) and on cross-border M&A (Bonaime et al., 2018; Cao et al., 2019).[3,4] For example, Bonaime et al. (2018) show that political uncertainty decreases aggregate M&A deal values and the

[2] Chari (2021) and Erel et al. (2022) provide an extensive review of the finance literature on cross-border M&A.

[3] The response of multinational enterprises (MNEs) to crises and their cross-country performance links has been relatively unexplored. Alfaro and Chen (2012a,b), comparing these effects in pre-crisis (2005-2007) and crisis (2007-2008) periods, show that vertical and financial linkages improved the resilience of foreign subsidiaries to negative market and financial shocks.

[4] There is a growing literature that examines the impact of trade restrictions on trade flows and global supply chains, including Fajgelbaum et al. (2020), Handley et al. (2020), Freund et al. (2023), and Grossman et al. (2023).

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 and discuss the industry diversification through cross-border M&A in Section 2. Section 3 introduces the measure of upstreamness between two industries. We discuss our empirical results in Section 4 and propose the model in Section 5. Section 6 concludes.

2 Data and Industry Diversification via M&A

This section introduces our primary datasets: cross-border M&A deals, US Input-Output (I-O) Tables, economic policy uncertainty indexes, and other industry variables. We also present a detailed analysis of the industry relationships between acquiring and target firms, specifically focusing on industry diversification via M&A.

2.1 Data

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 compiled 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. The industry classification is in NAICS 2017, and some of the acquiring and target firms have 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]

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 Antàs 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 requirement 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. An alternative measure, the total requirement coefficient, indicates 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]

Economic policy uncertainty indexes: We use two news-based economic policy uncertainty indexes that cover our data period from 2000 to 2022. We rescale economic policy uncertainty indexes by dividing them by 100 to make them comparable to our input-output relationship measures. The indexes have a monthly frequency.

The first index is the economic policy uncertainty (EPU) index developed by Baker et al. (2016). This index is constructed by text search on major newspapers for different

[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 my dataset.

[6]The majority of source countries include the US (20%), 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 (Antàs 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, $X_i - M_i$).

[8]The total requirement 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 since there are more I-O industries than NAICS. If a unique I-O industry code is matched with multiple NAICS codes, the direct and total requirement coefficients (with the I-O industry code) are equally allocated across the matched NAICS code.

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 weighted average of EPU indexes for 21 countries. We also use EPU indexes for the US and China.

The second index is the trade policy uncertainty (TPU) index introduced by Caldara et al. (2020). The TPU index is constructed by text search on the US major newspapers. Unlike the EPU index, the text search for the TPU index focuses particularly on terms related to trade policy, such as tariff, trade agreement, trade barrier, and (anti-)dumping.[11,12]

Industry variables: We use two industry variables for regression analysis. The first is the average intangible intensity (representing the ratio of intangibles to sales) for NAICS industries. We calculate that indicator using the financial information of US publicly-listed firm from 1980 to 2018, downloaded from the Compustat database. To construct US firms' intangible capital from 1980 to 2018, we follow the methodology of Peter and Taylor (2017) and Ewens et al. (2020).[13] After calculating the amount of intangible capital for each firm, we compute the ratio of intangibles over sales and then take the average over NAICS industries using data from 2002 to 2018.

The second industry variable is the intermediate inputs share. We compute this indicator using the I-O Use table. We observe the total intermediate inputs required to produce a $1 value of an output and the total sum of inputs, including intermediate inputs and other value-added components (such as labor inputs). We then calculate the ratio of intermediate inputs to the total inputs.

[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."

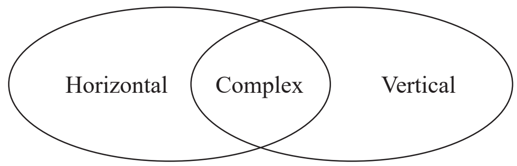
[11]The TPU index shows the relative frequency of newspaper articles that contain at least one of the trade policy related (TP) terms and the uncertainty (U) terms. Detailed terms are found in the supplementary material of Caldara et al. (2020).

[12]Baker et al. (2016) also provide 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, 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 trade policy related terms.

[13]A detailed explanation is provided in Takayama (2023).

2.2 Cross-border M&A and Industry Diversification

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 are 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.

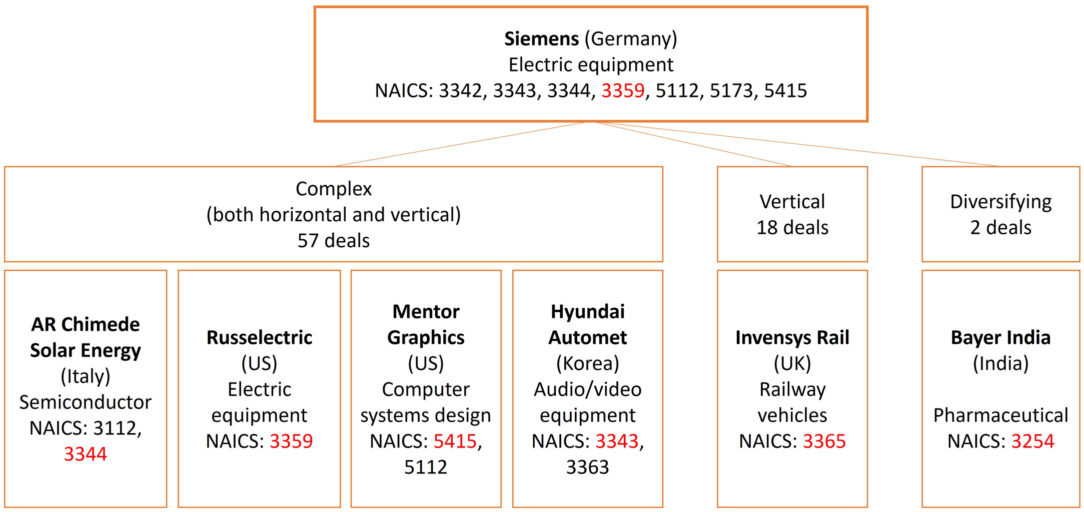
The complexity arises because both acquiring and target firms have multiple industry codes. To define the input-output relationship between the two firms, we create all industry pairs between acquirer and target industries, and match the direct requirements coefficient, dr_{ij}, for each industry pair (here, we consider 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 direct requirements coefficient, dr_{ij}, is larger than zero (i.e., as long as one of the commodities produced by a target firm is used to make one of the goods produced by an acquiring firm).[14]

Among the total 39,501 M&A deals, 20% of the deals are horizontal (7,889 deals), 37% are vertical (14,583 deals), 39% are complex (15,284 deals), and 4% are in the neither category.[15] Only one-fifth of the total deals are horizontal M&A, which suggests that majority

[14]For robustness, we also use the total requirements coefficients, tr_{ij}, instead of the direct requirements coefficient, dr_{ij}. We set a threshold of 0.0005 for the total requirements coefficients. Around 50% of the total industry pairs have coefficients larger than the threshold, while 59% of industry pairs have direct requirements coefficients larger than zero.

[15]We show the number of horizontal and vertical deals categorized by NAICS codes at different digit

Figure 2: Example: Types of FDI



Source: Cross-border M&A data downloaded from Zephyr. The highlighted NAICS codes represent the main industry codes for each firm.

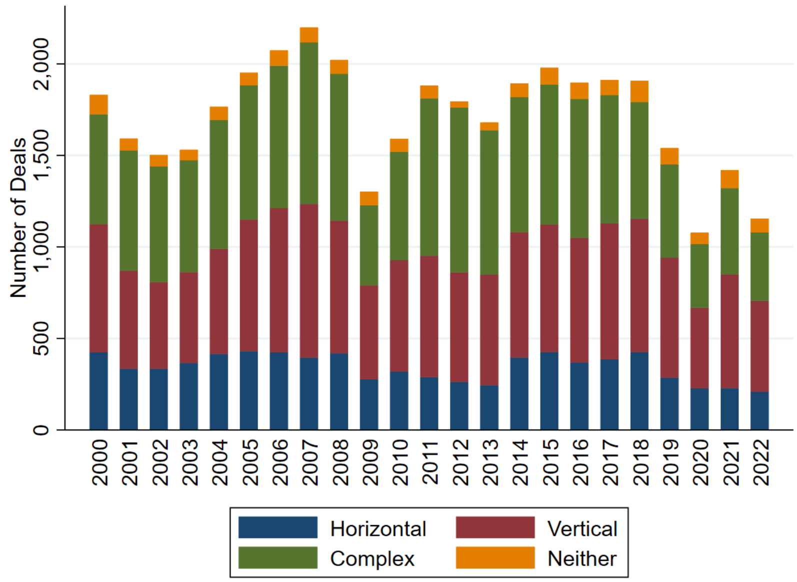
of M&A deals are associated with industry diversification (i.e., M&A deals are either vertical, complex, or neither). Figure 2 provides a detailed example of industry diversification through M&A. Siemens AG, a German firm producing electric equipment, conducted 83 cross-border M&A deals during our data period. The firm acquired new industries that are outputs of their existing industries in all deals, except only two deals.

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 3 shows the time trend with the total number of deals.[16] 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 war began. We observe a slightly different time trend with the share of M&A deals associated with industry diversification (i.e., the sum of vertical and complex M&A deals). The share increased from 2009 and reached a peak (84%) in 2012.

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 to vertical than horizontal at the four-digit level (Table B.1).

[16] 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.

Figure 3: 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.

3 M&A Industries on a Value Chain

In the previous section, we show that the majority of cross-border M&A deals involves industry diversification. While our classification enables us to identify whether acquirer and target industries have input-output relationships, it does not provide insight into the detailed relationship within a production value chain. In this section, we introduce a measure to map the positions of the two industries within the value chain. We also present our descriptive analysis.

3.1 Measuring the Input-output Relationship on a Value Chain

We use three different measure to analyze the input-output relationships for M&A industries on a production value chain.

3.1.1 Position of a Unique Industry

We follow Antràs et al. (2012) and measure the distance to final use for a unique industry, called *upstreamness*. We compute the following equation using the I-O Use table to measure the upstreamness for industry k, U_k:

$$U_k = 1 \times \frac{F_k}{Y_k} + 2 \times \frac{\Sigma_{l=1}^{N} d_{kl} F_l}{Y_k} + 3 \times \frac{\Sigma_{l=1}^{N} \Sigma_{m=1}^{N} d_{km} d_{ml} F_l}{Y_k} + \ldots,$$

where F_k is industry k's use as a final good, and Y_k is the value of gross output. There are N industries in the I-O table. Upstreamness, U_k, represents the average position of industry k in the value chain using direct requirements coefficient, d, as a weight.

We use this upstreamness measure in our M&A data to determine whether an acquirer or a target is positioned more downstream on a production value chain. Specifically, we compare the upstreamness of acquirer and target industries and designate the firm positioned more downstream as the output, denoted as j.[17] When focusing only on the main industry codes of both acquiring and acquired firms, we find that 40% of the deals involve acquirers and targets within the same industry. In the half of the remaining deals, acquirers are in the output industry (or positioned downstream). We assign acquirer industries to an output industry for the horizontal deals.[18]

As noted in Section 2.1, the I-O table used to compute upstreamness for each industry k, U_k, is in the I-O industry code, while the industry classification of the M&A data is NAICS 2017 codes. We use the concordance provided by the BEA and map the upstreamness measure to NAICS 2017. We take the simple mean of upstreamness, U_k, for NAICS codes that are matched with multiple I-O industries codes.

3.1.2 Relationship Between Two Industries

We determine whether an acquirer or a target is in input industry i or output industry j using the upstreamness, U_k, we introduced in the previous section. We next measure the relationship between two different industries, i and j, on the value chain using $upstreamness_{ij}$

[17]We do not observe the flow of commodities to wholesalers, retailers, transportation, and warehousing in the IO Use table, and therefore those industries are always assigned to inputs. For example, alcoholic beverage merchant wholesalers (NAICS 4248) are assigned to be an input to beverage manufacturing (NAICS 3121). In practice, wholesalers and retailers should be outputs, and thus we assigned the wholesale and retail industries as the output industries without comparing their upstreamness measures. We deleted observations with either a target or an acquirer in the transportation and warehousing industries. Those deals account for only 5% of the total deals.

[18]This follows Alfaro and Charlton (2009) and Alfaro et al. (2019), who set a parent firm in an output industry, and its affiliate in an input industry.

(Alfaro et al., 2019). We measure the relationship of input i and output j on the value chain by calculating the following equation:

$$Upstreamness_{ij} = \frac{dr_{ij} + 2\sum_{k=1}^{N} dr_{ik}dr_{kj} + 3\sum_{k=1}^{N}\sum_{l=1}^{N} dr_{ik}dr_{kl}dr_{lj} + \dots}{dr_{ij} + \sum_{k=1}^{N} dr_{ik}dr_{kj} + \sum_{k=1}^{N}\sum_{l=1}^{N} dr_{ik}dr_{kl}dr_{lj} + \dots}, \quad (1)$$

where dr_{ij} is the direct requirements coefficient.

The numerator of $Upstreamness_{ij}$ is the weighted average of how many stages removed from j the use of i is, using 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 $Upstreamness_{ij}$ is a total requirements coefficient. The weighted average over the number of the 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).[19] A higher level of $Upstreamness_{ij}$ indicates the larger contribution of input i to the production of output j that is further located from i on a value chain.

After we compute $Upstreamness_{ij}$ using the I-O Use table for each ij industry pair, we merge this measure with our M&A deals using the BEA concordance between I-O industry codes and NAICS 2017 codes. For a NAICS industry with multiple I-O industries, we take a simple mean over the matched I-O industry codes.[20] As previously mentioned, we use the upstreamness measure for a unique industry, U_k, and designate either an acquirer or a target primary industry as input i or output j. The upstreamness values in our data range from 1 to 5.7 (Table B.3).[21]

3.1.3 Ratio of Upstreamness

One potential issue with the $Upstreamness_{ij}$ measure is its focus on the main industries of acquirers and targets. Firms involved in M&A, particularly acquirers, are often large and

[19]The $Upstreamness_{ij}$ measure is also called an *average propagation length* (Dietzenbacher et al., 2005).

[20]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

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

may have multiple industry codes. For instance, 54% (or 27%) of acquirers report more than two (or three) industry codes. To address the complexity of multiple industry codes, we introduce the new measure, defined as the *ratio of upstreamness*. The ratio indicates the degree to which newly acquired stages are positioned more upstream compared to stages that are not integrated before the merger.[22]

We compute the measure based on a firm located downstream, and we denote the downstream firm as d. In each M&A deal, either an acquirer or target is the downstream firm d, and we consider its main industry as an output industry j. With a unique output industry j, we first identify the set of input industries i that have positive total requirement coefficients, tr_{ij}, $S(j) = \{i : tr_{ij} > 0\}$. Second, we define the group of inputs i that the downstream firm d has already integrated before the merger, as $I(d) \subseteq S(j)$, using the main and secondary industry codes of firm d. We define the remaining set of inputs i, that are not integrated by the firm d before the merger, as $NI(d) = S(j) \setminus I(d)$. In the set of non-integrated inputs, $NI(d)$, some of the inputs are newly integrated through the merger. The group of newly merged inputs is $M(d) \subseteq NI(d)$.

We are now ready to calculate the following equation:

$$Ratio\text{-}upstreamness_{jd} = \frac{\Sigma_{i\in M(d)}\theta_{ij}^{M(d)} upstreamness_{ij}}{\Sigma_{i\in NI(d)}\theta_{ij}^{NI(d)} upstreamness_{ij}},$$

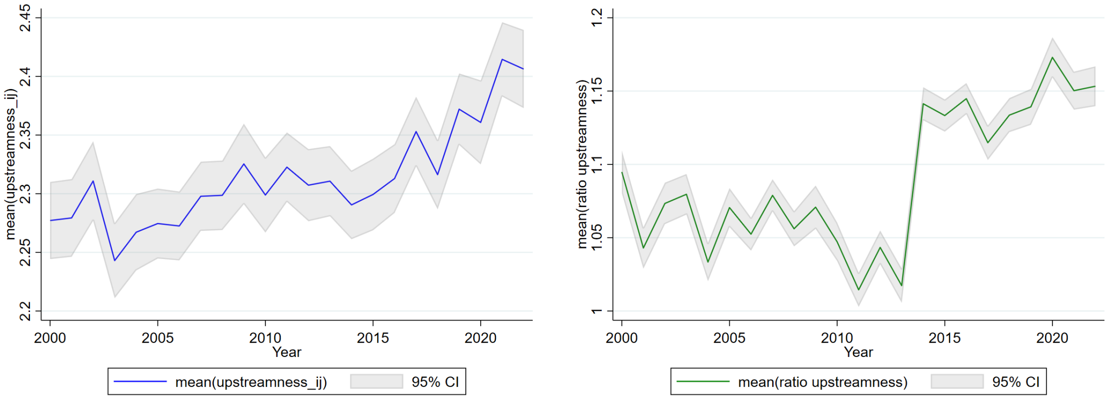
where $\theta_{ij}^{M(d)} = \frac{tr_{ij}}{\Sigma_{i\in M(d)} tr_{ij}}$ and $\theta_{ij}^{NI(d)} = \frac{tr_{ij}}{\Sigma_{i\in NI(d)} tr_{ij}}$. This indicator represents the weighted average upstreamness of newly-merged inputs relative to that of pre-merger non-integrated inputs. A greater ratio indicates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

3.2 Time Trend in M&A Industries

We introduced the measures that allow us to assess the distance between an acquirer and a target on a value chain. In this section, we explore the time trend of these measures to motivate our regression analysis. We calculate the the yearly average of $Upstreamness_{ij}$

[22]The idea is motivated by Alfaro et al. (2019).

Figure 4: Time Trend in M&A Upstreamness



(a) Average Upstreamness

(b) Average Ratio of Upstreamness

Notes: The average upstreamness (displayed in Panel (a)) is calculated using equation 2. Similarly, the average ratio of upstreamness (shown in Panel (b)) is computed using the same method, but with the ratio of upstreamness.

using the formula:

$$\overline{x}(upstreamness_{ij}) = \frac{\Sigma_{t=2000}^{2022} w_{ijt} \; upstreamness_{ij}}{\Sigma_{t=2000}^{2022} w_{ijt}}, \tag{2}$$

where w_{ijt} represents the number of deals in each industry pair, using as the weights.

Panel (a) of Figure 4 illustrates the time trend in $\overline{x}(upstreamness_{ij})$. We observe an increase in the weighted average upstreamness during the global financial crisis, with even more significant growth after 2014.[23] We premise that increasing trend in average upstreamness corresponds to significant economic events. To further explore this, we plot $\overline{x}(upstreamness_{ij})$ with GEPU and TPU indexes. Notably, Figure 5 exhibits the strong correlation between the average upstreamness and these policy uncertainty indexes.[24] Our findings suggest that an acquirer merges with a target located more distant on a production value chain when economic policy uncertainty is heightened.

[23]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.

[24]We also plot the figures with the average upstreamness and economic policy uncertainty indexes for the US and China. Appendix Figure A.4 also shows the positive correlations.

Figure 5: Average of Upstreamness and Economic Policy Uncertainty

(a) GEPU Index (b) TPU Index

Notes: These figures show the time trends of the average upstreamness and economic policy uncertainty indexes. We use the GEPU index in Panel (a) and the TPU index in Panel (b).

We also compute the yearly average of the ratio of upstreamness using a similar equation to equation 2. While the upstreamness measure is constructed only using the acquirer's and target's main industries, the ratio of upstreamness measure enables us to consider multiple industries. Panel (b) of Figure 4 shows the time trend in the ratio of upstreamness.[25] The time trend is similar to the one in the average upstreamness: a growing trend during the financial crisis and even a significant increase after 2014. We also observe the positive correlations with economic policy uncertainty indexes (Appendix Figure A.6). Our findings suggest that industries at farther distant production stages are merged through M&A compared to those not integrated before the merger.

4 Empirical Results

4.1 Cross-sectional Analysis Over M&A Industry-pairs

In this section, we exploit variation across acquirer and target industries and explore which industry pairs are more likely to get merged. We aggregate M&A deals by input-output

[25]In Figure A.5, we illustrates the trend of the ratio of upstreamness, distinguishing between the denominator (upstreamness of an acquirer's industries before the merger) and the numerator (upstreamness of a target's industries after the merger).

Table 1: Probability of M&A and Upstreamness$_{ij}$

	$\mathcal{I}[MA\_i, j = 1]$		Num of MA
	(1)	(2)	(3)
log(upstreamness_ij)	-0.119^{***}	-0.220^{***}	-9.372^{***}
	(0.006)	(0.008)	(1.266)
Input industry FE	No	Yes	Yes
Output industry FE	No	Yes	Yes
N	36,114	36,113	36,113

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by industry pairs.

industry pairs ij and then run the following linear probability regression:

$$\mathcal{I}[MA\_i, j = 1] = \beta_1 \times \log(upstreamness_{ij}) + \alpha_i + \alpha_j + \epsilon_{ij},$$

where MA_{ij} is an indicator for whether M&A occurs in the particular industry pair.[26] The main regressor is the logarithm of $Upstreamness_{ij}$. We control the regressions using input-industry fixed effects (FEs), α_i, and output-industry FEs, α_j. Standard errors are clustered by industry pairs.

Table 1 presents the results of the regressions. Column 1 shows that the coefficient of $\log(upstreamness_{ij})$ is negative and significant, which suggests that industry pairs closer in a production value chain are more likely to be merged. This result remains robust with input and output industry fixed effects (column 2). In column 3, we use the number of M&A deals in each industry pair as the dependent variable, instead of the indicator function. We continue to find the negative and significant coefficient. Overall, the results suggest that without considering time variation, industries closer in a value chain are more likely to be merged.[27]

[26] 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

Table 2: Upstreamness and Economic Policy Uncertainty Indexes

	log(upstreamness_ij)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GEPU	0.016***	0.007***	0.005***	0.005**				
	(0.004)	(0.002)	(0.002)	(0.002)				
TPU					0.019***	0.007***	0.007**	0.006**
					(0.005)	(0.002)	(0.003)	(0.003)
log(intangibles)			0.018**				0.018**	
			(0.007)				(0.007)	
log(input-share)				0.033***				0.033***
				(0.008)				(0.008)
Country-pair FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Output Ind FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Input Ind FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	38,282	38,259	20,538	21,175	38,282	38,259	20,538	21,175

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by monthly periods and industry pairs.

4.2 Upstreamness and Economic Policy Uncertainty

Our descriptive analysis introduced in Section 3.2 shows a notable fact: considering time variation reveals a positive correlation between the distance of industry pairs and the level of economic policy uncertainty. In this section, we examine this positive correlation using regressions. Specifically, we run the following regression:

$$\log(upstreamness_{ijt}) = \beta_1 \times Uncertainty_t + X_{ij} + \alpha_i + \alpha_j + country\text{-}FEs + \epsilon_{ijt}, \quad (3)$$

where $\log(upstreamness_{ijt})$ is the logarithm of $upstreamness_{ijt}$, and $Uncertainty_t$ is the economic policy uncertainty index (either GEPU or TPU indexes). We control the regressions using industry-pair variables, X_{ij}, such as the log of the difference in intangible intensity, log(intangibles), and the log of the difference in input shares, log(input-share).[28] We also add three types of FEs across country pairs, input industries, and output industries. Standard

(denoted as the denominator in equation 1) are zeros.

[27]For robustness, we run additional regressions using alternative measures of upstreamness. We consistently find negative and significant coefficients across all specifications (Table B.2).

[28]We take the absolute difference.

Table 3: Ratio of Upstreamness and Economic Policy Uncertainty

	Ratio of upstreamness							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GEPU	0.029***	0.016***	0.012***	0.011***				
	(0.004)	(0.003)	(0.003)	(0.003)				
TPU					0.040***	0.026***	0.017***	0.015***
					(0.008)	(0.005)	(0.004)	(0.004)
log(intangibles)			0.017***				0.017***	
			(0.006)				(0.006)	
log(input-share)				0.027***				0.027***
				(0.007)				(0.007)
Country-pair FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Output Ind FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Input Ind FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	23,309	23,284	18,278	18,899	23,309	23,284	18,278	18,899

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by quarterly periods and industry pairs.

errors are clustered by monthly periods and industry pairs. Summary statistics for the variables in the regressions are shown in Appendix Table B.3.

Table 2 shows the regression results. The main specification is the regression with country-pair, output-industry, and input-industry FEs. The result is in column 2. The coefficient of the GEPU index is positive and significant at the 1% level. Given that the GEPU index increases by around two over the period including the US-China trade war (from 2014 to 2019), the result suggests that the upstreamness increases by 1.4% as the economic policy uncertainty reaches the level observed after the US-China trade war. We continue to observe positive and significant coefficients in the regressions with the difference in intangible intensity and the difference in input shares (columns 3 and 4). The regression results with the TPU index are very similar to the ones with the GEPU index.[29]

Table 3 shows additional regressions examining the correlations between the ratio of upstreamness and policy uncertainty indexes. We control for main input and output industries, although the ratio of upstreamness includes multiple industry codes. We still observe the

[29]We also run regressions using US and Chinese EPU indexes. The results are in Appendix Table B.4. The upstreamness is positively correlated with the Chinese EPU index, while the results with US EPU index are insignificant.

positive and significant coefficients with economic policy uncertainty. Overall, our regression analysis suggests that acquirers integrate targets located further along a production value chain when economic policy uncertainty is heightened.

5 Model

In this section, we present a model that rationalizes our empirical findings. The model is from Antsàs and Chor (2013), who incorporate sequential stages producing each input on a value chain. Following Antràs and Helpman (2004) and Antràs and Chor (2013), we consider that firms need to make relation-specific investment (i.e., headquarters services), such as managerial inputs, to ensure each input can be supplied.

5.1 Setup

Production: A firm produces a final good using intermediate inputs, $x(i)$,and managerial inputs, ϕ. Each intermediate input is produced in a continuum of production stages, $i \in [0, 1]$, where a larger m indicates further downstream. The final-good producing firm is located in $i = 1$. The production process is sequential—a supplier i delivers its input to another supplier $i' > i$, and all of the production stages $i \in [0, 1)$ must be completed before producing the final good.

The production function of the final-good-producing firm is:

$$q = \theta \left(\frac{\phi}{\eta}\right)^{\eta} \left(\int_0^1 \left(\frac{x(i)}{1-\eta}\right)^{\alpha} I(i)di\right)^{\frac{1-\eta}{\alpha}}, \tag{4}$$

where θ is a productivity parameter, $\eta \in (0, 1)$ represents the intensity of the managerial inputs, and $\alpha \in (0, 1)$ is a substitution parameter across different inputs. An indicator function, $I(i)$, gives the sequential nature of production to this production function. The function, $I(i)$, turns to one if supplier i produces its input after all inputs $\hat{i} < i$ have been supplied; otherwise, it turns to zero.

Relation-specific investment: Both final-good producer and intermediate-input supplier make relation-specific investment. First, after all suppliers have been selected for each input i, the final-good producer provides managerial inputs, ϕ, so that each input can be supplied. The marginal cost of investing the managerial inputs ϕ is e. This investment is sunk when suppliers start producing inputs.

Each intermediate-input supplier also invests in making a compatible input, tailored for the final-good producer. We assume that each intermediate input is produced by a different supplier that has a contract with the final good producer. A supplier pays the marginal cost, c, to produce a compatible input for its final-good firm, while it can produce a non-compatible input by spending a negligible cost. The final-good firm and intermediate suppliers can complete their production stages using non-compatible inputs, but these non-compatible inputs do not add any value to the final-good production.

Preference: A representative consumer has a CES preference over the final-good varieties. Solving the utility maximization problem gives the demand function:

$$q = Ap^{\frac{-1}{1-\rho}}, \tag{5}$$

where ρ is the level of substitution across final-good varieties and A is the demand size. From equations 4 and 5, the revenue of the final-good producing firm is:

$$r = A^{1-\rho}\theta^{\rho}\left(\frac{\phi}{\eta}\right)^{\rho\eta}\left(\int_0^1\left(\frac{x(i)}{1-\eta}\right)^{\alpha}I(i)di\right)^{\frac{\rho(1-\eta)}{\alpha}}.$$

As I mentioned before, all intermediate-good suppliers can complete their stages by producing incompatible inputs, and thus we can consider $I(i) = 1$ for all $i < m$. The value secured to stage m is:

$$r(m) = A^{1-\rho}\theta^{\rho}\left(\frac{\phi}{\eta}\right)^{\rho\eta}\left(\int_0^m\left(\frac{x(m)}{1-\eta}\right)^{\alpha}di\right)^{\frac{\rho(1-\eta)}{\alpha}}. \tag{6}$$

Incomplete contracts: The final-good firm makes contracts with its suppliers, and each supplier promises the firm to deliver a compatible input. Each of the contracts states whether a supplier is integrated by the firm (i.e., merged through M&A) or not. If the firm integrates its supplier, it can gain a larger share of the supplier's contribution to the total revenue. We obtain supplier m's contribution to the total revenue by differentiating equation 6 with respect to m:[30]

$$r'(m) = \frac{\rho(1-\eta)}{\alpha}\left(A^{1-\rho}\theta^{\rho}\left(\frac{\phi}{\eta}\right)^{\rho\eta}(1-\eta)^{-\rho(1-\eta)}\right)^{\frac{\alpha}{\rho(1-\eta)}} r(m)^{\frac{\rho(1-\eta)-\alpha}{\rho(1-\eta)}} x(m)^{\alpha}. \tag{7}$$

Note that the contract between the final-good producer and its suppliers is incomplete because the contract is contingent on whether the inputs are compatible or not, and it cannot be enforced by third-parties. As noted above, an input supplier can produce an incompatible input without spending the cost c.

5.2 Solve the Model

Investment by stage-m supplier: After a supplier produces its input, the final-good firm and the supplier bargain over the supplier m's contribution to the total revenue $r'(m)$. We set the firm's bargaining share to β_V if the supplier is integrated, whereas the bargaining share is β_O if the supplier is outsourced (i.e., not integrated). The firm gains a larger share of $r'(m)$ by integration, which means $\beta_V > \beta_O$. The stage-m supplier gains the remaining share, $1 - \beta(m)$, of $r'(m)$ where $\beta(m) \in \beta_V, \beta_O$.

The stage-m supplier chooses its investment level $x(m)$ by maximizing its profit:

$$\max_{x(m)} \pi_s(m) = (1-\beta(m))r'(m) - cx(m). \tag{8}$$

The solution is

$$x(m) = \left[(1-\beta(m))\frac{\rho(1-\eta)}{c}\left(A^{1-\rho}\theta^{\rho}\left(\frac{\phi}{\eta}\right)^{\rho\eta}(1-\eta)^{-\rho(1-\eta)}\right)^{\frac{\alpha}{\rho(1-\eta)}}\right]^{\frac{1}{1-\alpha}} r(m)^{\frac{\rho(1-\eta)-\alpha}{\rho(1-\eta)(1-\alpha)}}. \tag{9}$$

This equation implies that the stage-m supplier increases investment $x(m)$ as the final-good firm inputs a larger managerial input ϕ. A larger bargaining power $\beta(m)$ decreases $x(m)$, which means outsourcing leads to higher investment. Additionally, the effect of the value of

[30] We apply Leibniz' rule to take a derivative.

the final good at stage m, $r(m)$ is governed by the size of $\rho(1-\eta)$ and α. If $\rho(1-\eta) > \alpha$, as upstream suppliers $i < m$ make larger investment, the stage-m supplier invests more (called *sequential complement* in Antrás and Chor, 2013). If $\rho(1-\eta) < \alpha$, the level of the investment made by upstream suppliers decreases the stage-m's investment (called *sequential substitute*).

Investment by upstream suppliers: We then consider the equilibrium investment level of all suppliers along the value chain. First, we get a differential equation in $r(m)$ that is the final good value at stage m. Substituting equation 9 to 7, we obtain:

$$r'(m) = \frac{\tilde{\rho}}{\alpha}\left(\frac{(1-\beta(m))\tilde{\rho}}{c}\right)^{\frac{\alpha}{1-\alpha}} A^{\frac{\alpha(1-\rho)}{\tilde{\rho}(1-\alpha)}} \left(\theta^{\rho}\left(\frac{\phi}{\eta}\right)^{\rho\eta}(1-\eta)^{-\tilde{\rho}}\right)^{\frac{\alpha}{\tilde{\rho}(1-\alpha)}} r(m)^{\frac{\tilde{\rho}-\alpha}{\tilde{\rho}(1-\alpha)}}, \tag{10}$$

where we set $\tilde{\rho} = \rho(1-\eta)$.

The equation above is a differential equation in $r(m)$. Using $r(0) = 0$, we get:

$$r(m) = A\left(\frac{1-\tilde{\rho}}{1-\alpha}\right)^{\frac{\tilde{\rho}(1-\alpha)}{\alpha(1-\tilde{\rho})}} \left(\frac{\tilde{\rho}}{c}\right)^{\frac{\tilde{\rho}}{1-\tilde{\rho}}} \left(\theta^{\rho}\left(\frac{\phi}{\eta}\right)^{\rho\eta}(1-\eta)^{-\tilde{\rho}}\right)^{\frac{1}{1-\tilde{\rho}}} \left[\int_0^m (1-\beta(i))^{\frac{\alpha}{1-\alpha}} di\right]^{\frac{\tilde{\rho}(1-\alpha)}{\alpha(1-\tilde{\rho})}}. \tag{11}$$

If we plug the above equation into equation 9, we can get the expression for the stage-m supplier's investment level:

$$x(m) = \hat{A}\left(\theta^{\rho}\frac{\tilde{\rho}}{c}\left(\frac{\rho}{\eta}\right)^{\rho\eta}(1-\eta)^{-\tilde{\rho}}\right)^{\frac{1}{1-\tilde{\rho}}} \left(\frac{1-\tilde{\rho}}{1-\alpha}\right)^{\frac{\tilde{\rho}-\alpha}{\alpha(1-\tilde{\rho})}} (1-\beta(m))^{\frac{1}{1-\alpha}} \left[\int_0^m (1-\beta(i))^{\frac{\alpha}{1-\alpha}} di\right]^{\frac{\tilde{\rho}-\alpha}{\alpha(1-\tilde{\rho})}}, \tag{12}$$

where $\hat{A} = A^{\frac{\tilde{\rho}-\alpha\rho}{\tilde{\rho}(1-\alpha)}}$. This equation suggests that the firm's integration decision (the level of $\beta(m)$) affects the size of the investment at stage m. Importantly, the investment level at stage m is also affected by the integration choices for the upstream suppliers and the sign of $\tilde{\rho} - \alpha$.

Final-good firm's investment: The final-good firm maximizes its revenue. The firm gains the part of suppliers' contribution to the total revenue along the value chain, and thus the revenue is represented as $\Pi = \int_0^1 \beta(i)r'(i)di$. The final-good firm is required to input the managerial service ϕ, and that input is necessary for suppliers to start producing their inputs.

The firm decides the level of its managerial service input by maximizing its net profit, $\Pi - e\phi$, and the gross profit Π is:

$$\Pi = \hat{A}\left(\theta^{\rho}\frac{\tilde{\rho}}{c}\left(\frac{\rho}{\eta}\right)^{\rho\eta}(1-\eta)^{-\tilde{\rho}}\right)^{\frac{1}{1-\tilde{\rho}}}\left(\frac{1-\tilde{\rho}}{1-\alpha}\right)^{\frac{\tilde{\rho}-\alpha}{\alpha(1-\tilde{\rho})}}\frac{\tilde{\rho}}{\alpha}\int_0^1 \beta(i)(1-\beta(i))^{\frac{\alpha}{1-\alpha}}\left[\int_0^i (1-\beta(k))^{\frac{\alpha}{1-\alpha}}dk\right]^{\frac{\tilde{\rho}-\alpha}{\alpha(1-\tilde{\rho})}} di. \tag{13}$$

The first-order condition for the maximization problem is:

$$\frac{\rho\eta}{a-\tilde{\rho}}\Pi = e\phi.$$

Plugging this solution back into equation 13, we find the final-good firm's profit depends only on the integration choice at each production stage, $\beta(i)$. By defining $v(i) = \int_0^i (1-\beta(k))^{\frac{\alpha}{1-\alpha}}dk$, we can present the profit function as:

$$\pi(v) = \kappa\int_0^1 \left(1 - v'(i)^{\frac{1-\alpha}{\alpha}}\right) v'(i)v(i)^{\frac{\rho-\alpha}{\alpha(1-\rho)}}di,$$

where $\kappa = \hat{A}(\frac{1-\rho}{1-\tilde{\rho}})(\theta^{\rho}\frac{\tilde{\rho}}{c}(\frac{\rho}{\eta})^{\rho\eta}(1-\eta)^{-\tilde{\rho}})^{\frac{1}{1-\tilde{\rho}}}(\frac{1-\tilde{\rho}}{1-\alpha})^{\frac{\tilde{\rho}-\alpha}{\alpha(1-\tilde{\rho})}}\frac{\tilde{\rho}}{\alpha}$.

Using the Hamiltonian maximizing condition, we obtain the optimal condition for the firm's integration decision at stage m:

$$\beta^*(m) = 1 - \alpha m^{\frac{\alpha-\rho(1-\eta)}{\alpha}}. \tag{14}$$

We use $\tilde{\rho} = \rho(1-\eta)$ above.

5.3 Model implication

Equation 14 implies the optimal integration decision for the final-good firm. In the case where $\alpha < \rho(1-\eta)$ (i.e., sequential complement case), the firm's optimal bargaining share $\beta^*(m)$ increases with m, which indicates that it is optimal for the firm to integrate relatively downstream suppliers. Conversely, if $\alpha > \rho(1-\eta)$ (i.e., sequential substitute case), the optimal strategy is to integrate more upstream suppliers.

We present a model of sequential production to explore how the integration decision responds to the level of economic uncertainty. Firms actively manage the risk of their supply chain disruptions during periods of uncertainty (Elliott et al., 2022; Grossman et al., 2023), and it is reasonable to assume heightened engagement in supply chain management during such times. In our model, the intensity of the firm's managerial input is denoted by η. An increase in η reflects intensified managerial input. For the case where $\alpha < \rho(1-\eta)$, as $\rho(1-\eta)$ diminishes, the scenario aligns with the sequential substitute case, indicating that the firm's optimal strategy is to integrate further upstream suppliers as managerial input intensifies. Alternatively, with $\alpha > \rho(1-\eta)$, a higher η contributes to a reduction in $\rho(1-\eta)$ and incentivizing the firm to integrate further upstream suppliers. In summary, irrespective of sequential complement or sequential substitute scenarios, a higher managerial input intensity motivates the firm to integrate further upstream, consistent with our empirical findings.

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 shaping supply chain networks. Firstly, we measure the distance between acquiring and acquired firms along the production value chain, following Alfaro et al. (2019). We find that firms tend to acquire targets located further upstream on the value chain in times of heightened economic policy uncertainty. Furthermore, we present the model, assuming that firms need to intensify their managerial inputs over the supply chains to ensure that all suppliers can deliver their inputs in times of economic uncertainty. The model implication is consistent with our empirical findings. One of our contributions is the emphasis on the role of M&A in industry diversification. We find that the input-output relationship of acquirer and target firms has changed over time. We also link firms' integration decisions 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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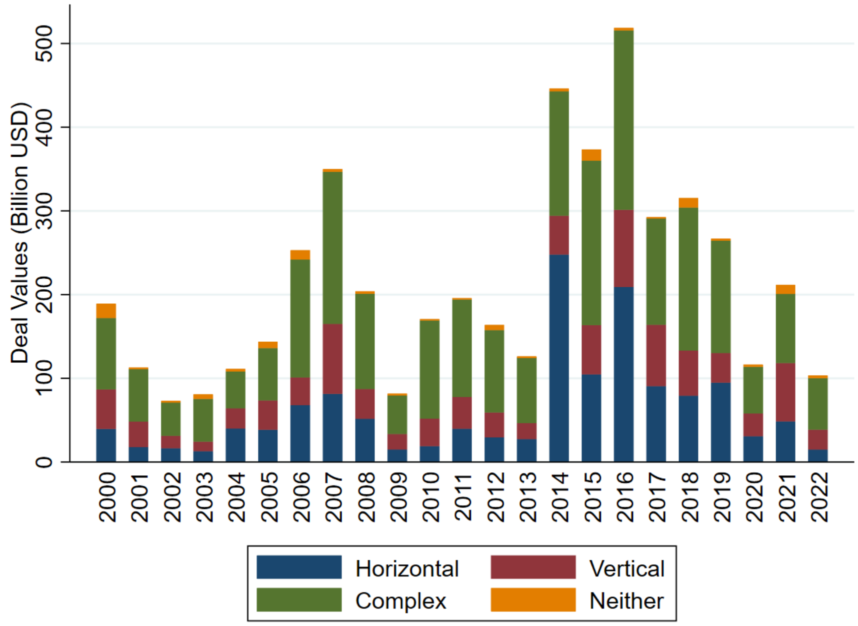
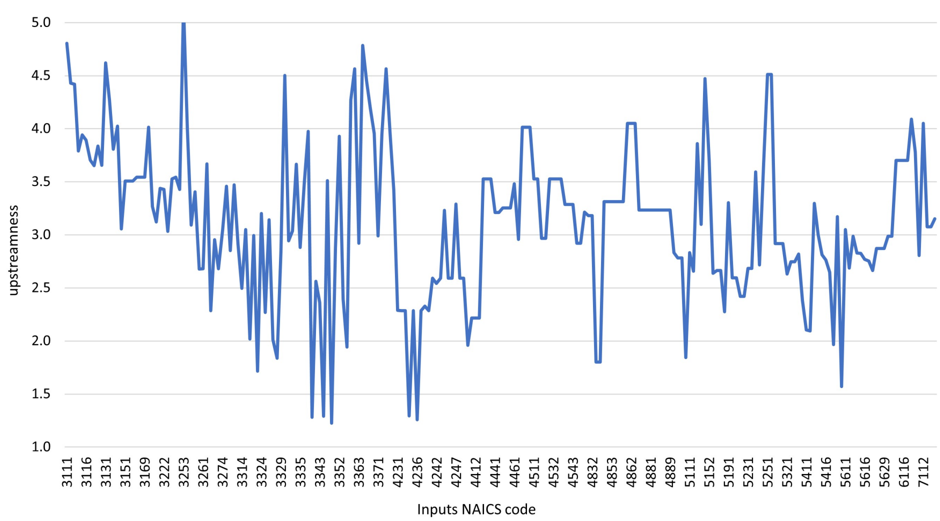
Appendix A Appendix Figures

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



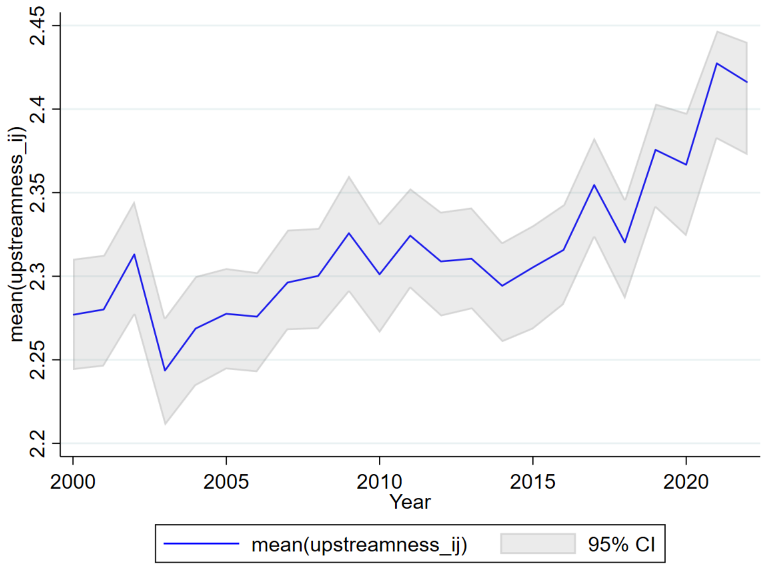
Source: Cross-border M&A data downloaded from Zephyr. Each M&A deal is classified into four types of FDI based on the rules outlined in this paper, and the year periods are based on their announcement dates.

Figure A.2: Upstreamness$_{ij}$ of Computer and Peripheral Equipment Manufacturing



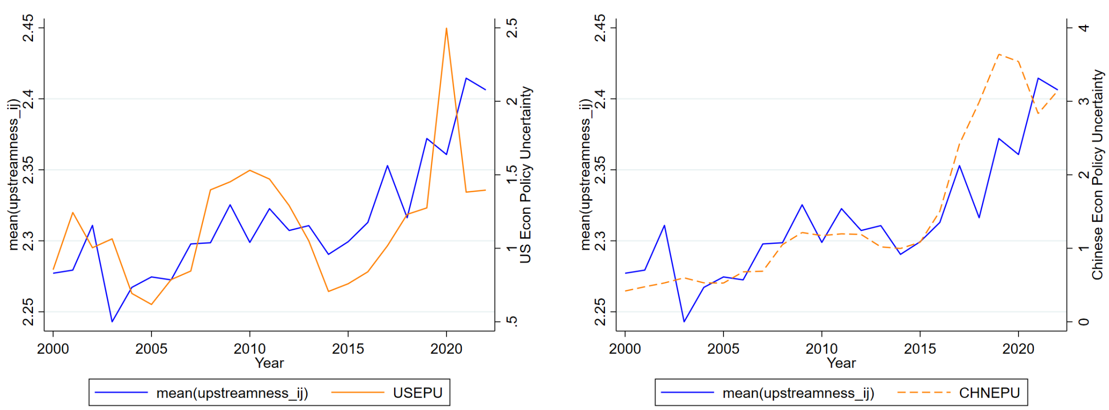
Notes: The figure displays the upstreamness of the computer and peripheral equipment manufacturing industry (NAICS 3341), calculated using the methods outlined in this paper.

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



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

Figure A.4: Average of Upstreamness and US/Chinese Economic Policy Uncertainty

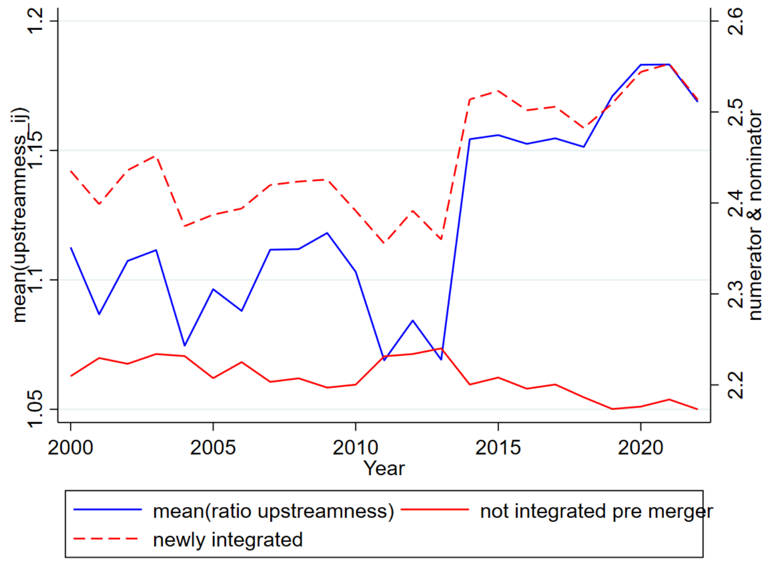


(a) US EPU Index

(b) Chinese EPU Index

Notes: These figures show the time trends of the average upstreamness and economic policy uncertainty indexes. We use the US EPU index in Panel (a) and the Chinese EPU index in Panel (b).

Figure A.5: Nominator and Denominator of the Ratio



Notes: This figure shows the time trend of the average ratio of upstreamness by distinguishing between the nominator (dotted line) and the denominator (solid line) mergers.

Figure A.6: Ratio of Upstreamness and Economic Policy Uncertainty

(a) GEPU Index

(b) TPU Index

Notes: These figures show the time trends of the average ratio of upstreamness and economic policy uncertainty indexes. We use the GEPU index in Panel (a) and the TPU index in Panel (b).

Appendix B Appendix Tables

Table B.1: Patterns of Cross-border M&A Using *Direct* Requirements Coefficients

	Four-digit	Three-digit	Two-digit	One-digit
Total	22,472	22,472	22,472	22,472
Horizontal	7,889	8,951	11,152	12,486
Vertical	14,583	13,521	11,320	9,986

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 B.2: Robustness: Probability of M&A and Upstreamness$_{ij}$

	$\mathcal{I}[MA\_i, j = 1]$			Num of MA		
	(1)	(2)	(3)	(4)	(5)	(6)
log(upstreamness-median)	-0.216***			-9.892***		
	(0.008)			(1.347)		
log(upstreamness-random-pick)		-0.151***			-5.967***	
		(0.007)			(0.969)	
log(upstreamness-tr-weighted)			-0.183***			-8.757***
			(0.007)			(1.036)
Input industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Output industry FE	Yes	Yes	Yes	Yes	Yes	Yes
N	36,113	36,113	36,113	36,113	36,113	36,113

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by industry pairs.

Table B.3: Descriptive Statistics

	Mean	Std Dev	Min	10th	Median	90th	Max
Upstreamness_{ij}	2.310	0.773	1.005	1.298	2.257	3.331	5.618
$\log(\text{upstreamness}_{ij})$	0.778	0.350	0.005	0.261	0.814	1.203	1.726
ratio of upstreamness	1.121	0.343	0.428	0.680	1.097	1.576	2.646
GEPU index	1.391	0.702	0.490	0.643	1.204	2.494	4.280
TPU index	0.474	0.441	0.113	0.227	0.310	0.971	2.660
US EPU index	1.103	0.588	0.382	0.575	0.932	1.840	5.553
Chinese EPU index	1.369	1.100	0.101	0.432	1.027	3.191	6.618
log(intangibles)	0.089	1.728	-8.026	-2.132	0.230	2.733	3.009
log(input-share)	-2.375	1.183	-8.643	-4.120	-2.154	-1.079	-.469

Notes: Upstreamness_{ij} is the mean of upstreamness_{ij}. The sample consists of 39,302 cross-border M&A deals with non-missing upstreamness_{ij}.

Table B.4: $\log(\text{upstreamness}_{ij})$ and US/Chinese Economic Policy Uncertainty

	log(upstreamness_ij)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
US EPU	0.004	0.004*	0.003	0.003				
	(0.003)	(0.002)	(0.002)	(0.002)				
Chinese EPU					0.011***	0.005***	0.004***	0.003***
					(0.003)	(0.001)	(0.001)	(0.001)
log(intangibles)			0.018**				0.018**	
			(0.007)				(0.007)	
log(input-share)				0.033***				0.033***
				(0.008)				(0.008)
Country-pair FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Output Ind FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Input Ind FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes
N	38,282	38,259	20,538	21,175	38,282	38,259	20,538	21,175

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered by quarterly periods and industry pairs.