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全球價值鏈與對外投資區位選擇：以電子業台商在大陸為例

Global Value Chain and FDI Location Choice: Evidence from Taiwanese Electronic Multinationals in China

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MASTER'S THESIS ACCEPTANCE CERTIFICATE
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全球價值鏈與對外投資區位選擇：

以電子業台商在大陸為例

Global Value Chain and FDI Location Choice:

Evidence from Taiwanese Electronic Multinationals in China

本論文係申大昀（R12323015）在國立臺灣大學經濟學系完成之碩士學位論文，於民國 115 年 1 月 14 日承下列考試委員審查通過及口試及格，特此證明。

The undersigned, appointed by the Department of Economics on 14th January 2026 have examined a Master's Thesis entitled above presented by Shen, Da-Yun (R12323015) candidate and hereby certify that it is worthy of acceptance.

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摘要

本研究探討廠商在全球價值鏈中的對外直接投資 (FDI) 區位選擇，聚焦於處於價值鏈不同位置的電子業台商，其進入中國大陸各地級市的投資決策。首先，本研究發現，相較於上游廠商，下游電子業廠商會明顯進入更多的地級市進行投資。進一步的分析顯示，這項差異源於臺灣相較於中國在上游產業的優勢。其次，本研究發現，上游廠商的大陸子公司傾向集中於距離臺灣較近的地級市，而下游廠商則有較高的機率進入距離較遠的地點。當考慮一個具有平均生產力的廠商、以及一個市場規模中等的地級市時，距離對對外投資進入決策所造成的負面影響，在最上游產業可高達在最下游產業的將近三倍。

關鍵字：對外直接投資、區位選擇、廠商異質性、全球價值鏈、上游程度、臺灣、中國

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Abstract

I study firms' FDI location choices within the global value chain. I focus on the decisions to enter Chinese prefectures made by Taiwanese electronic multinationals that differ in their value chain positions. First, I show that downstream electronic firms enter significantly more prefectures compared to upstream counterparts. I further show that this difference is due to Taiwan's relative advantage over China in the upstream segment of production. Second, I find that upstream firms concentrate their affiliates in prefectures closer to Taiwan while downstream firms have higher probability to enter more distant locations. When considering a firm with average productivity and a medium-sized prefecture, the adverse effect of distance on FDI entry for the most upstream firms is could be three times as large as that for the most downstream firms.

Keywords: FDI, Location choice, Firm heterogeneity, Global value chains, Upstreamness, Taiwan, China

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Chapter 1 Introduction

Foreign direct investment (FDI) is one of the most important economic activities that shape the globalized world. The literature has studied the characteristics of firms that participate more actively in FDI, mostly focusing on productivity heterogeneity.[1] Several studies further examine how firms with heterogeneous productivity choose to enter different sets of destination countries.[2] By contrast, evidence regarding multinational firms' location choices within a single destination country remains relatively limited. More broadly, dimensions of firm heterogeneity beyond productivity have received far less attention. In the mean time, we have witnessed the rise of global value chains, where productions are fragmented across different firms and across separate locations. Despite this trend, relatively little research examines how firms make their FDI decisions given their roles in the global value chain.

To motivate this question, it is interesting to look at Taiwanese electronic firm's FDI activity in China. China has been the primary host country for Taiwanese outward investment, and each year a substantial share comes from the electronics sector. Yet even within this broad sector, there are substantial differences. Many electronics contract manufacturers maintain multiple affiliates across China. For instance, Foxconn—the major con-

[1]See Head and Ries (2003); Girma et al. (2004); Girma et al. (2005) Helpman et al. (2004); Tomiura (2007) for studies of how firm productivity shapes its participation in FDI.

[2]See Aw and Lee (2008), Yeaple (2009), and Chen and Moore (2010) for analyses of how firms' with heterogeneous productivity exhibit different FDI location choices at the country level.

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tract manufacturer for Apple—operates subsidiaries in Shenzhen, Zhengzhou, Chengdu, Chongqing, and several other prefectures. In contrast, producers of electronic components typically have far fewer affiliates. Taiwan Semiconductor Manufacturing Company (TSMC), the world's leading chip foundry, has subsidiaries only in Shanghai and Nanjing, despite its enormous scale. Figure 1.1 illustrates this contrast by showing the distribution of affiliates for listed firms in two representative industries: "Semiconductors" and "Computers and Peripheral Equipment". As widely recognized and later confirmed by my calculation, the former is a highly upstream industry whereas the latter is highly downstream. Two clear patterns emerge from the figure. First, there are more affiliates from the downstream industry compared to the upstream industry.[3] Second, the affiliates from the downstream industry are scattered across more locations while those from the upstream industries are mostly located in central prefectures or prefectures close to Taiwan.

Motivated by these contrasting patterns, in this paper, I empirically investigate whether a Taiwanese electronic firm's position in the value chain is an important factor that affects how it conducts FDI in China. More specifically, I study whether upstream or downstream electronic firms enter more prefectures as well as whether the prefectures they enter differ systematically. To analyze the firms' production affiliate location choices, I utilize a dataset of listed Taiwanese electronic firms that records their basic affiliate information in China, from the database of Taiwan Economic Journal (TEJ). This data is more suitable than other possible data source for studying Taiwanese firms' FDI activity since it tracks the existence of the affiliates annually rather than only recording the initially approved

[3] One possibility is that this difference simply reflects a larger number of parent firms from the Computers and Peripheral Equipment industry investing in China. However, as shown later in Table 3.1, the sample actually contains more parent firms from the Semiconductor industry than from the Computers and Peripheral Equipment industry. The observed difference therefore operates along the intensive margin—the number of locations entered by each parent firm—rather than the extensive margin of investing parent firms.

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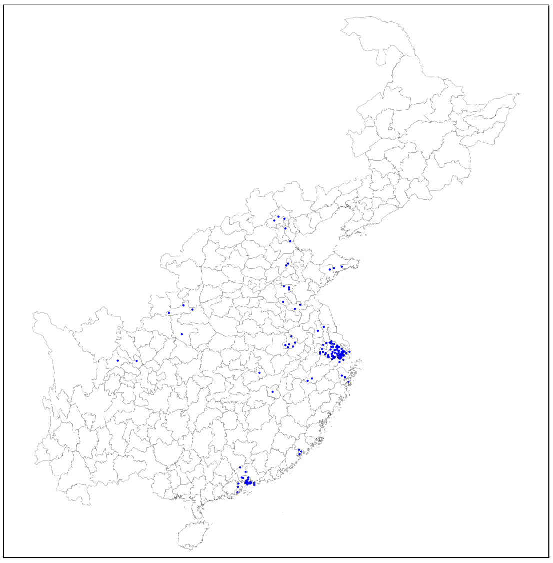
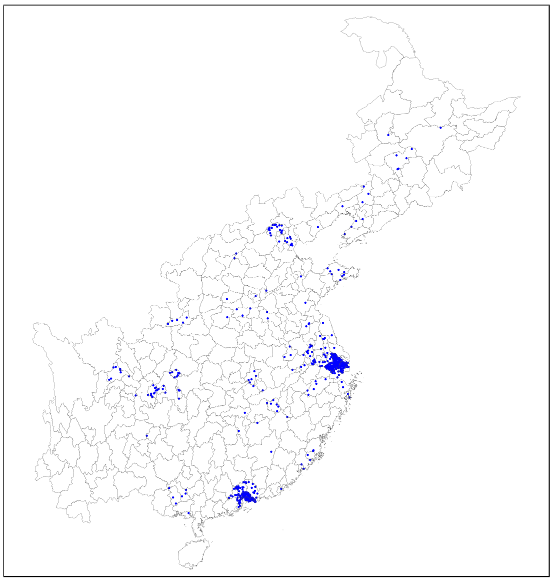
date. In order to examine the role of value chain position, I construct firm's upstreamness measure at the industry level following Antràs et al. (2012)'s method, based on Taiwan Input-Output table. As control variables, I also estimate firm-level productivity using the framework of Ackerberg et al. (2015) and control for Chinese prefectures' characteristics including market potential, average manufacturing wages, and distance to Taipei as a proxy for headquarters distance, which have been identified in the literature as important determinants of multinational firms' location choice.

Figure 1.1: Locations of Production Affiliates in China



(a) Semiconductor (261)



(b) Computer and Peripheral Equipment (271)

Notes: The figures display the geographical distribution of production affiliates in China for listed Taiwanese firms in two industries: "Semiconductor (261)" and "Computer and Peripheral Equipment (271)". The data is from Taiwan Economic Journal (TEJ) database (See Chapter 3 and Appendix A for detail). Observations are consolidated into parent–prefecture level. Provinces excluded from the map are: Xinjiang, Inner Mongolia, Qinghai, Xizang, Gansu, and Ningxia.

With these variables prepared, I conduct my analysis in two parts. In the first part of analysis, I study the number of prefectures which firms with different value chain positions enter to establish affiliates. I adopt the binary logit model in which the decision for a firm to enter a prefecture is specified to be a function of the firm's productivity and upstreamness as well as the prefecture's characteristics. Consistent with the literature, firms

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with higher productivity set up affiliates in more locations, with prefectures having larger market potential being particularly attractive. Central to this paper, I find that holding the prefecture characteristics and firm productivity constant, downstream firms establish their affiliates in significantly more prefectures compared to upstream firms. In terms of magnitude, being one production stage more closer to final consumers increases the log odds by 0.235. Moreover, this pattern is not driven by difference in firms' intrinsic needs for geographically dispersed production nor by firm-level capital intensity, thus pointing to an alternative explanation. Motivated by the perspective that Taiwan has a particular strength in upstream segment of electronic production, while China has established itself as a global manufacturing base in downstream activities, I construct a measure capturing Taiwanese firms' relative advantage over Chinese competitors in the upstream electronic industries. Specifically, for each industry, I compute the ratio of Balassa (1965)'s revealed comparative advantage index between Taiwan and China and define this ratio as Taiwan's relative comparative advantage over China in that industry. I then find that variation in this measure plays an important role in driving the difference in the entry propensity of upstream and downstream electronic firms.

In the second part of analysis, I examine the characteristics of prefectures which upstream and downstream firms enter respectively. Following the approach of Chen and Moore (2010), I estimate regressions that interact prefecture characteristics with firms' upstreamness measure. I show that a prefecture's geographic distance to Taipei is the key feature that distinguishes its relative attractiveness to upstreamn and downstream firms. In particular, upstream firms concentrates their affiliates in prefectures closer to Taiwan, whereas downstream firms are relatively more willing to go deep into farther locations. In terms of magnitude, I demonstrate that when considering a firm with average productivity

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and a prefecture with median level of market potential and wages, the adverse effect of distance on entry probability for the most upstream firms could be three times as large as that for the most downstream firms. I conclude by briefly discussing potential mechanisms that may underlie this result.

The rest of the thesis proceeds as follows. Chapter 2 reviews the related literature. Chapter 3 describes the data sources and the construction of variables. Chapter 4 examines how the number of prefectures entered varies across firms at different positions in the value chain. Chapter 5 explores how location characteristics affect firms' entry decisions differentially along the value chain. Chapter 6 concludes.

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Chapter 2 Literature Review

This paper is related to the literature that empirically studies the location choice of multinational firms. A large body of research has focused on the destination's characteristics or policy (Devereux and Griffith (1998); Keller and Levinson (2002); Head and Mayer (2004); Bénassy-Quéré et al. (2007), Basile et al. (2008)), and some of them inspect the question within China (Amiti and Javorcik (2008); Dean et al. (2009); Liu et al. (2010); Fung et al. (2014)). On the other hand, based on the seminal work by Helpman et al. (2004), some papers have emphasized the importance of firm heterogeneity in location choices. Aw and Lee (2008) focus on Taiwanese firms' decisions to enter the United States or China, documenting that firms investing in both the US and China are the most productive ones, followed by those entering only the US, and then the firms conducting FDI only in China. Yeaple (2009) examines the structure of US multinational activity and documents that more productive firms enter more countries and that in aggregate scale, average productivity of firms entering an attractive country will be lower compared to those entering a tough country. Chen and Moore (2010), with French MNEs data, further examines the differential effect of host-country characteristics at the firm level by adding interaction term of firm TFP and country attributes in the regression, corroborating Yeaple (2009)'s finding that firms with higher productivity are more capable of overcoming difficulties such as longer distance, smaller market potential, and higher production or entry

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cost. I contribute to this strand of literature by considering a new dimension of firm heterogeneity, the value chain position. To the best of my knowledge, I am also the first to conduct firm-level analysis of FDI location choice across locations within a single destination country. I demonstrate that in the case of Taiwanese electronic multinationals in China, the upstreamness of firm is a crucial factor in determining the extensive margin of location entry. As in Yeaple (2009) and in Chen and Moore (2010), I also examine how this effect differs across locations, with the result highlighting the importance of distance to headquarter. In addition, in contrast to previous works on FDI location choice in China, to the best of my knowledge, I am the first to analyze at prefecture level instead of province level, utilizing the estimates of trade costs between prefectures in Ma and Tang (2020) along with economic data from China City Statistical Year Book.

This paper also contributes to the literature that explores firm behavior in global value chains. Antràs and Chor (2013) develop a model that features sequentiality of production and incomplete contract to examine how firms decide whether to integrate their suppliers at different production stages. They also present supporting empirical evidence at industry level, where their downstream measure follows the spirit of Antràs et al. (2012). Alfaro et al. (2019) strengthens Antràs and Chor (2013)'s finding by providing empirical evidence. Kikuchi et al. (2018) investigates similar question but instead develop a model based on Coase (1937)'s framework of firm boundary, which is extended into a multi-country general equilibrium model by Fally and Hillberry (2018). In a more empirical-oriented study, Chor et al. (2021) documents how Chinese firms' position in the global production line had evolved over 1992-2014 and how this change affected their operations. Extending this line of research, I apply the concept of value chain position to Taiwan's context to study multinational firm's location decision. While there are previous studies that

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discuss the production location of different industries along the value chain in a general equilibrium framework (Costinot et al. (2013); Antràs and De Gortari (2020)), my analysis focuses on individual firm's decision—specifically, whether and where to establish foreign affiliates..

Finally, this paper joins the literature regarding Taiwanese firms' FDI activity in China. A part of this literature studies how Taiwanese firm's FDI activity in China affects its operation in Taiwan. Lin et al. (2025) examine firm's adjustment in employment after investing in China using natural experiment from Taiwan's FDI liberalization toward China in 2001, whereas Branstetter et al. (2021) study the firms' the innovation performances under similar context. Lee et al. (2013) study how Taiwanese firms' FDI in China affect their productivity by jointly considering the impact from their agglomeration behavior in Taiwan. Another part of the literature investigates the location choice of Taiwanese multinationals. As mentioned above, Aw and Lee (2008) examine how differences in underlying productivity lead firms to make different decisions about investing in the US or China. More close to this paper, Fung et al. (2014) study the location decisions within China, highlighting the importance of access to imported inputs. In contrast to Fung et al. (2014), who analyze the location choice at province level using industry-level statistics, I study the problem at prefecture level while also considering the heterogeneity between firms. In addition to the productivity heterogeneity as discussed in Aw and Lee (2008), I consider another dimension of firm heterogeneity, the position in the global value chain. I demonstrate that it is indeed an important factor that shapes Taiwanese electronic firms' FDI behavior in China.

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Chapter 3 Data and Variables

In this chapter, I describe the data and procedure for constructing variables used in the analysis. My goal is to test whether a firm's value chain position is an important factor behind Taiwanese electronic firms' location decision in China. Therefore, I exploit a dataset that contains the information of those firms' China affiliate locations. My main explanatory variable is a measure of upstreamness, which is computed based on input-output table. In addition, I control for firm-level productivity and China prefecture characteristics.

3.1 China Affiliates of Taiwanese Multinationals

China affiliate data for Taiwanese multinationals are drawn from Taiwanese Economic Journal database (TEJ). TEJ database, constructed and maintained by Taiwan Economic Journal Corporation, contains comprehensive information on companies publicly listed in Taiwan. In particular, I use an annual dataset that records China affiliate information of each company in TEJ database. I exploit the information in affiliates' names and address to identify their prefectures. Since the address entry does not have a unified form, with some having detailed information from province to street while others having only either province, county, or street information, it is not possible to recover the prefecture for all affiliates. For affiliate whose prefecture remaining unidentified, I instead use the

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affiliate's name to extract such information, due to the fact that an affiliate's name often contains the prefecture in which it is located. My sample consists of observations from 2010 and 2015, as these are the years for which other required data are available, as described later. On the other hand, this period falls after the signing of the major cross-strait trade agreement between China and Taiwan and before the onset of China's economic slowdown, the US-China trade war, and the COVID-19 pandemic. Hence, it captures a period of relatively high activity by Taiwanese multinationals in China.[1] Table 3.1 reports the number of firms and affiliates from each electronic industry for which prefecture information is identifiable in the TEJ data.[2]

Table 3.1: Affiliate Data Summary

Industry Code	Industry	Firm Count	Total Affiliate Count
261	Semiconductors	61	124
262	Electronic Passive Devices	31	93
263	Bare Printed Circuit Boards	52	131
264	Optoelectronic Materials and Components	70	232
269	Other Electronic Parts and Components	99	355
2711	Computers	47	341
2712	Monitors and Terminals	4	13
2719	Other Computer Peripheral Equipment	52	172
272	Communication Equipment	21	55
273	Audio and Video Equipment	8	20
274	Magnetic and Optical Media	7	20
275	Navigating and Control Equipment; Watch/Clocks	10	13
276	Irradiation and Electromedical Equipment	3	7
277	Optical Instruments and Equipment	15	42

Notes: The table shows the number of firms and affiliates for which prefecture information is identifiable in the TEJ data, which consists of companies publicly listed in Taiwan. The "Manufacture and Peripheral Equipment (271)" industry is further divided into "Computers (2711)", "Monitors and Terminals (2712)", and "Other Computer Peripheral Equipment (2719)" to match the industry classification in Taiwan Input-Output Table.

Before continuing, it is worthwhile to discuss other possible data source for FDI research on Taiwanese multinationals and highlight the advantage of TEJ data. The most

[1] In June 2010, Taiwan and China signed the Economic Cooperation Framework Agreement (ECFA).

[2] See Appendix A for further details regarding the China affiliate data. As discussed later, the "Computer and Peripheral Equipment (271)" industry is further divided into "Computers (2711)", "Monitors and Terminals (2712)", and "Other Computer Peripheral Equipment (2719)" to match the industry classification in Taiwan Input-Output Table.

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commonly used data is the list of approved projects from the Investment Commission, Ministry of Economic Affairs (MOEAIC). However, the dataset only reports at the time of approval and does not track over the affiliates' life cycle, rendering it impossible to check whether an affiliate has been shut down at any subsequent moment. Another possible source is the Outward FDI Survey in Manufacturing, again conducted by MOEAIC. Although the survey is conducted annually, the questions are consolidated at very aggregated level (activity in China or in other countries as a whole) rather than asking for individual affiliate's information. Hence, in Taiwan there is no official database that resembles the affiliate-level multinational production data used in the literature, such as the data on US MNEs from the Bureau of Economic Analysis (e.g. Yeaple (2009), Garreto et al. 2025) or Microdatabase Direct Investment (MiDi) from the German Bundesbank (e.g. Tintelnot (2017)). The TEJ dataset, despite having only limited information on affiliate's operation performance, is the closest counterpart.

3.2 Upstreamness Measure

I construct the industry-level upstreamness measure following Antràs et al. (2012).[3] Consider a closed economy with N industries. An industry's output is either used as final good for consumption or used as intermediate input to other industries (including itself) for further production. Thus for each industry i, we have the equality $Y_i = F_i + \sum_j Z_{ij}$, where Y_i industry i's gross output, F_i is the part used as final good, and Z_{ij} is the part used as intermediate input to industry j. In particular, we have $Z_{ij} = d_{ij} Y_j$, where d_{ij} is the

[3] Since I am examining the firms' FDI decisions, it is ideal to have a firm-level measure of their positions in the value chain. However, this requires either computing using firm-to-firm trade data or combining industry-level upstreamness measure with firm's product-level international trade data (e.g. Chor et al. (2021)). The Taiwanese data for the latter has been widely used, whereas the data for the former has just become available in recent years. Nevertheless, unfortunately at this point I do not have proper access to those datasets.

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(i, j)-th element of the direct requirement matrix, which has the interpretation "the dollar amount of industry i input needed to produce one dollar's worth of industry js output". Combining the two equations we get $Y_i = F_i + \sum_j d_{ij} Y_j$, and repeating the procedure above with respect to Y_j again and further, we obtain the following identity:

$$\begin{aligned} Y_i &= F_i \; + \sum_j d_{ij} Y_j \\ &= F_i \; + \sum_j d_{ij} \big(F_j + \sum_k d_{jk} Y_k \big) \\ &= F_i \; + \sum_j d_{ij} F_j \; + \sum_j \sum_k d_{ij} d_{jk} \big(F_k + \sum_l d_{kl} Y_l \big) \\ &= F_i \; + \sum_j d_{ij} F_j \; + \sum_j \sum_k d_{ij} d_{jk} F_k \; + \sum_j \sum_k \sum_l d_{ij} d_{jk} d_{kl} F_l + \ldots \end{aligned} \tag{3.1}$$

Looking at the last row, intuitively, the first term represents the amount of industry i's output that goes directly to final consumption. The second term represents the part that is handed to final consumer after one more production stage, and analogously, the subsequent terms represent the parts that are used as final consumption after specific number of production stages respectively. The upstreamness of industry i is then computed as the weighted average of stages that its output goes through before reaching final end consumer. Namely,

$$\begin{aligned} U_i \;&=\; 1 \cdot \frac{F_i}{Y_i} + 2 \cdot \frac{\sum_{j=1}^N d_{ij} F_j}{Y_i} \\ &+\; 3 \cdot \frac{\sum_{j=1}^N \sum_{k=1}^N d_{ik} d_{kj} F_j}{Y_i} \\ &+\; 4 \cdot \frac{\sum_{j=1}^N \sum_{k=1}^N \sum_{l=1}^N d_{il} d_{lk} d_{kj} F_j}{Y_i} \\ &+\; \ldots \end{aligned} \tag{3.2}$$

The larger the value, the more upstream part of the value chain industry i's output enters on average. It can be shown that as long as $\sum_{i=1}^N d_{ij} < 1$, the numerator is equal to the i-th element of column matrix $[I - D]^{-2} F$, where I is $N \times N$ identity matrix, D is the matrix

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whose (i, j)-the entry is d_{ij}, and F is a column matrix with F_i in row i. The upstreamness measure of industry i, U_i, is then obtained from dividing this numerator by Y_i.

For implementation, I use the Taiwan Input-Output Table from year 2010, since it is the year with finer industry classification that is close to the year of affiliate observation. It should be noted that the industry classification for IO table is slightly different from that for firm industries, and the concordance is provided in Table A.1 in Appendix A. Table 3.2 reports the upstreamness values computed. The industries with the highest upstreamness—Bare Printed Circuit Boards (263) and Semiconductors (261)—are those producing highly specialized components, whereas the most downstream industries tend to be those manufacturing final goods used directly by consumers. This pattern aligns with commonly held perceptions of production stages and supports the validity of the upstreamness measure.

Table 3.2: Upstreamness Measure

Industry Code	Industry Name	Upstreamness
263	Bare Printed Circuit Boards	5.9708
261	Semiconductors	5.5178
264	Optoelectronic Materials and Components	5.3214
262	Electronic Passive Devices	3.9873
269	Other Electronic Parts and Components	3.3694
276	Irradiation and Electrical Equipment	2.7247
277	Optical Instruments and Equipment	2.7247
274	Magnetic and Optical Media	2.1980
2719	Other Computer Peripheral Equipment	1.9979
2712	Monitors and Terminals	1.9979
273	Audio and Video Equipment	1.7500
272	Communication Equipment	1.7115
275	Navigating and Control Equipment; Watch/Clocks	1.6378
2711	Computers	1.2700

Notes: The table shows upstreamness measure computed following Antràs et al. (2012)'s method, using 2010 Taiwan Input-Output Table.

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3.3 Firm-Level Productivity

To estimate firm-level productivity, I adopt Ackerberg et al. (2015)'s framework. It specifies a structural valued-added production function, with output being Leontief in material and capital-labor composite: $Y_{it} = \min\{\beta_0 K_{it}^{\beta_k} L_{it}^{\beta_l} \exp(\omega_{it}), \beta_m M_{it} \exp \epsilon_{it}\}$. I choose this framework instead of gross output specification (e.g. Levinsohn and Petrin (2003)) because in the electronics industry, both intermediate materials and capital-labor input are essential. As the firms are not able to substitute one input with the other, a Leontief production function is more suitable.

As discussed in Chen and Moore (2010), estimating how a firm's productivity determine its FDI decision requires addressing several endogeneity concerns. First, the operation of foreign affiliates could conflate the firm's performance record in the financial statement. Moreover, participating in multinational production may itself affect the parent firm's productivity, giving rise to the reverse causality. I follow their strategy to address these issues. Specifically, I estimate firms' productivity using unconsolidated balance sheets and income statements, which allows me to derive firm's intrinsic productivity solely based on their operation in Taiwan. Moreover, I estimate productivity using data from the period 2004–2007, the period prior to my observation of China affiliates. The lag between productivity measure and affiliate observation helps mitigate the concern that feedback effect from investment in China might confound the estimate of productivity's effect on FDI decision.

I obtain the firms' unconsolidated financial statement information from TEJ. I use revenue (sales) as the measure of output, end-of-year employment number as measure of labor input, value of tangible fixed asset as measure of capital, and cost of goods sold

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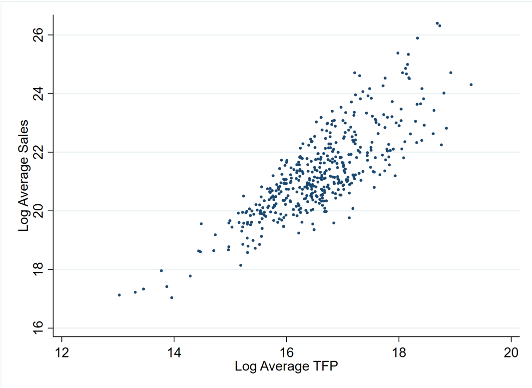
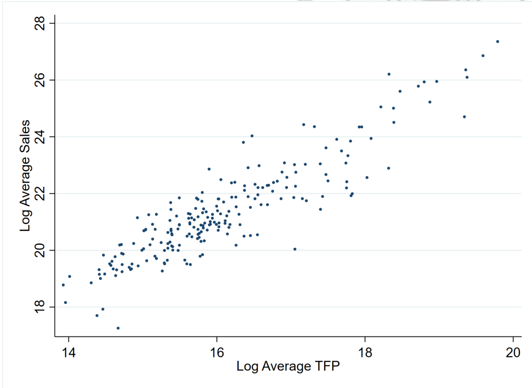
Figure 3.1: (Average) Log Productivity and (Average) Log Sales



(a) Electronic Parts and Components (26)



(b) Computers, Electronic, Optical Products (27)

Notes: The figures plot the average of log sales (2004-2007 within-firm average) against the average of log productivity (2004-2007 within-firm average, before normalization) for the two sectors.

(COGS) as measure of intermediate input use. [4] The firm-year productivity measures are aggregated to the firm level by taking their average across years. In light of the concern that there might be systematic difference across the two big sectors (Electronic Parts and Components (26) v.s. Computer, Electronic, and Optical Equipment (27)), especially in terms of the price value, I conduct the estimation within each sector. The resulting productivity estimates are further normalized relative to the mean within each sector. Figure 3.1 shows the relationship between firms' log revenues and estimated log TFPs (before normalizing). We can see that firm revenue is in general increasing in productivity, consistent with the empirical regularity well-established in the literature.

3.4 Geographic and Economic Variables

I employ several different sources to construct geographic and economic variables of China prefectures. The prefecture-level GDP is from China City Statistical Yearbook,

[4]Since output is measured by revenue rather than physical quantities, strictly speaking, I am estimating the TFPR of firms. See Appendix A for further details on the construction of the productivity estimation sample.

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and I downloaded a dataset that covers most prefectures from the database assembled by Henan ZhengZhou Uinversity City Development Center. Since , I focus on the GDP of "core cities (ShiXiaQu)", which are the closest Chinese counterpart to the central cities of U.S. metropolitan statistical areas (Baum-Snow et al. (2017)).

For wage measure, I use the prefecture-level manufacturing wage data collected by Fang and Huang (2022). Their data is also extracted from City Statistical Yearbook, although the aforementioned database does not include this variable. Provided that my focus is on electronic firms' foreign production, the manufacturing wage should capture the labor cost more accurately than overall wage. Since Fang and Huang (2022) only collects for 2010 and 2015, my analysis accordingly focus on these two years, as described earlier in 3.1.

As mentioned in the literature, distance to headquarter is an important factor determining FDI activity. Here I consider only the distance between Taipei and each prefecture, while remaining agnostic about the precise headquarter location of each Taiwanese firm. The distance is computed using Python *geodesic* package.

To calculate market potential for the prefectures, I use the prefecture GDP data described above and the bilateral trade cost data for any given pair of prefectures. The latter is obtained from Ma and Tang (2020). They calibrated a quantitative spatial economic model using data in 2005, producing an estimate for iceberg trade cost between prefectures. Each prefecture i's market potential is then calculated as $MP_i = \sum_j \frac{GDP_j}{\tau_{ij}}$, which is the trade-cost-weighted sum of prefecture GDPs (including prefecture i's owns). Table 3.3 presents the summary statistics of variables used in the regression.

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Table 3.3: Variable Summary

Variable	Mean	Standard deviation	Minimum	Maximum	Median
TFP	16.501	1.032	13.024	19.790	16.476
R&D intensity	0.042	0.048	0.000	0.415	0.026
Capital intensity	1.965	2.353	0.008	20.313	1.352
Upstreamness	3.781	1.662	1.270	5.971	3.369
Market potential	1201.148	329.788	656.039	1738.238	1076.915
Manufacturing wage	35939.136	13796.850	133.478	87581.000	34716.500
Distance to Taipei	1306.448	542.148	255.000	2720.666	1288.578

Notes: The table shows the summary statistics of variables used in the analysis. "TFP", "R&D intensity", and "Capital intensity" are at firm-level. "TFP" is estimated using Ackerberg et al. (2015)'s framework and then normalized relative to mean within each sector (Electronic Parts and Components (26); Computers, Electronic and Optical Products(27)). "Capital intensity" is calculated as $FixedAsset/Employment$, where $FixedAsset$ is in units of millions. "R&D" intensity is calculated as $R\&DExpenditure/Sales$. "Upstreamnes" is at industry0level and computed following Antràs et al. (2012). "Market potential", "Manufacturing wage", and "Distance to Taipei" are economic and geographic variables for Chinese prefectures. "Market potential (MP)" is calculated as $MP_i = \sum_j \frac{GDP_j}{\tau_{ij}}$, where τ_{ij} is obtained from Ma and Tang (2020) and GDP_j is in units of millions. "Manufacturing wage" is from Fang and Huang (2022). "Distance to Taipei" is computed using Python *geodesic* package.

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Chapter 4 Which Firms Enter More Locations

Given the data constructed, now I empirically investigate the role of value chain position in the FDI decision of Taiwanese firms in China. In the first part of analysis, I examine whether industry upstreamness is an important factor for explaining Taiwanese firm's propensity to establish affiliate in a given China prefecture. This is motivated by the first observation noted in Figure 1.1. In addition, I will discuss possible mechanisms behind and present preliminary evidence.

4.1 Empirical Strategy and Baseline Result

Following Chen and Moore (2010) and others, I adopt the binary logit model:

$$\Pr(Y_{ijt} = 1) = \Phi\Big(\text{const} + \alpha_1\theta_i + \alpha_2 U_i + \sum_k \beta_k X^k_{jt} + g_j + h_{st} + \epsilon_{ijt}\Big), \tag{4.1}$$

where $\Phi(\cdot)$ is the logistic cumulative distribution function. The dependent variable Y_{ijt} equals one if the Taiwanese firm i has an affiliate in China prefecture j during year t, and equals zero otherwise. θ_i is the productivity of firm. U_i, the upstreamness measure of industry to which firm i belongs, is the variable of interest. X^m_{jt} include prefecture j's log

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market potential and log wage at year t. In contrast to Chen and Moore (2010), I specify a panel data structure. I do so mainly to control for unobserved (time-invariant) prefecture characteristics, achieved via prefecture fixed effect g_j. In addition, I include sector-year fixed effect, which helps to absorb yearly shock common to all firms within each sector.[1]

As described in Section 3.3, to address potential endogeneity in productivity, I follow Chen and Moore (2010)'s approach by focusing on firms' productivity during the period prior to the affiliate sample year and estimating it solely based on their operations in Taiwan. With respect to the upstreamness measure, I treat firms' positions in the value chain as predetermined and therefore unaffected by their activities in China.

Table 4.1 presents the estimation result. For all columns, the coefficient on TFP is positive and statistically significant, in accordance with the well established fact that more productive firms enter more location.[2] It also shows that for any given firm, prefectures with larger market potentials are more attractive for setting up affiliate.[3] On the other hand, the coefficient on wage is not significant, not being able to reflect the adverse effect of higher production cost. This could be due to the limited magnitude in wage change across different years or due to the fact that the variable might still subsume the "big city" effect despite already controlling for market potential. Yet, it is not rare to obtain such insignificant estimate for wage in the study of multinational firm's location choice (e.g. Head and Mayer (2004); Also see Liu et al. (2010) for potential solution using control function approach).

Column (2) in Table 4.1 shows that the variable of interest, upstreamness, has a neg-

[1] In the appendix, I also tried the alternative specification that includes sector-year fixed effect and prefecture-year fixed effect (instead of prefecture fixed effect), which entirely controls for prefecture characteristics. The result is similar. See Table B.2 in Appendix B for the result.

[2] Yeaple (2009); Chen and Moore (2010)

[3] Head and Mayer (2004); Amiti and Javorcik (2008)

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Table 4.1: Which Firms Enter More Locations

	(1)	(2)	(3)	(4)
TFP	0.437***	0.422***	0.416***	0.396***
	(0.090)	(0.090)	(0.087)	(0.079)
Log market potential	12.150***	12.204***	12.209***	12.227***
	(3.590)	(3.607)	(3.608)	(3.611)
Log manufacturing wage	-0.134	-0.134	-0.134	-0.134
	(0.101)	(0.101)	(0.101)	(0.101)
Upstreamness		-0.235***	-0.291***	-0.309***
		(0.050)	(0.081)	(0.084)
Industry geographic dispersion			0.414	0.328
			(0.335)	(0.324)
Capital intensity				0.042
				(0.026)
Prefecture FE	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes
Observations	100,980	100,980	100,980	100,980

Notes: The table reports estimation result of the firm-prefecture-year level logit model in Equation (4.1). The dependent variable is a dummy variable which equals one if the firm has a production affiliate in the prefecture in the given year and equals zero otherwise. Firm-level "TFP" is estimated and normalized within each sector (Electronic Parts and Components (26); Computers, Electronic and Optical Products(27)). The industry-level "Upstreamness" is computed following Antràs et al. (2012) using 2010 Taiwan Input-Output Table. "Industry geographic dispersion" is defined as the average number of Taiwanese cities in which firms in a given industry have plant operations, based on 2023 Factory Operation Census. All specifications include prefecture fixed effect and sector-year fixed effect. Standard errors are clustered by firm and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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ative and statistically significant estimate. This suggests that holding the prefecture characteristics and firm productivity constant, a downstream Taiwanese electronic firm are more likely to establish an affiliate compared to an upstream electronic Taiwanese firm. In terms of magnitude, being one more stage downstream increases the log odds by 0.235. This negative relationship resonates the pattern shown in Figure 1.1, which illustrates that there are much more affiliates of downstream firms compared to upstream ones.

One potential explanation for this pattern is the incentive for firms to locate near their buyers. It could be that final consumers are scattered more broadly across different prefectures while the downstream producers might be concentrated in few locations, and that this difference in buyers' distribution is driving the larger extensive margin of downstream firms' entry into prefectures. To test the plausibility of this mechanism, I control for industry's degree of geographic dispersion based on the firms' operation in Taiwan, and see whether the negative effect of upstreamness fades out. Specifically, for each industry I calculate the average number of cities in which the firms in that industry operate their plants, using plant information from 2023 Factory Operation Census. Column (3) in Table 4.1 reports the result. In fact, it shows that the negative effect of upstreamness becomes even larger after accounting for industry's intrinsic degree of dispersion.[4]

In Table 4.1 Column (4), I further control for firm's capital intensity, which may represent the relative importance of headquarters' activity (headquarter intensity) and thus could affect firm's incentive to establish affiliates abroad.[5] In addition, given China's relatively low labor cost, Taiwanese firms from labor-intensive industries have been par-

[4] In the appendix, I also try using Krugman concentration index as an alternative measure of an industry's degree of dispersion. The main implication remains robust. See Table B.3 in Appendix B for the result.

[5] See, for example, Antràs (2003) and Antràs and Helpman (2004) for studies of how headquarter intensity affects firms' intrafirm trade and FDI decisions.

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ticularly active in investing in China.[6] If there is substantial difference in capital versus labor requirement across industries along the value chain, then it could confound the estimate of the effect of upstreamness. Yet, the result shows that the negative relationship between upstreamness and the probability to establish affiliate remains robust after taking capital intensity into account. To sum up, column (3) and (4) indicate that the effect of upstreamness is neither simply reflecting the industry's intrinsic tendency for geographic dispersion nor related to capital intensity, and thus there must be other underlying mechanism driving this result.

4.2 Role of Comparative Advantage

Now I propose another explanation: the upstream Taiwanese electronic firms avoid conducting FDI extensively in China in order to preserve their advantage over their Chinese counterparts. The FDI literature has widely documented the productivity spillover from foreign multinationals to local firms (See Javorcik (2004); Haskel et al. (2007); Keller and Yeaple (2009) among others). Also, firms may be reluctant to expand operations in China due to concerns regarding forced technology transfer through joint venture or knowledge leakage.[7] In particular, Taiwan is renowned for its significance in the supply chain of upstream electronic industries—including semiconductors and display panels —whereas in downstream electronic industries—such as computers and other electronic device manufacturing—China has become the primary hub for global production. Accordingly, upstream firms may have stronger incentives to preserve their technological

[6]See Liu et al. (2007) for relevant statistics.

[7]See Prud'homme et al. (2018); Jiang et al. (2018); Lee (2020) for discussions of forced technology transfer in China, and see Lee (2023) for Chinese firms' trade secret misappropriation in the semiconductor industry. One well-known example is TSMC's lawsuit against SMIC (Semiconductor Manufacturing International Corporation) over intellectual property theft and patent infringement.

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lead by limiting their investment in China, while downstream firms are less constrained by such concerns and instead seek to exploit China's production advantages.

To assess the plausibility of this channel, I first consider firm-level R&D intensity as a measure for firm's incentive to preserve their advantage. To more comprehensively capture the advantage of Taiwanese firms over Chinese competitors, I resort to the notion of comparative advantage. Specifically, I first compute Balassa (1965)'s revealed comparative advantage indices for each electronic industry i in Taiwan and in China:

$$BalassaCA_{ni} := \frac{X_{n,i}/X_n}{X_{World,i}/X_{World}}, \quad n \in \{\text{Taiwan}, \text{China}\}, \tag{4.2}$$

where $X_{n,i}$ is country n's export to country i and X_n is country n's total export. Then for each industry i, I divide the index of Taiwan by that of China and use this resulting number, which I call relative comparative advantage and denote by $RelaCA_i^{TW,CN}$, as a proxy for the advantage of Taiwanese electronic firms over Chinese counterparts.[8] That is:

$$RelaCA_i^{TW,CN} := \frac{Balassa_{TW,i}}{Balassa_{CN,i}} \tag{4.3}$$

I use data from UN COMTRADE for year 2007 to compute this relative comparative advantage index.[9] Figure 4.1 plots the correlation between this relative comparative advantage measure with the upstream index computed above. It shows that in general, Taiwan has larger advantage over China in industries that are more upstream.[10]

[8]An alternative approach is to use Costinot et al. (2012)'s framework to back out the underlying productivity level.

[9]Since UN COMTRADE does not include Taiwanese trade data, for any given country, I identify its import from Taiwan as its import from the category called "other Asia, not elsewhere specified" recorded in the database, following Hallak and Schott (2011).

[10]One potential concern regarding this approach is that China's relatively strong comparative advantage in the donwstream industries may be partly driven by the relatively larger number of downstream Taiwanese firms' affiliates operating there. To assess this possibility, in Figure B.1 in Appendix B, I plot the evolution of the relative comparative advantage indices over a longer period of time. It shows that China's relative comparative advantage in the donwstream industries did not increase dramatically during the 2000-2001 period, when many Taiwanese computer and peripheral equipment firms began to invest in China due to

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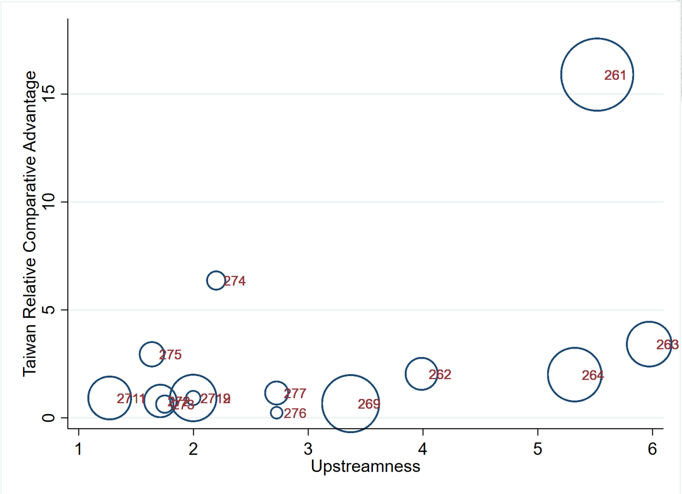
Figure 4.1: Industry Upstreamness and Taiwan's Relative Comparative Advantage



Notes: The figure plots Taiwan's relative comparative advantage (over China) in each electronic industry against the upstreamness measure. Taiwan's relative comparative advantage index is computed following Equation (4.3) using data from UN COMTRADE for year 2007. The red numbers are the industry codes presented in Table 3.2. The size of each circle is proportional to the number of firms in the corresponding industry.

Table 4.2 reports the estimation result after incorporating firm-level R&D intensity and Taiwan's relative comparative advantage into the regression. Column (2) shows that R&D intensity has a significant negative coefficient, suggesting that firms putting more effort in R&D activity are indeed less willing to invest in China, partly supporting the claim above. However, this effect does not subsume the role of firm's position in the global value chain, as the coefficient on upstreamness remains significant as in the baseline specification (Column 1). This indicates that upstream firms' lower propensity to invest in China arise from aspects other than their engagement in R&D activities.

Column (3) in Table 4.2 shows that the relative comparative advantage is indeed a crucial factor determining the firms' FDI decisions, with significant negative impact. More importantly, the coefficient on upstreamness becomes much smaller and less significant once I control for Taiwan's relative comparative advantage. This indicates that the lower propensity for upstream electronic firms to invest in China mainly reflects Taiwan's

policy change. This suggests that Taiwanese firms' investments are unlikely to be the primary driver of China's comparative advantage in downstream industries.

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greater advantage over China in these industries, in which firms have stronger incentives to avoid nurturing the Chinese competitors through FDI. Besides, the coefficient of R&D intensity also becomes less significant in column (3) compared to column (2). This suggests that the relative comparative advantage index subsumes the edge-preserving motive captured by R&D intensity. Overall, Table 4.2 shows that firm's value chain position and R&D intensity are respectively important aspects that affect its decision to establish affiliates in China, with Taiwan's advantage in the upstream segment of production serving as a more fundamental factor underlying both channels.

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Table 4.2: Which Firms Enter More Locations: Role of Relative Comparative Advantage

	(1)	(2)	(3)
Upstreamness	-0.309***	-0.301***	-0.148*
	(0.084)	(0.083)	(0.085)
TFP	0.396***	0.370***	0.420***
	(0.079)	(0.082)	(0.084)
Log market potential	12.227***	12.240***	12.295***
	(3.611)	(3.616)	(3.632)
Log wage	-0.134	-0.134	-0.134
	(0.101)	(0.101)	(0.101)
Industry geographic dispersion	0.328	0.366	0.363
	(0.324)	(0.312)	(0.273)
Capital intensity	0.042	0.041	0.045*
	(0.026)	(0.026)	(0.024)
R&D intensity		-2.256**	0.017
		(0.992)	(1.052)
Relative comparative advantage			-0.056***
			(0.012)
Prefecture FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Observations	100,980	100,776	100,776

Notes: The table reports estimation result of the firm-prefecture-year level logit model in Equation (4.1) while adding R&D intensity and the relative comparative advantage index. The dependent variable is a dummy variable which equals one if the firm has a production affiliate in the prefecture in the given year and equals zero otherwise. Firm-level "TFP" is estimated and normalized within each sector (Electronic Parts and Components (26); Computers, Electronic and Optical Products(27)). The industry-level "Upstreamness" is computed following Antràs et al. (2012) using 2010 Taiwan Input-Output Table. R&D intensity is calculated as $R\&DExpenditure/Sales$. The relative comparative advantage index for each industry is computed following Equation (4.3), using data from UN COMTRADE for year 2007. All specifications include prefecture fixed effect and sector-year fixed effect. Standard errors are clustered by firm and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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Chapter 5 Where Do the Firms Go

In the second part of analysis, I investigate whether there is systematic difference in affiliate location choice between upstream and downstream firms, motivated by the second observation in Figure 1.1.

5.1 Empirical Strategy and Result

The empirical strategy again follows Chen and Moore (2010). In the paper, they include the interaction terms of firm TFP and location characteristics to examine whether more productive multinationals have larger proportion of foreign affiliates in "tougher" countries, in the sense of smaller market potential, higher labor cost, and longer distance from headquarter. For my analysis, I extend their regression model by adding the interaction terms of prefecture characteristics and firm's upstreamness measure. The resulting logit model is then:

$$\begin{aligned}\Pr(Y_{ijt} = 1) = \Phi\Big(&\text{const} + \alpha_1\theta_i + \alpha_2 U_i + \sum_k \beta_k X_{jt}^k + \sum_k \gamma_k \theta_i X_{jt}^k + \gamma_{Dist}\theta_i Dist_j \\ &+ \sum_k \delta_k U_i X_{jt}^k + \delta_{Dist} U_i Dist_j + g_j + h_{st} + \epsilon_{ijt}\Big)\end{aligned} \tag{5.1}$$

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As above, X_{jt}^k includes prefecture j's market potential and manufacturing wage in year t. When interacting firm features with prefecture characteristics, I additionally consider prefecture's physical distance to Taipei, which serves as a measure for the distance from the headquarter.[1] The interaction terms $\gamma_k \theta_i X_{jt}^k$, $\gamma_{Dist} \theta_i Dist_j$, $\delta_k U_i X_{jt}^k$, and $\delta_{Dist} U_i Dist_j$ govern how the effect of productivity and upstreamness vary across prefectures with different market potential, manufacturing wage, and distance to Taipei.[2]

Table 5.1 presents the estimation result. First, column (1) shows that more productive firms are able to conduct FDI in locations farther away from headquarter, consistent with the phenomenon documented in Yeaple (2009) and in Chen and Moore (2010). Yet, for the other two prefecture variables, namely the market potential and manufacturing wage, the heterogeneous effect is not pronounced as in those papers. Moving on to column (2), the interaction term between upstreamness and distance to Taipei has a significant and robust negative coefficient estimate. This suggests that the entry decisions of downstream firms are less sensitive to a prefecture's distance from the headquarters, or describing in other way, the adverse effect of distance is more pronounced for upstream firms. Column (3) further shows that the result is robust to adding interaction terms of productivity and prefecture variables.

To illustrate how the negative impact of upstreamness varies across distance, I plug in different percentile values of prefecture's distance to Taipei in the sample to calculate the probability of establishing an affiliate. Specifically, consider several prefectures with equal market potential and manufacturing wage (set to median in the sample) but with

[1] This variable is not included in the analysis during previous section because it is a time-invariant feature of prefecture and is thus absorbed by the prefecture fixed effect.

[2] Similar to the previous section, in the appendix, I also tried the alternative specification that includes sector-year fixed effect and prefecture-year fixed effect, which entirely controls for prefecture characteristics. The result is similar. See Table B.4 in Appendix B for the result.

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Table 5.1: Where Do the Firms Go

	(1)	(2)	(3)
TFP	-2.183*	0.418***	-1.857*
	(1.185)	(0.087)	(1.124)
Log market potential (logMP)	11.856***	12.197***	11.978***
	(3.594)	(3.634)	(3.636)
Log manufacturing wage (logWage)	-0.105	-0.338**	-0.309**
	(0.113)	(0.147)	(0.141)
TFP × logMP	0.104		0.085
	(0.107)		(0.099)
TFP × logWage	-0.043		-0.025
	(0.063)		(0.053)
TFP × logDistTP	0.346**		0.286**
	(0.160)		(0.146)
Upstreamness		1.652*	1.377*
		(0.846)	(0.821)
Upstreamness × logMP		-0.093	-0.082
		(0.090)	(0.088)
Upstreamness × logWage		0.066*	0.061*
		(0.039)	(0.036)
Upstreamness × logDistTP		-0.287***	-0.252***
		(0.091)	(0.083)
Prefecture FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Observations	100,980	100,980	100,980

Notes: The table reports estimation result of the firm-prefecture-year level logit model in Equation (5.1). The dependent variable is a dummy variable which equals one if the firm has a production affiliate in the prefecture in the given year and equals zero otherwise. "TFP × logMP", "TFP × logWage", and "TFP × logDistTP" are the interaction terms between firm TFP and prefecture variables. "Upstreamness × logMP", "Upstreamness × logWage", and "Upstreamness × logDistTP" are the interaction terms between upstramness measure and prefecture variables. "logDistTP" refers to the log of distance between the given prefecture and Taipei (km). All specifications include prefecture fixed effect and sector-year fixed effect. Standard errors are clustered by firm and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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different distances to Taipei. Also suppose that we are considering a average-productivity firm. Table 5.2 lists the probability for this hypothetical firm to enter these prefectures respectively. The first row shows that for the most downstream industry (2711 Computers), the probability decreases by 5.5 percentage point as we move from prefecture with 10th-percentile distance to prefecture with median distance.[3] In contrast, the last row shows that for the most upstream industry (263 Bare Printed Circuit Boards), the corresponding decrease in probability is 15 percentage point.[4] This demonstrates that the adverse effect of distance could be almost three times as large in the most upstream industry as in the most downstream industry.

Table 5.2: Probability of Establishing Affiliate at Different Distances

Industry code and name	Upstreamness	10th-percentile	25th-percentile	50th-percentile	75th-percentile	90th-percentile
2711 Computers	1.2700	0.4514	0.4262	0.3965	0.3756	0.3635
275 Navigating and Control Equipment; Watch/Clocks	1.6378	0.4346	0.4025	0.3651	0.3392	0.3243
272 Communication Equipment	1.7115	0.4312	0.3978	0.3589	0.3321	0.3167
273 Audio and Video Equipment	1.7500	0.4295	0.3953	0.3557	0.3284	0.3127
2712 Monitors and Terminals	1.9979	0.4183	0.3797	0.3354	0.3053	0.2881
2719 Other Computer Peripheral Equipment	1.9979	0.4183	0.3797	0.3354	0.3053	0.2881
274 Magnetic and Optical Media	2.1980	0.4093	0.3672	0.3194	0.2873	0.2691
277 Optical Instruments and Equipment	2.7247	0.3859	0.3354	0.2794	0.2431	0.2230
276 Irradiation and Electrical Equipment	2.7247	0.3859	0.3354	0.2794	0.2431	0.2230
269 Other Electronic Parts and Components	3.3694	0.3580	0.2983	0.2349	0.1956	0.1746
262 Electronic Passive Devices	3.9873	0.3322	0.2651	0.1970	0.1570	0.1364
264 Optoelectronic Materials and Components	5.3214	0.2798	0.2019	0.1314	0.0948	0.0776
261 Semiconductors	5.5178	0.2725	0.1937	0.1235	0.0878	0.0712
263 Bare Printed Circuit Boards	5.9708	0.2562	0.1756	0.1068	0.0733	0.0582

Notes: The table lists the calculated probability for an average-productivity firm from each industry to enter a median-size prefecture with different distance from Taipei, based on the estimates in column (3) of Table 5.1.

5.2 Potential Mechanisms

The analysis so far has shown that the negative effect of distance is more pronounced in the upstream industries. One possible explanation is to connect to the advantage preserving motive discussed in Section 4. The upstream firms may want to maintain a larger control over its affiliates in China in order to ensure that their advantage does not leak to Chinese competitors. As argued in Giroud (2013), the headquarter's ability to monitor

[3]The difference in probability of entry is calculated as $0.4514 - 0.3965 = 0.0549$.
[4]The difference in probability of entry is calculated as $0.2562 - 0.1068 = 0.1494$.

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its plant decreases as travel time cost increase. In the context of Taiwanese multinationals operating in China, to the extent that geographic distance proxies for travel time, this mechanism could be the underlying reason for upstream firms to locate their affiliates in prefectures near Taiwan, where they are able to preserve a higher degree of control.

Another possible mechanism could be the cost of knowledge transfer. As often discussed in the multinational production literature (e.g.Keller and Yeaple (2013); Ramondo and Rodríguez-Clare (2013); Arkolakis et al. (2018)), the knowledge transfer cost is increasing in distance. If the upstream firms require more such knowledge transfer during production substantially compared to downstream firms, then it is reasonable that they sort into locations closer to the headquarters in Taiwan.

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Chapter 6 Conclusion

In this paper, I study the role of value chain position in determining multinational's FDI location choice. Using data on Taiwanese electronic firms' production affiliates in China, I show that downstream firms are substantially more likely to establish affiliates in a given prefecture. I further demonstrate that upstream firms' lower propensity to invest is closely linked to their relative advantage over Chinese competitors, which I have designed a relative comparative advantage index to capture. In the second part of the analysis, I examine firms' sorting across prefectures with different characteristics. The results reveal that distance to Taipei plays a central role in differentiating the location choices of upstream and downstream firms: upstream firms are considerably more deterred by distance. For a typical prefecture and a firm with average productivity, the adverse effect of distance could be three times stronger for upstream firms than for downstream firms.

These findings open several avenues for further research. While this paper focuses on Taiwanese firms' FDI in China, extending the analysis to Taiwanese firms' global FDI patterns would be equally relevant. Moreover, the explanation for the upstream−proximity nexus remains open and requires deeper investigation. Another important direction is to examine how Taiwan's and China's comparative advantages along the global value chains —identified here as the key drivers of upstream firms' lower investment propensity— have evolved over time. Moreover, in light of China's recent growth slowdown and the

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rising geopolitical uncertainty, reassessing whether these patterns persist or have shifted significantly would be of particular interest.

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Appendix A Data Appendix

China Affiliate Data of Publicly Listed Taiwan Companies

As described in the main text, China affiliate data is extracted from the Taiwan Economic Journal (TEJ) database, which records financial statement information of companies that are publicly listed in Taiwan. Specifically, I use the dataset "大陸投資明細", which is under the category of "TEJ Company DB". (Another potential dataset is the "關係企業營運概況明細" under the category "TEJ IFRS Finance - 國際會計準則", which I just discovered recently and thus have not had enough time to examine.) Since the address column does not have a unified structure, for the affiliates whose address information is incomplete, I identify their prefectures based on their names. For example, Formosa Plastics Corporation (台塑)'s affiliate 台塑電子 (寧波), whose address is recorded as "中國大陸", is identified as located in the Ningbo prefecture. I only keep the affiliates whose prefecture information can be identifies from their address or name. In addition, in the analysis I exclude the prefectures in the following provinces: Xinjiang, Inner Mongolia, Qinghai, Xizang, Gansu, and Ningxia.

In this paper, I focus on firms' multinational production activities and thus consider only affiliates established for production purposes. Affiliates that primarily serve sales, service, or financial functions are excluded from the analysis. I classify an affiliate's activ-

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ity based on the “product items (產品項目)” column. Specifically, an affiliate is classified as a non-production affiliate if this column contains any keywords associated with sales, services, or financial activities (零售, 批發, 銷售, 販賣, 經營, 服務, 開發, 業務, 維修, 買賣, 管理, 諮詢, 經銷, 投資, 貿易, 量販, 行銷, 代理) and does not contain any keywords associated with production activities (製造, 生產, 產銷, 組裝, 加工, 測試, 製作, 代工). These non-production affiliates are excluded from the sample. The remaining affiliates are thus classified as production affiliates and constitute the analysis sample.

Balanced Sheet and Income Statement of Publicly Listed Taiwan Companies

As described in the main text, I use firms' unconsolidated balance sheet and income statement information during 2004-2007 from the TEJ database to estimate firm-level productivity. It can be accessed via following steps: “TEJ IFRS Finance - 國際會計準則” → “非合併財務 (含附註)” → “IFRS 非合併 (個別 + 個體) 財報 (累計)-一般產業 IV”. I use revenue (sales) as the measure of output, end-of-year employment number as measure of labor input, value of tangible fixed asset as measure of capital, and cost of goods sold (COGS) as measure of intermediate input use. The R&D expenditure used to calculate firm-level R&D intensity is also from this dataset.

I prepare the data for productivity estimation as follows. First, I drop firms that report missing, zero, or negative sales for more than two years during the 2004–2007 period. Among the remaining firms, I retain those with complete sales information as well as those reporting missing, zero, or negative sales only in the first year, or in the first and second years, of their observation window. Firms reporting missing, zero, or negative sales in the second, third, or fourth year of observation are excluded. Next, I drop firms that report missing cost of goods sold (COGS) for more than one year. For the remaining firms,

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missing COGS values are imputed using the previous year's observation. I then drop firms that report missing employment for more than one year. For the remaining firms, missing employment is imputed using the subsequent year's observation, as all missing employment values occur in the first year of observation. Finally, I impute missing values of tangible fixed assets using data from adjacent years—using the subsequent year if the missing value occurs in the first year, and the previous year otherwise. The resulting dataset constitutes the sample used for productivity estimation and subsequent analysis.

Taiwan 2010 Input-Output Table

The input−output data used to construct the upstreamness measure is "產業關聯統計-商品對商品 (CXC)100 年 166 部門進口品交易表 (C.I.F.+ 進口稅淨額)", which is publicly available from Taiwan's Government Open Data Platform (政府資料開放平台 https://data.nat.gov.tw/).

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Concordance between Taiwan's Official Industry Classification and Its Input-Output Table Categories

Table A.1: Concordance between Official Industry Classification and IO Table Categories

	Taiwan Official Industry Classification		Taiwan Input-Output Table Category
261	Semiconductors 半導體製造業	079	Semiconductors 半導體
262	Electronic Passive Devices 被動電子元件製造業	080	Electronic Passive Devices 被動電子元件
263	Bare Printed Circuit Boards 印刷電路板製造業	081	Bare Printed Circuit Boards 印刷電路板
264	Optoelectronic Materials and Components 光電材料及元件製造業	082	Optoelectronic Materials and Components 光電材料及元件
269	Other Electronic Parts and Components 其他電子零組件製造業	083	Other Electronic Parts and Components 其他電子零組件
2711	Computers 電腦製造業	084	Computers 電腦產品
2712	Monitors and Terminals 顯示器及終端機製造業	085	Computer Peripheral Equipment 電腦週邊設備
2719	Other Computer Peripheral Equipment 其他電腦週邊設備製造業	085	Computer Peripheral Equipment 電腦週邊設備
272	Communication Equipment 通訊傳播設備製造業	086	Communication Equipment 通訊傳播設備
273	Audio and Video Equipment 視聽電子產品製造業	087	Audio and Video Equipment 視聽電子產品
274	Magnetic and Optical Media 資料儲存媒體製造業	088	Magnetic and Optical Media 空白資料儲存媒體
275	Navigating and Control Equipment; Watch/Clocks 量測、導航、控制設備及鐘錶製造業	089	Navigating and Control Equipment; Watch/Clocks 量測、導航、控制設備及鐘錶
276	Irradiation and Electromedical Equipment 輻射及電子醫學設備製造業	090	Irradiation and Electromedical Equipment; Optical Instruments 輻射及電子醫學設備、光學儀器
277	Optical Instruments and Equipment 光學儀器及設備製造業	090	Irradiation and Electromedical Equipment; Optical Instruments 輻射及電子醫學設備、光學儀器

Notes: The table presents the concordance between Taiwan's official industry classification and the categories in Input-Output Table.

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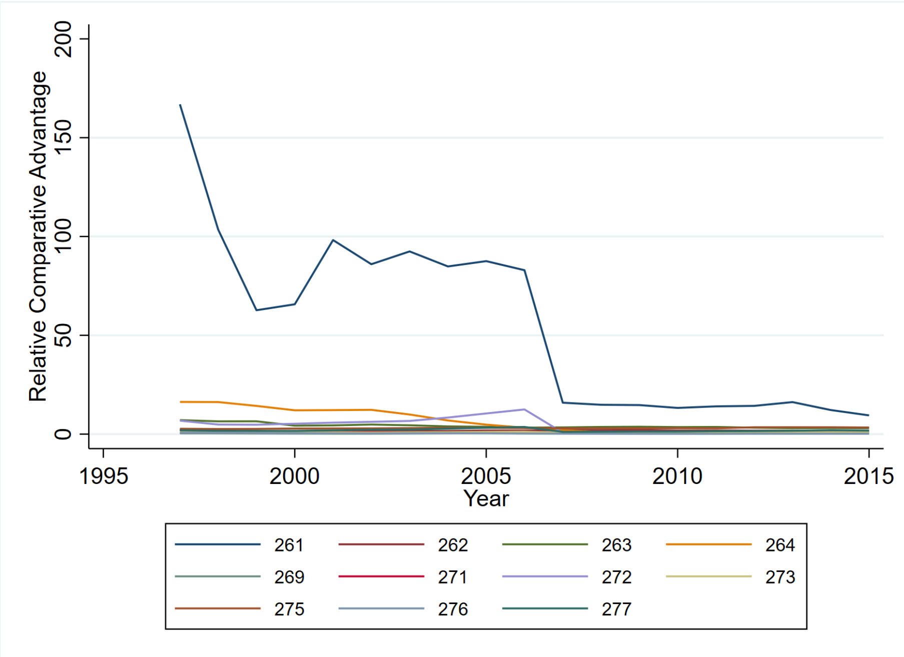
Appendix B   Additional Results

Figure B.1: Evolution of Taiwan's Relative Comparative Advantage



Notes: The figure plots Taiwan's relative comparative advantage (over China) in each electronic industry over the period 1997-2015. The relative comparative advantage index is computed following Equation (4.3). The names of industries are presented in Table 3.2.

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國立臺灣大學 · 愛國 · 愛學 · 勤勉 · 大學 · 國立臺灣大學

Table B.2: Which Firms Enter More Locations: Robustness Check with Prefecture-Year Fixed Effect

	(1)	(2)	(3)	(4)	(5)	(6)
TFP	0.438***	0.423***	0.416***	0.396***	0.370***	0.420***
	(0.090)	(0.090)	(0.087)	(0.079)	(0.082)	(0.084)
Upstreamness		-0.236***	-0.291***	-0.309***	-0.301***	-0.148*
		(0.050)	(0.081)	(0.084)	(0.083)	(0.085)
Industry geographic dispersion			0.414	0.328	0.366	0.363
			(0.335)	(0.324)	(0.312)	(0.273)
Capital intensity				0.042	0.041	0.045*
				(0.026)	(0.026)	(0.024)
R&D intensity					-2.257**	0.018
					(0.992)	(1.052)
Relative comparative advantage						-0.056***
						(0.012)
Prefecture-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	87,615	87,615	87,615	87,615	87,438	87,438

Notes: The table reports estimation results analogous to Table 4.1 and Table 4.2, by including prefecture-year fixed effect instead of prefecture fixed effect. Column (1)-(4) are analogous to the columns in Table 4.1, and column (4)-(6) are analogous to the columns in Table 4.2. The dependent variable is a dummy variable which equals one if the firm has a production affiliate in the prefecture in the given year and equals zero otherwise. All specifications include prefecture-year fixed effect and sector-year fixed effect. Standard errors are clustered by firm and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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Table B.3: Which Firms Enter More Locations: Robustness Check with Krugman Concentration Index

	(1)	(2)	(3)	(4)	(5)	(6)
TFP	0.437***	0.422***	0.418***	0.394***	0.369***	0.416***
	(0.090)	(0.090)	(0.089)	(0.078)	(0.081)	(0.082)
ln_MP	12.150***	12.204***	12.205***	12.225***	12.237***	12.299***
	(3.590)	(3.607)	(3.607)	(3.611)	(3.616)	(3.635)
ln_wage	-0.134	-0.134	-0.134	-0.134	-0.134	-0.134
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)
Upstreamness		-0.235***	-0.243***	-0.278***	-0.267***	-0.119*
		(0.050)	(0.056)	(0.060)	(0.061)	(0.065)
Krugman Concentration Index			0.147	0.210	0.229	0.607**
			(0.332)	(0.324)	(0.321)	(0.308)
Capital intensity				0.047*	0.046*	0.054**
				(0.027)	(0.027)	(0.025)
R&D intensity					-2.122**	0.466
					(0.991)	(1.045)
Relative comparative advantage						-0.063***
						(0.012)
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	100,980	100,980	100,980	100,980	100,776	100,776

Notes: The table reports estimation results analogous to Table 4.1 and Table 4.2, by considering Krugman concentration index as a measure of industry's intrinsic geographic dispersion. Column (1)-(4) are analogous to the columns in Table 4.1, and column (4)-(6) are analogous to the columns in Table 4.2. The dependent variable is a dummy variable which equals one if the firm has a production affiliate in the prefecture in the given year and equals zero otherwise. "Krugman Concentration Index" for industry i is calculated as $KC_i = \sum_i |s_k^i - \bar{s}_k|$, where s_k^i denotes the share of industry i's plants located in Taiwanese city k relative to the total number of plants in industry i nationwide, and $\bar{s}_k$ denotes city k's share of total manufacturing plants across all industries in Taiwan. City-level plant counts by industry are obtained from the 2007 Factory Operation Census. All specifications include prefecture fixed effect and sector-year fixed effect. Standard errors are clustered by firm and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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Table B.4: Where Do the Firms Go: Robustness Check with Prefecture-Year Fixed Effect

	(1)	(2)	(3)
TFP	-1.893*	0.418***	-1.596
	(1.101)	(0.087)	(1.047)
TFP × logMP	0.063		0.050
	(0.104)		(0.097)
TFP × logWage	-0.044		-0.026
	(0.063)		(0.053)
TFP × logDistTP	0.347**		0.287*
	(0.161)		(0.146)
Upstreamness		1.456*	1.218
		(0.823)	(0.804)
Upstreamness × logMP		-0.064	-0.058
		(0.092)	(0.090)
Upstreamness × logWage		0.065	0.061*
		(0.040)	(0.036)
Upstreamness × logDistTP		-0.288***	-0.253***
		(0.091)	(0.083)
Prefecture-Year FE	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	Yes
Observations	87,615	87,615	87,615

Notes: The table reports estimation results analogous to Table 5.1, by including prefecture-year fixed effect instead of prefecture fixed effect. The dependent variable is a dummy variable which equals one if the firm has a production affiliate in the prefecture in the given year and equals zero otherwise. All specifications include prefecture-year fixed effect and sector-year fixed effect. Standard errors are clustered by firm and reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

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