Product Cycle, Contractibility, and Global Sourcing

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Abstract

This paper examines the organizational structure of global sourcing over the product cycle. This paper combines a new product list data set with China's customs data. The analysis finds that multinationals first produce within their foreign subsidiaries. When the product matures, firms start to outsource their production to external foreign suppliers. International outsourcing appears earlier along the product cycle when contractibility is better.

Keywords: Global Sourcing; Offshoring; Product cycle; Contractibility; Difference-in-difference-in-differences estimation

JEL Codes: F12, F23, L23, D23

1 Introduction

International fragmentation has become a common strategy for the organization of production. Using data from 10 Organisation for Economic Co-operation and Development (OECD) countries and four emerging market countries, Hummels, Ishii, and Yi (2001) document that international fragmentation of production accounted for 21 percent of exports in these countries in 1990, and explained more than 30 percent of the growth in exports between 1970 and 1990. Johnson and Noguera (2014) extend the analysis to 52 countries from 1970 to 2009. They find that the extent of international fragmentation increased by about 10 percentage points worldwide, and the increase was much faster post-1990 compared with pre-1990. Given this landscape change, an important question confronting researchers and practitioners is how to organize global sourcing.[1]

Antràs (2005) proposes a framework where the optimal choice of global sourcing strategies changes along the product cycle. The framework incorporates the product cycle effect proposed by Vernon (1966) into the framework of production fragmented across borders with incomplete contracts. Antràs (2005) shows that along the product cycle, manufacturing is first conducted in the home country where product development takes place, then moves to low-wage foreign countries within the firm's boundary (referred to as *FDI-based offshoring*), and finally is outsourced to foreign external suppliers (referred to as *contract-based offshoring*). However, other than anecdotal evidence and case studies, there is little systematic investigation of the product cycle effect on the choice of offshoring strategies. Using new data on a new product list and a unique feature in China's trading system to measure different offshoring modes, we provide the first analysis to quantify the product cycle effect on global sourcing.

Understanding the evolution of offshoring strategies over product cycle is important for both origin countries (mostly developed countries) and destination countries (in particular, developing countries) of multinationals. While offshoring is concerned with the employment displacement and wage inequality in the developed countries (e.g., Feenstra and Hanson, 1996, 1997; Hummels, Jorgensen, Munch, and Xiang, 2014), the composition of offshoring also matters. Calibrating a general equilibrium model to match the aggregate U.S. data, Garetto (2013) finds that offshoring via multinational production increases the welfare for the U.S. economy by around 0.23 percent of consumption per capita. Detecting the product cycle effects on the choice of offshoring modes can then shed light on how globalization affects source countries of multinationals over time. Meanwhile, multinational production involves transferring proprietary technologies to their foreign affiliates, which is a main hub for technology spillovers in developing countries. The extent of technology transfers by multinationals hinges on the institutional quality in the host countries and the length of product cycle. Using the data on U.S. firms' global

[1] Global sourcing and offshoring are used interchangeably in this paper.

operation across 37 industries and 92 countries during 1982–2004, Bilir (2014) finds that "a one-standard deviation increase in measured patent protection attracts between 10 and 20 percentage points more multinational activity in the seventy-fifth percentile sector than in the tenth-percentile sector by product life-cycle lengths." Quantifying the sourcing trade-off by multinational firms over product cycle can help us understand how developing countries may benefit from international technology diffusion.

Our empirical analysis uses a product list compiled by Xiang (2014) that classifies Harmonized System (HS) 10-digit products into the categories of new and old products. We match that list to China's customs data and calculate the percentage of HS 10-digit new products within each of the 5,000+ HS 6-digit products.[2] China has a special trade regime—processing trade—that allows processing plants in China to import inputs free of tariffs, but they must export all the output, which allows us to infer total output from total exports. By matching the China customs data to a survey of foreign invested enterprises (FIEs) in 2001 (which accounted for around 75 percent of all FIEs in China), we obtain the home country identity of foreign multinationals in China. We classify imports by foreign multinationals from their home countries as intra-firm trade, and, based on that, construct an index of the share of FDI-based offshoring for each foreign country, HS 6-digit product, and year in our sample. Section 3 provides details on the data, variable construction, and measurement issues.

To isolate the product cycle effect on global sourcing from other non-product cycle effects, we compare the evolution of the share of FDI-based offshoring along the product cycle in China for firms from developed and developing countries among new and old products, a difference-in-difference-in-differences (DDD) estimation strategy. In section 2, we provide an illustration of and guidance for our estimation strategy. We first embed firm heterogeneity into Antràs's (2005) framework as in Antràs and Helpman (2004), and then extend the model to a setting of three countries—one home country and two foreign countries—in which foreign countries consider their offshoring strategies in the home country. We find that as a product matures, foreign multinationals in China outsource more of their manufacturing to external suppliers, which is consistent with the prediction by Antràs (2005). This pattern is borne out in China Customs data from 2001 to 2013. The results are robust to various checks on the measurement of global sourcing strategies, omitted variables, and estimation samples.

Antràs (2005) assumes a setting in which contracts are not ex post enforceable. We extend the framework to incorporate the possibility that a fraction of components is contractible, following the framework in Antràs and Helpman (2008). When contracts are complete, producers' incentives are unaffected by the ownership type, and the organization choice relies only on production costs (i.e., fixed costs and wage difference in our

[2] We are not able to carry out the analyses at the HS 10-digit level because the HS classification used in China is only comparable to that in the United States at the HS 6-digit level.

setting). As a result, no product cycle effects are apparent. With contract incompleteness, ownership affects investment by headquarters and component suppliers. FDI-based offshoring dominates in the early stages of the product cycle, and contract-based offshoring is advantageous in later stages of the product cycle. With better contractibility, the difference between these two modes of offshoring narrows, and multinationals tend to choose contract-based offshoring, which involves lower fixed costs. To test the prediction of product cycle effects with contractibility, we use a contractibility index constructed by Nunn (2007), which varies across industries. Building on the method by Rauch (1999), Nunn (2007) considers goods that are neither reference priced nor sold on exchange markets as relationship-specific ones. Nunn then computes the proportion of relationship-specific inputs for each NASIC 1997 industry. The empirical findings support the theoretical predictions of the product cycle effects with contractibility.

Our study is related to the recent literature on the organization of multinationals (for reviews, see Antràs and Rossi-Hansberg, 2009; Yeaple, 2013; Antràs and Yeaple, 2014). In a seminal work, Antràs and Helpman (2004) use the property rights framework to investigate how firms with different productivity levels choose their organizational structures, specifically, domestic versus global sourcing.[3] This research framework has been expanded in several dimensions. For example, Du, Lu, and Tao (2009) and Schwarz and Suedekum (2014) extend the theoretical framework to show the existence of hybrid sourcing structures, i.e., firms that outsource and produce their components in-house at the same time. Antràs and Chor (2013) consider how firms choose their organizational structures when their production entails multiple sequential stages. They show that the choice depends on the relationships among different production stages (complementary or substitute) and the location in the production chain (early versus late stages). Alfaro, Antràs, Chor, and Conconi (2015) test this prediction based on Dun & Bradstreet's WorldBase with firm production across 100 countries, and show that contractibility plays an important role in determining the organizational structures of firms. Our study follows the analysis by Antràs (2005), who considers the role of the product cycle in the determination of global sourcing structures. Our contribution lies in being the first study to test the product cycle theory of global sourcing systematically.

Our study also belongs to the large literature on the product cycle proposed by Vernon (1966). Theoretical studies explore how product cycles relate to trade patterns (Krugman, 1979), innovation (Grossman and Helpman, 1991), and skill premium (Thoenig and Verdier, 2004; Zhu, 2003). Recent studies use data to test various predictions from these product cycle theories. For example, Feenstra and Rose (2000) test the product cycle theory by showing that developed countries export products earlier to the U.S. than to developing countries. Zhu (2005) tests whether skill upgrading in developed and devel-

[3] Their theoretical findings are subsequently tested and confirmed by Yeaple (2006); Tomiura (2007); Corcos, Irac, Mion, and Verdier (2013); Defever and Toubal (2013); Nunn and Trefler (2013); and others.

oping countries since the 1970s can be explained by product cycles (i.e., the relocation of U.S. production). To confront the product cycle theory more closely, Xiang (2014) constructs a product-level list of new products for U.S. manufacturing imports, and shows that the North's new product imports to the U.S., relative to the South's, exhibits an inverse-U shape over time, consistent with the prediction of the product cycle theory. Our study builds on Xiang (2014) to investigate the organization of multinationals over the product cycle.

Lastly, this paper also relates to a large literature on the measurement of offshoring (for a review, see Hummels, Munch, and Xiang, 2016). Feenstra and Hanson (1999) propose the proportionality assumption and use data on final goods imports and input purchases to measure offshoring as imported intermediate inputs. Hummels, Ishii, and Yi (2001) use OECD input-ouput tables and measure the value added content of exports. Johnson and Noguera (2012) and Koopman, Wang, and Wei (2014) use inter-country input-output tables and generalize the measure of value-added trade. Kee and Tang (2016) use China's customs data and provide a measure of the ratio of value-added to total exports at the firm level. Feenstra and Hanson (2005) and Fernandes and Tang (2012) use the unique trade regime in China and firm ownership to measure firms' offshoring and vertical integration. Our study follows Feenstra and Hanson (2005) and Fernandes and Tang (2012), and constructs different offshoring modes.

The paper is organized as follows. Section 2 presents the model as well as model predictions. Our empirical strategy is discussed in Section 3. Section 4 contains our main empirical findings. And section 5 concludes.

2 Model

In this section, we build a simple model to illustrate firms' offshoring decisions over the product cycle and guide our empirical estimation. We first embed firm heterogeneity into Antràs's (2005) framework as in Antràs and Helpman (2004), and then extend the model to include one more country as a control for non-product cycle factors affecting firms' global sourcing decisions in the empirical estimation.

2.1 Basic Setup

We consider a world with three countries (i.e., a home country C and two foreign countries N and S) and one production factor (i.e., labor). Consumers are infinitely lived and have identical preferences, which are given by

$$U_t = y_{0t} + \frac{1}{\mu} \sum_{j=1}^{J} Y_{jt}^{\mu}, \tag{1}$$

where t indicates period; y_{0t} is consumption of a homogeneous good; $Y_{jt} = \left(\int y_{jt}(i)^{\alpha} di\right)^{1/\alpha}$ is the aggregate consumption of different varieties $y_{jt}(i)$ in product j at period t, where the range of i will be endogenously determined; μ represents the constant elasticity of substitution across products; and α represents the elasticity of substitution among different varieties within each product with $0 < \mu < \alpha < 1$.

Given the utility function (1), we can derive the inverse demand function for each variety i in product j at period t as

$$p_{jt}(i) = Y_{jt}^{\mu-\alpha} y_{jt}(i)^{\alpha-1}. \tag{2}$$

Labor supply is assumed to be perfectly elastic in each country. Denote the wage rates in three countries as w^N, w^S, and w^C, respectively for North, South, and China. We normalize $w^C = 1$ and assume that $w^N > w^S > 1$.

To produce any products, two product-specific inputs, h and m, are jointly required, which are referred to as headquarters services (such as research and product development, marketing, etc.) and manufactured components, respectively. Correspondingly, there are two kinds of producers: final good producers (denoted by H), who provide the product-specific headquarters services (h), and component makers (denoted by M), who supply the product-specific manufactured components (m). Each unit of h and m requires one unit of labor. As our analysis primarily concerns the sourcing patterns of foreign multinationals in China, we restrict final good producers to be located in foreign country N or S, while component makers can be chosen domestically or from home country C.[4] Every final good producer organizes the production process by combining the headquarters services and the manufactured components in a Cobb-Douglas fashion to make the final product as follows[5]

$$y_{jt}(i) = \theta(i) \left[\frac{h_{jt}(i)}{1 - z_{jt}}\right]^{1-z_{jt}} \left[\frac{m_{jt}(i)}{z_{jt}}\right]^{z_{jt}}, \ 0 < z_{jt} < 1, \tag{3}$$

where $\theta(i)$ is random productivity term drawn from a known distribution $G(\theta)$ for variety i in a certain product category; and z_{jt} is headquarters services intensity for product j in period t. z_{jt} is the key parameter in our analysis, which captures the extent of the product cycle and will be defined later.

Ownership structure can be vertical integration V or outsourcing O. The supplier M may locate in either the same country as H or in China C. We also assume that the fixed organizational costs satisfy the following relationship

$$f_V^C > f_O^C > f_V^N = f_V^S > f_O^N = f_O^S, \tag{4}$$

[4] We do not consider the case where country N chooses a component maker from country S.

[5] To simplify our notation, we drop the product/industry index j in the next subsection, since each product is symmetric. Later, when we introduce new and old products, they only differ in their z values.

where f_k^l denotes the fixed organizational cost for organizational structure k with M in country l.

Our data do not contain information on domestic sourcing outcomes by foreign multinationals (i.e., the production in their origin countries), but do contain information on their global sourcing outcomes (i.e., component production in China). Therefore, we assume that if the final good producer H (from country N or S) sources the components in its origin country, it produces in-house (a mode referred to as headquarters manufacturing). But if the final good producer sources the components in country C, there are two options for organizing the production of components: H can contract with an external supplier in country C for the supply of the manufactured component (contract-based offshoring), or H can set up its own subsidiary in country C and make the component in-house (FDI-based offshoring).

As in Antràs and Helpman (2004) and Antràs (2005), we consider a setting of incomplete contracts in the global sourcing scenario, which is especially the case in China given its weak contracting institutions. Later, we will relax this assumption by considering a setting where a fraction of the components can be perfectly contracted as in Antràs and Helpman (2008). The incomplete contract setting assumes that the precise nature of the required inputs is difficult to specify ex ante, and that, once revealed ex post, the nature of the required inputs is still not verifiable by a third party. It is further assumed that ex ante investments for input production and sales revenue are not contractible. As a result, the final good producer H and component supplier M bargain over the surplus value from trade after they make their own input investments. Following the property rights theory of the firm, we assume that bargaining takes place in both outsourcing and insourcing, and is modelled via the generalized Nash bargaining framework with the final good producer claiming a fraction β of the ex post revenue. Specifically, when the bargain fails in the contract-based offshoring mode, both parties end up with nothing. However, in the case of the FDI-based offshoring, the final good producer H can fire its component division manager M and retain δ share of the components if the bargain fails, whereas M gets nothing after being fired.[6]

2.2 Firm Behavior

From now on, we discuss the organization choice for firms (varieties) within a particular product j, as all products are symmetric. The only difference across products is the headquarters service intensity $1 - z$. We drop the product index j as well as the time index t from all variables as long as it does not cause any confusion. If H and M agree

[6]Note that we follow Antràs and Helpman (2004) in assuming the same δ for local integration and integration with Chinese suppliers. This is because we will mainly focus on the choice between FDI-based and contract-based offshoring in China. The analysis does not test the integration choice between local integration and global integration.

in the bargaining, the potential revenue from the sale of final goods is $R(i) = p(i)y(i)$. Using (2) and (3), we have

$$R(i) = Y^{\mu-\alpha}\theta(i)^{\alpha}\left[\frac{h(i)}{1-z}\right]^{\alpha(1-z)}\left[\frac{m(i)}{z}\right]^{\alpha z}. \tag{5}$$

If H outsources components, when H and M fail to agree, both outside options are zero regardless of the location of M (local or in China). In this case, H gets $\beta R(i)$ and M gets $(1-\beta)R(i)$ from the bargaining.

If H sources components through vertical integration, when H and M fail to agree, H still retains δ share of the final goods, which is revenue $\delta^{\alpha}R(i)$. The quasi rents for the bargaining is thus $(1-\delta^{\alpha})R(i)$. In this case, H gets its outside option plus a fraction of the quasi rent, which is $\delta^{\alpha}R(i) + \beta(1-\delta^{\alpha})R(i)$, and M gets $(1-\beta)(1-\delta^{\alpha})R(i)$. Thus, H gets a higher fraction of the revenue under integration compared with outsourcing. Denoting the payoff of H under ownership structure k with M locating in country l by $\beta_k^l R(i)$, we then have

$$\beta_V^N = \beta_V^S = \beta_V^C > \beta_O^N = \beta_O^S = \beta_O^C = \beta. \tag{6}$$

Since the delivery of inputs $h(i)$ and $m(i)$ is not contractible ex ante, the parties choose their quantities non-cooperatively. We focus on North's and South's sourcing strategies in China, and show the case for North's final good producers. The case for South is analogous. In particular, H provides an amount of headquarter services that maximizes $\beta_k^l R(i) - w^N h(i)$, whereas M provides an amount of components that maximizes $(1-\beta_k^l)R(i) - w^l m(i)$. Combining the first-order conditions of these two, using (5), we can express the total operating profits as

$$\pi_k^l(\theta; z) = Y^{(\mu-\alpha)/(1-\alpha)}\theta^{\alpha/(1-\alpha)}\psi_k^l(z) - w^N f_k^l, \tag{7}$$

where

$$\psi_k^l(z) = \frac{1-\alpha[\beta_k^l(1-z) + (1-\beta_k^l)z]}{\{1/\alpha(w^N/\beta_k^l)^{1-z}[w^l/(1-\beta_k^l)]^z\}^{\alpha/(1-\alpha)}}. \tag{8}$$

θ is the firm-specific productivity term. z is the product-level component intensity, which represents the extent of product cycle or product standardization. Y is endogenous to the product but exogenous to each firm producing one variety of a certain product. Upon observing its productivity level θ, a final-good producer H chooses the ownership structure and location of component supplier M that maximizes (7)

$$\pi(\theta; z) = \max_{k\in\{V,O\}, l\in\{N,C\}} \pi_k^l(\theta; z)$$

or exits and forfeits the fixed entry cost $w^o f_E$ if the productivity is too low, such that

$\pi(\theta; z) = 0$, which implicitly defines the lowest operating productivity threshold $\underline{\theta}$. The free entry condition ensures that the expected operating profits equal the fixed cost of entry, and thus provides an implicit solution to the product-level real consumption index Y.

The choice of organization structure faces two types of trade-offs. In terms of location choice for supplier M, the variable cost is lower in China but the fixed cost is higher. In terms of vertical integration choice, integration entails higher fixed costs and gives H a larger fraction of the revenue, as in (6). This gives H higher profits if headquarter services are important enough. However, it may give H lower profits if M's components supply matters more for final goods production. As a result, the choice of organization depends on the input intensity z, i.e., the product cycle status of the product. As shown in Antràs and Helpman (2004), when z is small enough, headquarter services are more important in production. Therefore, it is relatively more important to incentivize H, and integration is more attractive. This case is reflected in the slopes of the profit functions: π_V^l is steeper than π_O^l for $l = N, C$ because $\psi_V^l(z) > \psi_O^l(z)$. However, when z is large enough, the marginal output of the components is high, making underinvestment in m especially costly and outsourcing attractive. In this case, outsourcing will dominate integration in either location choice for M. FDI-based offshoring will occur only for firms with a high enough productivity level.

Our focus in this paper is the share of FDI-based offshoring in total offshoring.[7] When product is mature enough, i.e. z is large enough, there will only be contract-based offshoring; hence, the share of FDI-based offshoring approaches 0.

When product is new (i.e., z is small), the relative prevalence of different organizational forms depends on the slope of the profit function under those forms. We focus on the case when $\psi_V^l(z) > \psi_O^l(z)$ for $l = N, C$; and $\psi_O^C(z) > \psi_V^N(z)$.[8] In this case, the organizational forms will be FDI-based offshoring in China, contract-based offshoring in China, domestic integration, and domestic outsourcing, for firms with high, medium high, medium, and low productivity levels, respectively. In particular, we are interested in how the relative prevalence of the two offshoring modes changes with z, which is also a function of time, as will be shown in the next subsection. In this benchmark case, the cutoff productivity levels for different organizational choices, from low to high, are given

[7] The Appendix in Antràs and Helpman (2004) shows that the shares using firm counts or firm sales yield the same results.

[8] There are two other cases: (1) when $\psi_O^l(z) > \psi_V^l(z)$ for $l = N, C$; and $\psi_O^C(z) > \psi_O^N(z)$; and (2) when $\psi_V^l(z) > \psi_O^l(z)$ for $l = N, C$; and $\psi_O^C(z) < \psi_V^N(z)$. In both cases, there is only one type of offshoring (either FDI-based offshoring or contract-based offshoring in China) and, hence, the ratio of FDI-based offshoring is one or zero.

by

$$\begin{aligned}
\underline{\theta} &= Y^{(\alpha-\mu)/\alpha}\left[\frac{w^N f_O^N}{\psi_O^N(z)}\right]^{(1-\alpha)/\alpha}, \ \theta_O^N = Y^{(\alpha-\mu)/\alpha}\left[\frac{w^N(f_V^N - f_O^N)}{\psi_V^N(z)-\psi_O^N(z)}\right]^{(1-\alpha)/\alpha}, \\
\theta_V^N &= Y^{(\alpha-\mu)/\alpha}\left[\frac{w^N(f_O^C - f_V^N)}{\psi_O^C(z)-\psi_V^N(z)}\right]^{(1-\alpha)/\alpha}, \ \theta_V^C = Y^{(\alpha-\mu)/\alpha}\left[\frac{w^N(f_V^C - f_O^C)}{\psi_V^C(z)-\psi_O^C(z)}\right]^{(1-\alpha)/\alpha}. \quad (9)
\end{aligned}$$

Following Antràs and Helpman (2004), we assume $G(\theta)$ to be a Pareto distribution, i.e., $G(\theta) = 1 - \left(\frac{b}{\theta}\right)^a$ for $\theta \geq b > 0$, where a is large enough to ensure a finite variance of the size distribution of firms. The fraction of firms that choose organization form (k, l) denoted by σ_k^l, where k is the ownership structure and l is the location of M, is given by

$$\begin{aligned}
\sigma_O^N &= 1 - \left[\frac{\psi_V^N(z)-\psi_O^N(z)}{\psi_O^N(z)}\frac{f_O^N}{f_V^N - f_O^N}\right]^{a(1-\alpha)/\alpha}, \\
\sigma_V^N &= \left[\frac{\psi_V^N(z)-\psi_O^N(z)}{\psi_O^N(z)}\frac{f_O^N}{f_V^N - f_O^N}\right]^{a(1-\alpha)/\alpha} - \left[\frac{\psi_O^C(z)-\psi_V^N(z)}{\psi_O^N(z)}\frac{f_O^N}{f_O^C - f_V^N}\right]^{a(1-\alpha)/\alpha}, \\
\sigma_O^C &= \left[\frac{\psi_O^C(z)-\psi_V^N(z)}{\psi_O^N(z)}\frac{f_O^N}{f_O^C - f_V^N}\right]^{a(1-\alpha)/\alpha} - \left[\frac{\psi_V^C(z)-\psi_O^C(z)}{\psi_O^N(z)}\frac{f_O^N}{f_V^C - f_O^C}\right]^{a(1-\alpha)/\alpha}, \\
\sigma_V^C &= \left[\frac{\psi_V^C(z)-\psi_O^C(z)}{\psi_O^N(z)}\frac{f_O^N}{f_V^C - f_O^C}\right]^{a(1-\alpha)/\alpha}. \quad (10)
\end{aligned}$$

When a product matures, i.e. headquarters services intensity decreases and component intensity z increases, foreign outsourcing is favored relative to domestic outsourcing, and outsourcing is favored relative to integration. That is, the ratios $\psi_O^N(z)/\psi_O^C(z)$ and $\psi_V^l(z)/\psi_O^l(z)$ for $l = N, C$ decrease as the value of z increases. The change in the latter ratio reflects that outsourcing is more profitable when component intensity increases at any given location l. The change in the former ratio as z increases can be seen from (8). The only difference between $\psi_O^N(z)$ and $\psi_O^C(z)$ is the wage in the denominator. The larger z is, the larger is the difference. Since $\psi_O^N(z)$ is always smaller than $\psi_O^C(z)$, as z increases, the ratio $\psi_O^N(z)/\psi_O^C(z)$ decreases.

Given the changes in the two ratios with respect to z, the share of offshoring given by $\sigma_V^C + \sigma_O^C$ increases and σ_V^C/σ_O^C decreases with z. This also means that the share of FDI-based offshoring in total offshoring, $\sigma_V^C/(\sigma_V^C + \sigma_O^C)$, decreases as z increases. Hence, we have the following proposition

Proposition 1 *When a product matures and component intensity increases, the share of offshoring increases and the share of FDI-based offshoring in total offshoring decreases.*

In the next subsection, we describe the heterogeneous evolution of product cycles in North and South. We will explore this heterogeneity to guide our empirical estimation of organizational changes over product cycles.

2.3 Product Cycle

A crucial component of Vernon's (1966) product cycle theory is that as a good matures, it becomes more and more standardized. We follow Antràs (2005) in modeling this standardization process:

$$\begin{aligned} z_t &= f(t), with\ f'(t) > 0, \\ f(0) &= 0, \text{and } \lim_{t\to\infty} f(t) = 1. \end{aligned} \tag{11}$$

We differentiate four types of products in the model: (1) old or new products; and (2) products by final good producers from country N or country S. Old products refer to those with substantial standardization, i.e., $t \to \infty$ and $z_t \to 1$, whereas new products are assumed to follow the standardization process (11) over time, i.e., $z_t = f(t)$ for new products. Old products in N and S are assumed to share similar features, but the standardization processes of new products in N and S are different. Specifically, new products mature faster in N at early stages of the product cycle. Whereas at late stages of the product cycle new products mature faster in S. This pattern of product standardization process in N and S can be based on the literature on innovation diffusion (e.g., Trajtenberg and Yitzhaki, 1989; Hall and Kahn, 2003). We follow Xiang (2014) to assume that $z_t^N = f_N(t)$ to be first-order-statistically dominated by $z_t^S = f_S(t)$.

To illustrate this assumption, we provide an example for the variety diffusion process. There are multiple varieties of each product. And the product standardization process is a function of new varieties m_t available at each point in time, i.e., $f_N(t) = f(m_t^N)$, $f_S(t) = f(m_t^S)$. When a new product emerges in this world, North and South can immediately gain knowledge of the product and develop their own varieties over time. Let t be time, and m_t^N and m_t^S be measures of new varieties that have diffused to country N and country S by time t, respectively. The diffusion processes are assumed to be:

$$\ln m_t^N = F_N(t) \ln \bar{m};\ \ln m_t^S = F_S(t) \ln \bar{m} \tag{12}$$

where $\bar{m}$ is the equilibrium measure of varieties for this product; and $F_N(t)$ and $F_S(t)$ are cumulative distribution functions over time. The product cycle hypothesis is incorporated by assuming that $F_S(t)$ first-order statistically dominates $F_N(t)$, which means that the number of new varieties increases faster in country N in the early period of the product cycle, and country S catches up in the middle or later period, reaching the same final equilibrium number of total varieties. Product standardization is assumed to accelerate with more varieties, i.e., z is a monotonic increasing function of m, $z(m)' > 0$ and $z(m)'' > 0$.[9] Combined, $f_S(t)$ first-order *statistically* dominates $f_N(t)$.

[9] We can simply assume that product standardization is an exogenous function of time. With successful standardization, an increase in z is a Poisson arrival event for each variety-producing firm. Once the

2.4 Offshoring over the Product Cycle

We now derive the offshoring patterns for new and old products and final good producers from country N and country S in country C. We first consider the patterns for old products. As old products are standardized to a substantial extents (i.e., $z_t \to 1$), final good producers (from country N and country S) outsource all their component production to independent suppliers in country C. As a result, there is no significant difference between the FDI-based offshoring shares for producers of old products in N and S over time.

For new products, however, the optimal choice of offshoring structure depends on the standardization process defined in equation (11), which differs across country N and country S. As $f_N^{-1}(.)$ first-order statistically dominates $f_S^{-1}(.)$, a given product matures faster in country N than in country S. In the early stages, offshoring from country C is more attractive to final-good producers in N than to those in S. The fractions of offshoring firms and firms using contract-based offshoring increase first in country N, and lag in country S. In the middle stages, the product standardization process in country S catches up, causing producers in S to offshore more and use more contract-based offshoring. In the later stages, the speed of product maturation in S is greater than that in N, and relatively more contract-based offshoring is adopted in country S. Eventually, that the products are fully mature, and there is no significant difference in offshoring structures between N and S.

Denote $y = \sigma_V^C/(\sigma_V^C + \sigma_O^C)$ as the FDI-based offshoring share of total offshoring. For new products, over time the relative share of FDI-based offshoring in country N and to that in country S, y_{Nt}/y_{St}, follows a non-monotonic pattern. Specifically, we have the following proposition:

Proposition 2 *The relative share decreases in the early stages of the product cycle, when the speed of maturation is faster in country N. In the middle stages, the relative share of FDI-based offshoring decreases as the speed of product maturation catches up in country S. The relative share increases in the later stages, when the speed of product maturation is higher in country S. Finally, the relative share approaches a steady state when the product is fully mature.*

In our empirical exercise, we identify this pattern evolution of y using processing trade data from China. To capture the non-monotonic pattern, we will use nonparametric estimation and a third-order polynomial approximation (with first a concave decline, then a convex increase, and finally concavely approaching a steady state). We will also calculate the turning point from declining to increasing.

product is standardized for one variety, it immediately spills over to all existing varieties. With more varieties, there is naturally a higher probability of successful product standardization.

2.5 Offshoring over the Product Cycle with Contractibility

In this section, we extend the model to incorporate the possibility that a fraction of inputs can be contractible, and investigate how contractibility affects the choice of offshoring strategies over the product cycle. We then use the variations in relationship-specific investment intensity across industries (a measure constructed by Nunn (2007)) to test these predictions.

Denote γ as contractibility of different sectors. In the extreme case of perfect contractibility, when contract is complete, production costs (wage and fixed costs) are the only concern for final goods producers. Given offshoring, the trade-off between FDI-based and contract-based offshoring purely depends on the fixed costs of the two organizational choices. It is obvious that all firms will choose contract-based offshoring (conditional on the offshoring decision) as $\psi_V^C(z) = \psi_O^C(z)$ and $f_V^C > f_O^C$. As a result, in sectors with very high contractibility, we will not observe any change in the share of FDI-based offshoring $\sigma_V^C/(\sigma_V^C + \sigma_O^C)$ over time.

However, when contractibility is not high enough, it will have a role on the organizational choice across sectors. Contract incompleteness creates the incentive to motivate investments by final goods producers and component suppliers. Depending on which investments are more important for total quasi revenue, optimal organizational choice varies between integration and outsourcing. Specifically, when the product is less mature and the intensity of headquarters services is high, integration is preferred to outsourcing. As the product matures, investments by component suppliers become more important and outsourcing is thus preferred.

With better contractibility, for any given component intensity z, the difference between integration and outsourcing is mitigated, i.e., $\psi_V^C(z)$ is larger than $\psi_O^C(z)$ but the difference is smaller when contractibility is better. As a result, firms tend to choose more contract-based offshoring, as it involves lower fixed costs. As the product matures (i.e. z increases), outsourcing becomes increasingly preferred to integration for any given level of contractibility. Taken together, in sectors with higher contractibility, the FDI-offshoring share drops faster as the product matures. That is, the second-order derivative of the FDI-based offshoring share with respect to z and contractibility is negative:

$$\frac{\partial y}{\partial z} < 0, \ \frac{\partial^2 y}{\partial z \partial \gamma} < 0. \tag{13}$$

This immediately implies that the relative share of FDI-offshoring for final goods producers in countries N and S, y_{Nt}/y_{St}, drops more in sectors with higher contractibility γ.

Although equation (13) cannot be directly tested in the empirical framework, we examine the effect of contractibility γ on the turning point of the nonlinear evolution

pattern for the relative share of FDI-based offshoring, as elaborated in the previous section. At the turning point (denote as T), we have

$$\frac{\partial y_{Nt}/y_{St}}{\partial t} = 0 \Leftrightarrow \frac{\partial y_{Nt}}{\partial z_N}\frac{\partial z_N}{\partial t} y_{St} = y_{Nt}\frac{\partial y_{St}}{\partial z_S}\frac{\partial z_S}{\partial t}. \tag{14}$$

This holds for all turning points T across sectors, as the level contractibility has a symmetric effect on the derivatives $\frac{\partial y_{Nt}}{\partial z_N}$ and $\frac{\partial y_{St}}{\partial z_S}$. The reason is that contractibility changes the weight of the quasi revenue subject to bargaining in the total revenue function, inclusive of the optimal revenue generated from contractible activities. As a result, contractibility affects the trade-off between organizational choices proportionately, i.e., $\left.\frac{\partial y_{Nt}/\partial z_N}{\partial y_{St}/\partial z_S}\right|_{T_\gamma} = \left.\frac{\partial y_{Nt}/\partial z_N}{\partial y_{St}/\partial z_S}\right|_{T_{\gamma'}}$ for the two turning points T_γ and $T_{\gamma'}$ in two sectors with contractibility γ and γ', respectively. Equation (14) then implies

$$\left.\left(\frac{y_{Nt}}{y_{St}}\frac{\partial z_S/\partial t}{\partial z_N/\partial t}\right)\right|_{T_\gamma} = \left.\left(\frac{y_{Nt}}{y_{St}}\frac{\partial z_S/\partial t}{\partial z_N/\partial t}\right)\right|_{T_{\gamma'}}. \tag{15}$$

Notice that $y_{Nt} < y_{St}$ as the product matures faster in country N. From equation (13), the cumulative effect of a higher level of contractibility is that the relative magnitude of y_{Nt}/y_{St} is smaller than that in sectors with a lower level contractibility at the turning point, i.e., $(y_{Nt}/y_{St})|_{T_\gamma} < (y_{Nt}/y_{St})|_{T_{\gamma'}}$ for $\gamma > \gamma'$. As a result, the speed of product maturation in country S (relative to that in country N) needs to be large enough, i.e., $\left.\left(\frac{\partial z_S/\partial t}{\partial z_N/\partial t}\right)\right|_{T_\gamma} > \left.\left(\frac{\partial z_S/\partial t}{\partial z_N/\partial t}\right)\right|_{T_{\gamma'}}$. Hence, we have the following proposition

Proposition 3 *The turning point T appears later in sectors with a better level of contractibility.*

3 Estimation Strategy

3.1 Specification

Offshoring strategies in product j by foreign multinationals in China from country c can be summarized as follows. For new products, more productive foreign firms produce in their subsidiaries in China, while less productive ones outsource to companies in China. And when new products mature, the ratio of outsourcing in China increases as more foreign firms change from FDI-based offshoring to contract-based offshoring. Denote y_{jct} as the share of FDI-based offshoring over total offshoring in China in product j by foreign firms from country c in year t. Hence, $y_{jct} = g_c(t)$ is a decreasing function of t, where $j \in J_n$; and J_n is a set of new products. For old products, all foreign firms outsource in China; hence, $y_{jct} = 0$, where $j \in J_o$; and J_o is the set of old products.

Empirically, following a similar practice as Xiang (2014), we divide countries into two groups, the North and the South, and assume that the standardization process is the same for all new products within each country group, but differs across the two country groups. Specifically, we classify 61 countries with average GNI per capita in 1999-2000 exceeding \$10,000 to be in the North group (e.g., the U.S., the U.K.), and other 106 countries to be in the South group (e.g., Indonesia, most African countries).[10] Countries in the North and South groups are listed in Appendix Table A1. Using the same classification of North and South groups as in Xiang (2014) (i.e., countries with average per capita GDP in 1972-1996 exceeding \$7,000 are North and the rest is South) generates similar findings (results available upon request).

To control for other non-product cycle factors that may determine the choice of offshoring strategies, we conduct a DDD estimation. Specifically, we use the following estimation equation

$$y_{jct} = \boldsymbol{\beta} New_j \times North_c \times g(t) + \lambda_{jt} + \lambda_{ct} + \lambda_{jc} + \varepsilon_{jct}, \tag{16}$$

where j, c, and t represent product, country, and year, respectively; New_j indicates the new product; $North_c$ indicates the group of North countries; λ_{jt} is the product-time fixed effects, capturing product-specific, time-varying determinants of offshoring strategies on top of the product cycle theory; λ_{ct} is the country-time fixed effects, capturing country-specific, time-varying determinants of offshoring strategies on top of the product cycle theory; λ_{jc} is the product-country fixed effects, capturing product-country-specific, time-invariant determinants of offshoring strategies on top of the product cycle theory; and ε_{pct} is the i.i.d. error. Standard errors are clustered at the product level to deal with potential serial correlation and heteroskedasticity issues (see Bertrand, Duflo, and Mullainathan, 2004).

Our outcome, y_{jct}, concerns the ratio of FDI-based offshoring over total offshoring (including contract-based and FDI-based offshoring) by foreign multinationals from country c in product j in year t, and is denoted as *Share of the FDI-Based Offshoring.* We will introduce how to measure this outcome variable in detail in the next section.

$g(t)$ is a nonlinear function of time t, which reflects the evolutionary effects of the product cycle on the share of FDI-based offshoring. $\boldsymbol{\beta}$ are our parameters of interest, capturing the product cycle effects elaborated in the previous section. Specifically, according to our theoretical prediction, $g(t)$ decreases in the first stage of the product cycle because of the faster speed of maturation in country N than in country S; then, $g(t)$ slows down as the speed of product maturation catches up in country S; then, $g(t)$ increases when the speed of product maturation becomes higher in country S; and finally, $g(t)$ ap-

[10] To address concern about *round-trip* foreign investment, we also experiment with the exclusion of Hong Kong and Macau from the analysis.

proaches a steady state as the product is fully mature. To approximate this nonlinearity, we use a third-order time polynomial function, i.e.,

$$y_{jct} = \sum_{k=1}^{3} \boldsymbol{\beta}_k New_j \times North_c \times t^k + \lambda_{jt} + \lambda_{ct} + \lambda_{jc} + \varepsilon_{jct}. \tag{17}$$

And $\beta_1 < 0$, $\beta_2 > 0$, and $\beta_3 < 0$.

We also experiment with a nonparametric approximation of $g(t)$; that is, we replace $g(t)$ with year dummies, and hence the estimation equation becomes

$$y_{jct} = \sum_{t} \boldsymbol{\beta}_t New_j \times North_c \times \lambda_t + \lambda_{jt} + \lambda_{ct} + \lambda_{jc} + \varepsilon_{jct}, \tag{18}$$

where $\boldsymbol{\beta}_t$ is a vector of estimates corresponding to each year effect.

To illustrate our estimation strategy, consider the case of two products, old (o) and new (n), and two countries, North (N) and South (S). If we focus on the share of FDI-based offshoring for the new product from North, we have

$$E\left[y_{nNt}\right] = \boldsymbol{\beta} g_N(t) + \lambda_{nt} + \lambda_{Nt} + \lambda_{nN}. \tag{19}$$

Hence, other non-product cycle factors originated from the new product λ_{nt}, the country North λ_{Nt} and the product-North combination λ_{nN} biases the estimate of product-cycle effect $\boldsymbol{\beta} g_N(t)$ from $E\left[y_{nNt}\right]$.

To get rid of these non-product-cycle confounders, we add new products from South, and old products from North and South, i.e.,

$$\begin{aligned} E\left[y_{nSt}\right] &= \boldsymbol{\beta} g_S(t) + \lambda_{nt} + \lambda_{St} + \lambda_{nS} \\ E\left[y_{oNt}\right] &= \lambda_{ot} + \lambda_{Nt} + \lambda_{oN} \\ E\left[y_{oSt}\right] &= \lambda_{ot} + \lambda_{St} + \lambda_{oS}. \end{aligned} \tag{20}$$

Then we have

$$E\left[y_{nNt}\right] - E\left[y_{nSt}\right] = \boldsymbol{\beta} g(t) + (\lambda_{Nt} - \lambda_{St}) + (\lambda_{nN} - \lambda_{nS}), \tag{21}$$

where $g(t) \equiv g_N(t) - g_S(t)$; and

$$\left(E\left[y_{nNt}\right] - E\left[y_{nSt}\right]\right) - \left(E\left[y_{oNt}\right] - E\left[y_{oSt}\right]\right) = \boldsymbol{\beta} g(t) + \left[(\lambda_{nN} - \lambda_{nS}) + (\lambda_{oN} - \lambda_{oS})\right]. \tag{22}$$

Given $(\lambda_{nN} - \lambda_{nS}) + (\lambda_{oN} - \lambda_{oS})$ does not change over time, $\boldsymbol{\beta}$ can be identified by checking the time trends of $\left(E\left[y_{nNt}\right] - E\left[y_{nSt}\right]\right) - \left(E\left[y_{oNt}\right] - E\left[y_{oSt}\right]\right)$. In other words, the first difference between North and South for the new product in equation (21) helps remove all product-specific factors common to both countries. The second difference

in equation (22) uses the difference between North and South for the old product to condition out all country-specific factors (common to both products) in the first difference (21). Finally, the time variation in (22) helps us control for time-invariant differences in new and old products across North and South.

3.2 Data and Variables

Data.—Our empirical analysis combines three data sets. The first data set is a product list compiled by Xiang (2014) that classifies HS 10-digit products into the categories of new and old products. Specifically, Xiang (2014) matched newly produced products in the U.S. from 1972 to 1987 that are identified by Xiang (2005) at the SIC level to the HS 10-digit product categories contained in the imports data.[11] For more details on the matching and examples of new products, see the online Appendix in Xiang (2014). Xiang (2014) also discusses in detail the advantage of this method over the identification of new products through year-to-year changes in the numerical codes.

The second data set is a survey of FIEs in China, which was conducted by the National Bureau of Statistics of China in 2001. This is the most comprehensive survey of foreign multinationals in China, and it has around 150,000 observations, accounting for more than 75 percent of total foreign firms in China in 2001. Key to our research, this data set contains information on origin countries of foreign firms.

The third data set is China's customs data, from 2001 to 2013. The data set is at the firm-product-destination-year level, covering the universe of all import and export transactions by Chinese exporters and importers. The customs data include product information (at the HS 8-digit level), trade value, identity of Chinese importers and exporters, and import and export destinations.

New and Old Products.—As the HS coding systems in the U.S. and China are only comparable at the HS 6-digit level, we first match the first and third data sets at the HS 6-digit level, and then classify each HS 6-digit product category into new or old products. However, one concern with the binary classification of new/old products at the HS 6-digit level is that our list of new products may be over-sampled—e.g., an HS 6-digit new product might consist of mostly HS 10-digit old products and few HS 10-digit new products, which would lead to an underestimation of our product cycle effects. To address this concern, we use the percentage of HS 10-digit new products within an HS 6-digit product category as the measurement of new products at the HS 6-digit level.

Appendix Table A2 provides some examples of new and old products at the HS 6-digit level. Examples of new products listed are HS 6-digit products with 100 percent of HS 10-digit new products, such as "Textured yarn nes, nylon, polyamide <50dtex not retail",

[11] Using the classification of new/old products at the SIC level produces similar results (available upon request).

"Artificial flowers foliage fruit, articles, plastic", "Laboratory, hygienic or pharmaceutical glassware", "Microfilm, microfiche or other microform readers", etc. Examples of old products are HS 6-digit products without any new HS 10-digit new products, such as "Potatoes seed, fresh or chilled", "Silica sands and quartz sands", "Float glass etc sheets, absorbent or reflecting layer", etc. In the baseline estimation, we focus on a sample of products that existed in the first year of our sample period, to alleviate the concern that product entry may drive and hence complicate the explanation of our estimates. In a robustness check, we include all newly entered products during the sample period.

Another concern with the new/old products measurement is that the list compiled by Xiang (2014) essentially identifies products that were newly developed in the 1980s, around two decades earlier than our analysis period. This raises questions about whether the new products have already matured into old ones.[12] However, as our model in Section 2 and Antràs (2005) show that when new products are developed, firms first conduct production in their home country. Production is reallocated to the South once the product matures to a certain degree. Moreover, case studies in Antràs (2005) show that it takes around 18 years for a new product to mature enough for firms to reallocate their production to the South countries, which fits the timeline of our research setting. In other words, our sample period starts around the time when the new products identified by Xiang (2014) became mature enough that foreign multinationals started to offshore in China, which then enables us to investigate the effects of the product cycle on offshoring structures using the data in China.

Country Identity of Foreign Multinationals.—For our empirical analysis, we need to know the home country identity of each foreign multinational. Such information is missing in the Chinese customs data, but it is contained in the survey of FIEs data. Hence, we need to match the two data sets. Of the firms in the FIE data, 63.74 percent correctly reported their 10-digit customs identity code, which can be used to link to firms in the Chinese customs data. The remaining firms in the FIE data did not report customs identity codes or reported the wrong code. We then use all available firm information (such as firm names, name of representative persons, telephone number, and firm address) to match firms in the two data sets. In the end, we have around 80 percent of foreign multinationals in the Chinese customs data matched to firms in the FIE data, and obtain their home country identity.[13]

Offshoring Measurement.—To measure the share of FDI-based offshoring by foreign

[12] A related concern is that new products may remain as new given the new innovations in these products. Our estimation framework remains valid as long as some of the new products become mature over time. In particular, with the existence of some new products not maturing over time, our estimates represent a lower bound of the product cycle effects.

[13] Since the FIE data are for one year, our analysis essentially tracks the outsourcing behavior by foreign firms existing in 2001 over the next decade.

multinationals in China, we use a unique feature of China's trade system, the processing trade regime. When China adopted the "reform and opening" policy in 1978, it wanted to open its economy to attract new investment and technologies, but it also worried about the vulnerability of its already fragile domestic economy to foreign competition. As a compromise, China only allowed import-processing firms (mostly foreign invested firms in China) to import materials free of tariffs and export all their outputs, the so-called processing trade regime. There are two types of processing trade, the pure-assembly regime and the import-and-assembly regime.[14] Under the pure-assembly regime, a factory in China receives orders from, imports the materials supplied by, and delivers the processed outputs to its foreign client. Under the import-and-assembly regime, a factory in China imports materials from foreign suppliers and sells the processed outputs to foreign clients, both on its own account. Processing factories in China can be foreign-owned or indigenous. For more discussion on the processing trade regime in China, see Feenstra and Hanson (2005), Fernandes and Tang (2012), and Yu (2015).

The specific features of the processing trade regime provide us with the opportunity to measure the offshoring outcomes by foreign multinationals in China. First, the share of FDI-based offshoring by foreign multinationals in a product category hinges on the size distribution of the firms, specifically, the distribution of productivity in the theoretical model and the distribution of total output in the empirical analysis (e.g., Helpman, Melitz, and Yeaple, 2004). Ordinary traders can sell output in the domestic market and also export to foreign markets, the former of which is not available in the data. As processing traders are required to export all their output, we can infer their total output from export values contained in the customs data. Second, processing trade accounted for about 57 percent of China's total exports and over 80 percent of exports by foreign invested firms in China in 2005. As our study focuses on the offshoring of foreign firms in China, using the sample of processing traders allows us to capture the overall behavior of foreign firms.

One way to measure the share of FDI-based offshoring by foreign firms in China is to follow the measurement used in the literature (e.g., Feenstra and Hanson, 2005; Fernandes and Tang, 2012). Specifically, the case of a processing factory in China being foreign-owned is considered as the FDI-based offshoring scenario; the case of a Chinese domestic processing factory is assigned as the contract-based offshoring scenario. Then, we can calculate

$$y^1_{jct} = \frac{Processing\ Export^F_{jct}}{Processing\ Export^F_{jct} + Processing\ Export^D_{jct}}, \tag{23}$$

[14] In China's customs data, pure assembly trade is coded as "Processing and assembling" and the import-and-assembly trade is coded as "Processing with imported materials." There are other types of processing trade regimes coded in the data, but they account for a very small portion of total trade.

where $Processing\ Export^F_{jct}$ is the total exports by foreign-owned processing firms from country c in product j at time t; and $Processing\ Export^D_{jct}$ is the total exports by Chinese domestic processing firms. However, a concern with this measurement is that foreign multinationals may outsource assembly to processing factories owned by other foreign multinationals in China. For example, Foxconn, a Taiwanese multinational in China, conducts extensive processing trade for Apple, which is a U.S. company. To alleviate this concern, we use the advantage of our merged data, which contain information on the home country identity of foreign multinationals and their import sourcing countries. We refine the measurement (23) by assigning only imports from the home country of foreign multinationals as the case of FDI-based offshoring. Specifically, we use the following variable as our outcome

$$y^2_{jct} = \frac{Processing\ Export^F_{jct} \times share^F_{jct}}{Processing\ Export^F_{jct} + Processing\ Export^D_{jct}}, \tag{24}$$

where $share^F_{jct}$ is the share of imports from the home country c of foreign multinationals. We further discuss the potential measurement error with this refined measure of the degree of FDI-based offshoring by foreign multinationals in the next subsection.

Contractibility.—We use the contractibility index constructed by Nunn (2007). Specifically, Nunn uses data from Rauch (1999), who classifies goods into three groups: goods traded on an organized exchange, goods that are reference priced in a trade publication, and goods that are neither sold on an exchange nor reference priced. Nunn considers intermediate inputs that are neither sold on an organized exchange nor reference priced as relationship-specific, and then constructs a weighted average for each final goods with the weight being the proportion of each input in the production of good. Nunn (2007) aggregates each 4-digit SITC industry in Rauch's (1999) original classification to Bureau of Economic Analysis (BEA) I-O industry classification of NAICS 1997 using the concordance table from the BEA in the U.S. For estimation, we match the BEA's I–O industry level to the HS 10-digit product level and then aggregate the HS 10-digit data to the HS 6-digit data using the concordance table from the BEA.

3.3 Identification Issues

Our identification requires that conditional on all the fixed effects, the error term is uncorrelated with our regressor of interest, i.e., $cov\left[New_j \times North_c \times g(t), \varepsilon_{jct} | \lambda_{jt}, \lambda_{ct}, \lambda_{jc}\right] = 0$ in the baseline equation (17). There are two possible threats to this identifying assumption—measurement errors associated with y_{jct} and omitted variables.

Measurement Errors Problem.—To alleviate the concern that foreign multinationals may outsource assembly to processing factories owned by other foreign multinationals in

China, we only consider imports from the home country of the foreign multinationals in constructing our outcome in equation (24). However, there may still be a concern that this measurement is biased; specifically, foreign multinationals may outsource to other foreign multinationals from the same origin country in China. Specifically, denote $\tilde{y}_{jct}$ as the true measure of the degree of FDI-based offshoring by foreign multinationals from country c in product j in year t. We then have

$$y^2_{jct} = \tilde{y}_{jct} + m_{jct}, \tag{25}$$

where m_{jct} denotes the measurement error. Accordingly, our baseline estimation specification (17) becomes

$$y^2_{jct} = \sum_{k=1}^{3} \boldsymbol{\beta}_k New_j \times North_c \times t^k + \lambda_{jt} + \lambda_{ct} + \lambda_{jc} + m_{jct} + \varepsilon_{jct}. \tag{26}$$

Note that the use of outsourcing to other foreign-owned processing factories from the same home country in China may largely be country-specific, in which case our inclusion of the country-time fixed effects λ_{ct} in equation (16) has well taken care of this issue. If this strategy is similar in the same product category, the measurement problem has been addressed by the product-time fixed effects λ_{jt} in equation (16). Meanwhile, if this strategy is country-product specific but does not change frequently over time (i.e., across years), the measurement problem is also controlled by the country-product fixed effects λ_{jc} in equation (16). In other words, let

$$m_{jct} \equiv m_{ct} + m_{jt} + m_{jc} + \tilde{m}_{jct}, \tag{27}$$

where m_{ct} captures the country-specific use of outsourcing to other foreign processing factories from the same home country; m_{jt} reflects the product-specific use of this outsourcing strategy; m_{jc} captures the time-invariant country-product-specific adoption of this outsourcing strategy; and $\tilde{m}_{jct}$ is the remaining measurement error, varying at the country, product, and time levels simultaneously.

There may still be a concern that $\tilde{m}_{jct}$ is correlated with our regressors of interest (i.e., $New_j \times North_c \times t^k$, and $k = 1, 2, 3$) in the estimation, consequently biasing our estimates. That is, outsourcing to other foreign multinationals in China from the same home country varies with country across products and time. Denote the conditional correlation between $\tilde{m}_{jct}$ and $New_j \times North_c \times t^k$ as ρ^k, i.e., $\rho_k \equiv \frac{cov\left(New_j \times North_c \times t^k, \tilde{m}_{jct}\right)}{var\left(New_j \times North_c \times t^k\right)}$. As elaborated in section 3.1, the product cycle effects imply that $\beta_1 < 0$, $\beta_2 > 0$, and $\beta_3 < 0$. Hence, if our estimates of $\boldsymbol{\beta}_k$ were entirely caused by measurement error, we should have $\hat{\boldsymbol{\beta}}_k = \rho_k$ such that $\rho_1 < 0$, $\rho_2 > 0$ and $\rho_3 < 0$. To examine whether this hypothetical case indeed occurs, we acknowledge the scenario that imports by foreign

multinationals in China from country other than their home countries do not represent intra-firm trade, and the use of such imports to construct the measure of the share of FDI-based offshoring reflects only the measurement error $\tilde{m}_{jct}$. To this end, we construct another outcome

$$y^m_{jct} = \frac{Processing\ Export^F_{jct} \times oshare^F_{jct}}{Processing\ Export^F_{jct} + Processing\ Export^D_{jct}}, \tag{28}$$

where $oshare^F_{jct}$ is the share of imports by foreign multinationals from countries other than their home country. We re-estimate equation (17) with the replacement of y_{jct} by y^m_{jct}, i.e.,

$$y^m_{jct} = \sum_{k=1}^{3} \boldsymbol{\beta}^m_k New_j \times North_c \times t^k + \lambda_{jt} + \lambda_{ct} + \lambda_{jc} + \varepsilon_{jct}. \tag{29}$$

Given that y^m_{jct} only reflects measurement error $\tilde{m}_{jct}$, we have $\hat{\boldsymbol{\beta}}^m_k = \rho_k$, which allows us to test how our estimates of $\boldsymbol{\beta}_k$ are biased due to the existence of $\tilde{m}_{jct}$.

Omitted Variables Bias.—Even with the inclusion of flexible fixed effects, there could still exist some omitted variables (that vary at the country-product-year level) in our DDD estimation. One example is the tariff rate; that is, China's different trading partners charge different product tariffs in different years.[15] To address this concern, we add the country-product-year specific tariff rate in the analysis.

It is also possible that other industry characteristics, such as R&D intensity and skill intensity, are generating the differential time-varying effects on the share of FDI-based offshoring between North and South countries, thereby biasing our estimates. To address this concern, we include the interaction among $North_c$, λ_t (year fixed effects), and R&D intensity (measured as the average ratio of R&D investment to value added in 2003-2005 at the 4-digit industry level), and the interaction among $North_c$, λ_t, and skill intensity (measured as the ratio of high-skilled employment at the 4-digit industry level in 2004; adopted from Fernandes and Tang, 2012). Meanwhile, improvement in the production efficiency of domestic firms relative to foreign firms over time and/or the liberalization of FDI policies in China that incentivize foreign firms relative to domestic ones can also generate the time path of the share of FDI-based offshoring without relevance to the product cycle effects. To address this concern, we include the interaction among $North_c$, λ_t, and relative TFP (measured as the relative ratio of the average TFP by foreign firms over that of domestic firms at the 4-digit industry level in 1998-2000).[16]

Moreover, there were large changes in the availability of suppliers and industry com-

[15] Since Chinese product tariffs do not discriminate across foreign countries, they have been controlled for by product-year fixed effects.

[16] Ideally, we want to include a time-varying, industry-level relative measure TFP. However, the Chinese surveys of manufacturing firms (the so-called above-scale firm data) can only measure firm TFP up to 2007, while our analysis sample is from 2001 to 2013.

position in China during our sample period. These might in turn affect the choice of outsourcing versus insourcing by foreign multinationals in China, even without product cycle effects. Note that we include product-time fixed effects in all the regressions, which effectively control for all changes over time at the product level (and the industry level). Nonetheless, to incorporate the possibility that these industry changes may affect North and South countries differently, we include two additional controls; that is, the interaction between $North_c$ and the time-varying number of suppliers at the 4-digit industry level, and the interaction between $North_c$ and the time-varying 4-digit industry capital-labor ratio (reflecting the changes in the composition of capital and labor at the industry level).

North and South countries tend to specialize in different types of products, given their comparative advantage. For example, North countries usually produce more capital-intensive products in which FDI and vertical integration are more prevalent, while South countries have comparative advantage in producing labor-intensive goods where outsourcing has dominance (Antràs, 2003). Note that these country-specific production patterns have been controlled for by the inclusion of country-year fixed effects; essentially, our estimates come from the comparison of new and old products over time from the same country. Nonetheless, to alleviate the concern that country-specific comparative advantage may interact with new/old product features, we further include two controls; that is, the interaction between New_j and the time-varying country capital-labor ratio, and the interaction between New_j and the time-varying degree of country development (captured by the GDP per capita).

Finally, anecdotal evidence shows that the geographic distribution of Chinese exporters is highly uneven in some industries (for example, clustering in the coastal regions instead of inland cities), and such geographic patterns may also be different for foreign firms. These differential geographic clustering patterns may raise concern about whether our estimates are biased due to the geographic location of firms. To address this concern, we divide the sample into two—firms from coastal regions and those from inland cities—and examine whether our results are robust to the two samples.[17] However, as our processing firms were overwhelmingly located in the coastal regions (i.e., 96 percent of the firms located in the coastal areas), we are unable to obtain stable estimates in the sample of inland cities, due to the large number of regressors and small sample size. Hence, we report the estimates from the coastal regions sample, and compare them with those from the full sample.

A Further Look and Placebo Test.—Here we take a closer look at the identification

[17] Ideally, we can construct the share of FDI-based offshoring at the product-city-country-year level, and run a regression with a four-dimension interaction term being the regressor of interest and the three-dimension interaction fixed effects as controls (i.e., product-city-country fixed effects, product-city-year fixed effects, etc). However, in such an extremely large sample with an extremely large number of regressors, we cannot obtain estimates because of the computational capacity constraint.

issue. Specifically, let $\varepsilon_{jct} = \gamma\omega_{jct} + \upsilon_{jct}$, where ω_{jct} captures all the omitted variables and measurement errors; and υ_{jct} is the uncorrelated error. Estimation equation (17) becomes

$$y^2_{jct} = \sum_{k=1}^{3} \boldsymbol{\beta}_k New_j \times North_c \times t^k + \lambda_{jt} + \lambda_{ct} + \lambda_{jc} + \gamma\omega_{jct} + \upsilon_{jct}, \tag{30}$$

and our estimator $\hat{\boldsymbol{\beta}}_k$ is

$$plim\ \hat{\boldsymbol{\beta}}_k = \boldsymbol{\beta}_k + \gamma\boldsymbol{\delta}, \tag{31}$$

where $\boldsymbol{\delta} \equiv \frac{cov\left(New_j \times North_c \times t^k, \omega_{jct}\right)}{var\left(New_j \times North_c \times t^k\right)}$. And $\hat{\boldsymbol{\beta}}_k \neq \boldsymbol{\beta}_k$ if $\gamma\boldsymbol{\delta} \neq 0$.

As a further check on this identifying issue, we conduct a placebo test, following Hanson and Xiang (2004) and Xiang (2014). Specifically, we randomly divide products into new or old product categories, and generate a *false* new product indicator, New_j^{false}. The randomization ensures that New_j^{false} should not have any product cycle effect on the organization of foreign multinationals, i.e., $\boldsymbol{\beta}_k^{false} = 0$; hence, if our DDD estimation is correctly specified (which implies $\gamma\boldsymbol{\delta} = 0$), we shall have $\hat{\boldsymbol{\beta}}_k^{false} = 0$. We conduct this random data-generating process 500 times to avoid contamination by any rare events (e.g., $\hat{\boldsymbol{\beta}}_k^{false} \neq 0$).

4 Empirical Findings

4.1 Baseline Results

We first estimate the time effects of $g(t)$ nonparametrically via equation (18). The estimated yearly coefficients are plotted in Figure 1. The coefficients decline sharply first, then slow down, and finally bottom up. This pattern confirms the product cycle argument of global sourcing proposed by Antràs (2005) and further developed in section 2. That is, in the early stage of the product cycle, as maturation speed is faster in the North than in the South, the estimated effects (which capture the difference in the shares of FDI-based offshoring between multinationals in the North and South) decrease; in the middle stages, when the product maturation speed catches up in the South, the decline in the estimated effects slows down; and in the later stages, when the product maturation speed is higher in the South than in the North, the estimated coefficients start to increase.

[Insert Figure 1 Here]

Table 1 presents the parametric estimation via the equation (17). From columns 1 to 5, we stepwisely include controls to address various omitted variables concerns elaborated in section 3.3. Specifically, three industry controls (R&D intensity, skill intensity, and TFP of foreign multinationals relative to domestic firms) in column 1 address the concern

that omitted industry characteristics may generate time-varying effects on the offshoring choices across countries; two additional industry controls in column 2 (number of suppliers and capital-labor ratio) address the concern that large changes of industry composition in China may generate differential effects across countries; country capital-labor ratio and GDP per capita in columns 3 and 4 address the concern that the country comparative advantage due to factor endowment and economic development may cause countries to specialize in different products; and export tariffs in column 5 address the concern that the use of exports in constructing the outcome may be affected by external tariffs.

[Insert Table 1 Here]

Across the specifications, we consistently find that $New_j \times North_c \times t$ is negative and statistically significant; $New_j \times North_c \times t^2$ is positive and statistically significant; and $New_j \times North_c \times t^3$ is negative and statistically significant. Figure 2 plots the time trend of the effects based on the estimates in the last column in Table 1. Similar to Figure 1, there is a concave decline in the first phase, confirming that the speed of decrease slows down over time; and then there is a transition to an increasing trend that eventually stabilizes, consistent with the catching up by the South at the late stage of product maturation. Meanwhile, we calculate that the turning point from decline to increase is at 4.13, implying that after conducting business in China for about four years, outsourcing by South multinationals catches up with that by North multinationals.

[Insert Figure 2 Here]

4.2 Robustness Checks

In this subsection, we present a battery of further robustness checks on our aforementioned estimation results.

Inclusion of Newly Entered Products.—Our baseline analyses focus on products that existed in the beginning of the sample period, to alleviate the concern about product entry. As a robustness check, we use all the products in the data, including product that entered during the sample period. The estimation results are reported in Table 2, column 1. Clearly, we find similar estimates, suggesting that product entry does not bias our estimates.

[Insert Table 2 Here]

Exclusion of Multinationals from Hong Kong and Macau.—To alleviate the concern that *round-trip* FDI may drive our findings, we exclude multinationals from Hong Kong and Macau in column 2 in Table 2. We find consistent results.

Exclusion of State-owned Enterprises (SOEs).—SOEs in China may have different incentives to conduct processing trade and different management practices, which may then affect the construction of our outcome variable. To alleviate the concern that our estimates are caused by the changing behavior of SOEs, we exclude them from the analysis. The estimates in column 3 in Table 2 show that our results remain robust to the sample without SOEs.

Coastal Regions Sample.—The distributions of industry activities as well as foreign ownership are uneven in China, with most concentrated in the coastal regions. To check whether our findings are generated by such geographic patterns of production in China, we intended to compare the estimates from coastal regions and inland places. However, as 96 percent of processing firms were located in the coastal areas, we were unable to obtain stable estimates in the sample of inland cities, due to the large number of regressors and small sample size. Alternatively, we focus on the sample of coastal regions and compare the estimates with the full sample. As shown in column 4 in Table 2, the estimates from the coastal regions sample have the same pattern as those from the full sample (i.e., column 5 in Table 1), and their magnitudes are quite close, implying the robustness of our findings.

A Further Check on the Measurement Error.—To further examine the measurement error associated with our outcome due to the missing information on intra-firm trade, we conduct an exercise elaborated in section 3.3. That is, we use an alternative outcome that is known to carry only the measurement error of the FDI-based offshoring share, and examine whether its overall time pattern can fully explain our observed product cycle effects in Table 1. The estimates are reported in column 5 in Table 2. Interestingly, we find that the coefficients are just the opposite to our main estimates in Table 1; that is, the estimated coefficients for this mismeasured FDI-based offshoring share are positive in the interaction of t, negative in the interaction of t^2, and positive in the interaction of t^3. Note that our expected product cycle effects are negative in the interaction of t, positive in the interaction of t^2 and negative in the interaction of t^3, consistent with the estimates in Table 1. These results suggest that the existence of potential measurement error associated with our outcome may generate an underestimation of the product cycle effects.

A Placebo Test.—As a further check, we conduct a placebo test by randomizing the designation of new and old products. If our results are mostly explained by the misclassification of global sourcing strategies and other confounding factors, instead of the product cycle effect, we should expect similar negative and statistically significant effects for these randomized samples. We ran the randomization 500 times, and report the average and standard deviation of the 500 estimates in column 6, Table 2. The average of our

estimate of interest is found to be close to zero and highly insignificant, suggesting that our estimates are not driven by the misclassification of offshoring strategies and other confounding factors. Meanwhile, the standard deviation of the 500 estimates is similar to the estimated standard errors of our parameters of interest in Table 1, lending support to the confidence in the calculated standard errors.

4.3 Product Cycle and Contractibility

To examine the differential product cycle effects with industry contractibility, we first use the contractibility index constructed by Nunn (2007) (details are explained in section 3.2), and then divide the sample into three quantiles based on this contractibility index, i.e., industries with high, medium, and low contractibility.

The estimation results are reported in Table 3. We find that the estimates for industries with high contractibility are statistically insignificant and small in magnitude. These results are consistent with the argument that when contracts are (almost) complete, ownership structure does not matter, and, hence, we do not observe product cycle effects. The estimates for industries with medium and low contractibility are significant and have similar patterns as our main results. Based on these estimates, we calculate that the turning point for medium contractibility is 6.06, and that for low contractibility is 4, which confirms the prediction derived in section 2.5 that the turning point appears later when contractibility is better.

[Insert Table 3 Here]

Figure 3 reports the time trend of effects for industries with medium and low contractibility, respectively, based on the estimates in columns 2 and 3 in Table 3. First, the overall trends are similar to that in Figure 2, further confirming the product cycle effects laid out by Antràs (2005) and in section 2. Second, the turning point from decreasing to increasing appears earlier in the low contractibility scenario than that in the medium contractibility scenario, confirming the prediction in Section 2.5.

[Insert Figure 3 Here]

5 Conclusion

In this paper, we investigate the global sourcing pattern of foreign firms over the product cycle. Using data on processing firms in China, we measure foreign firms' offshoring modes in China. Using product-level trade data and a classification of new/old products, we then investigate foreign multinationals' sourcing strategies over the product cycle. We find strong support for the predictions in Antràs (2005) that when a product matures,

foreign multinationals in China start to outsource more of their manufacturing to external suppliers.

While Antràs (2005) and Antràs and Helpman (2004) assume a setting in which contracts are not ex post enforceable, we extend the framework to incorporate the possibility that a fraction of components is contractible, following the framework by Antràs and Helpman (2008). We confirm a similar sourcing pattern in this partially contractible framework, and further show that when contractibility is better, international outsourcing appears earlier along the product cycle. We test and confirm this prediction using variations in the intensity of relationship-specific investment across industries, following Nunn (2007).

Multinational firms' sourcing strategy, i.e., the organization of production, is an important and comprehensive problem. We believe our results can help researchers and practitioners better understand this problem, by describing the role of the product cycle and contractibility. Other factors that might affect sourcing strategies, such as the demand elasticity for different products, may be investigated in future research.

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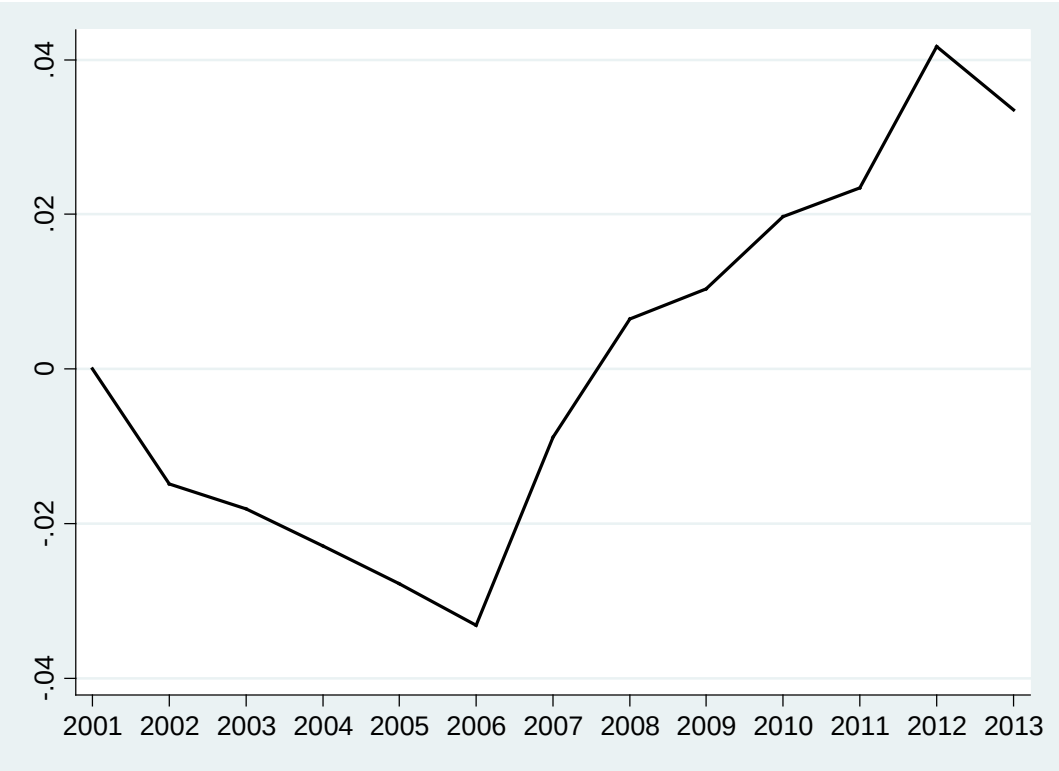
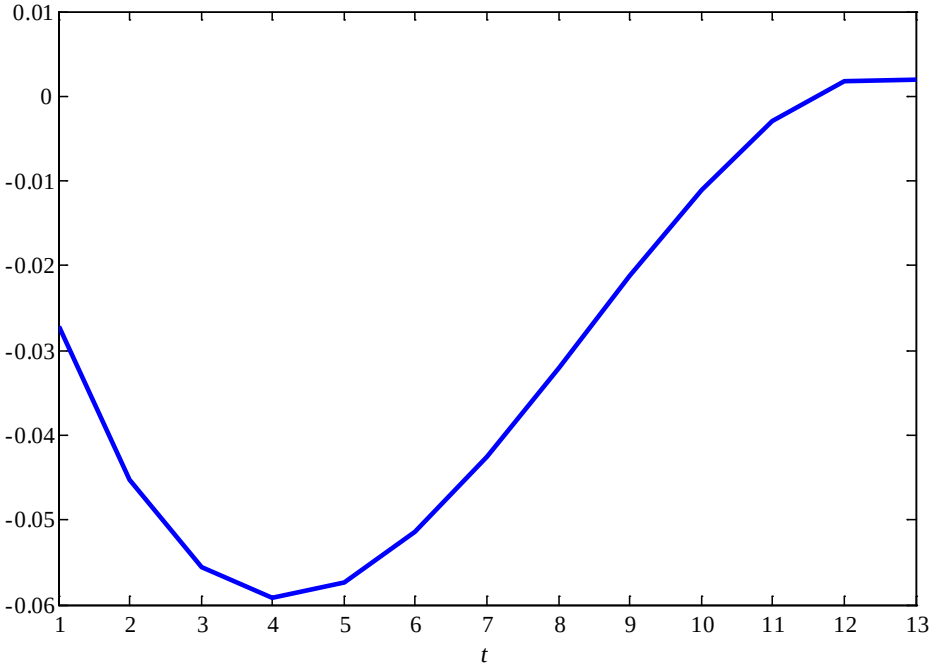
Figure 1 Nonparametric estimation



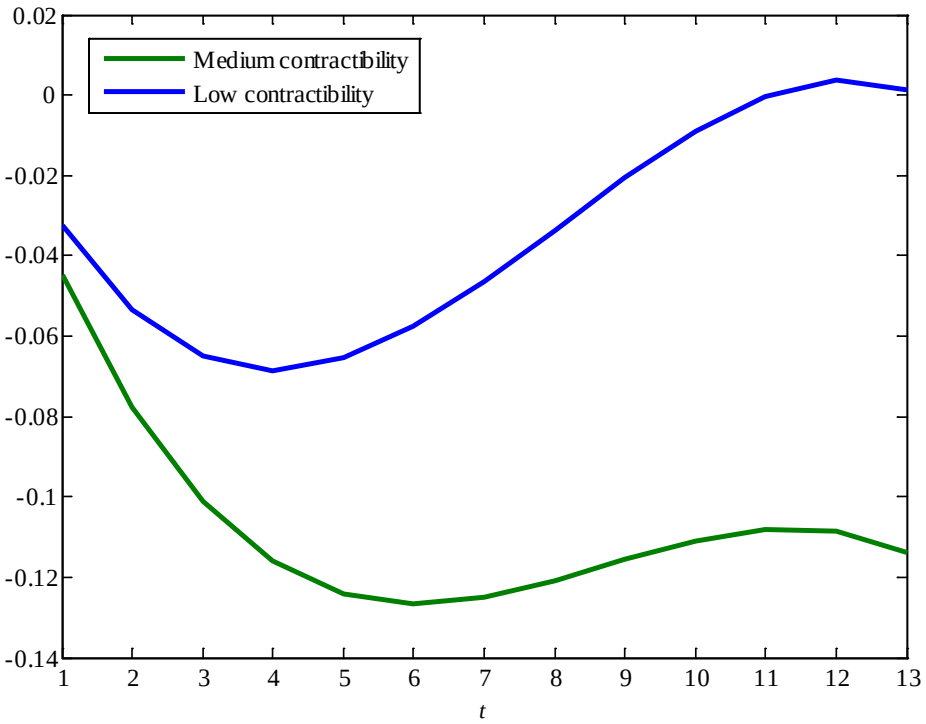
Note: This figure plots the estimated yearly coefficients from 2001-2013 using equation (19) in the text.

Figure 2 Parametric estimation



Note: This figure plots the time trend of the effects using the estimates in column (5) in Table 1.

Figure 3 Product Cycle and Contractibility



Note: This figure plots the time trend of effects for industries with medium and low contractibility, respectively, based on the estimates in columns 2 and 3 in Table 3.

Table 1 Main results

	R&D intensity, skill intensity, and TFP ratio	# suppliers, and industry composition	Factor endowment	GDP per capita	Tariffs
Dependent variable: share of FDI-based offshoring	(1)	(2)	(3)	(4)	(5)
New × *North* × t	−0.0252**	−0.0248**	−0.0259**	−0.0278***	−0.0322***
	(0.0101)	(0.00995)	(0.0104)	(0.0103)	(0.0110)
New × *North* × t^2	0.00405***	0.00391***	0.00408**	0.00452***	0.00518***
	(0.00150)	(0.00152)	(0.00161)	(0.00156)	(0.00166)
New × *North* × t^3	−0.000163***	−0.000154**	−0.000160**	−0.000179***	−0.000207***
	(0.0000627)	(0.0000640)	(0.0000677)	(0.0000646)	(0.0000689)
T	4.15	4.23	4.22	4.05	4.13
Product-year fixed effects	X	X	X	X	X
Country-year fixed effects	X	X	X	X	X
Product-country fixed effects	X	X	X	X	X
R&D intensity × *North* × Year dummies	X	X	X	X	X
Skill intensity × *North* × Year dummies	X	X	X	X	X
TFP ratio × *North* × Year dummies	X	X	X	X	X
log (# suppliers) × *North*		X	X	X	X
Industry composition × *North*		X	X	X	X
New × log K/L			X	X	X
New × log GDPpc				X	X
Tariffs					X
Observations	234,048	232,948	231,052	231,052	209,964

Note: Dependent variable is the share of FDI-based offshoring. *New* is measured as the percentage of HS 10-digit new products within an HS 6-digit product category. *North* is a dummy for north country. T is the turning point from declining to increasing in the share of FDI-based offshoring. R&D intensity is measured as the average ratio of R&D investment to value added of each industry. Skill intensity is measured as the ratio of high-skilled employment of each industry. TFP ratio is measured as the relative ratio of the average TFP by foreign firms over that of domestic firms of each industry. # suppliers is measured as the number of suppliers of each industry. Industry composition is measured as the composition of capital and labor of each industry. K/L is measured as the capital-labor ratio of each country. GDPpc is measured as the GDP per capita of each country. Tariffs is a control for export tariffs. The regressions are weighted by total exports in each product. Standard errors are clustered at the product level. ***, ** and * denote significance at the 1, 5 and 10% level respectively.

Table 2 Robustness checks

	Newly entered products included	Hong Kong and Macao included	SOEs excluded	Coastal	Measurement error	Placebo test
Dependent variable: share of FDI-based offshoring	(1)	(2)	(3)	(4)	(5)	(6)
New × *North* × t	−0.0310***	−0.0292***	−0.0429*	−0.0295***	0.0874**	0.0004
	(0.0110)	(0.0101)	(0.0239)	(0.0112)	(0.0422)	(0.0147)
New × *North* × t^2	0.00500***	0.00479***	0.00679**	0.00485***	−0.0121*	−0.00011
	(0.00166)	(0.00152)	(0.00342)	(0.00169)	(0.00696)	(0.00227)
New × *North* × t^3	−0.000199***	−0.000191***	−0.000260*	−0.000194***	0.000488*	0.000006
	(0.0000683)	(0.0000633)	(0.000138)	(0.0000703)	(0.000291)	(0.000096)
T	4.11	4.01	4.15	4.00	–	–
Product-year fixed effects	X	X	X	X	X	X
Country-year fixed effects	X	X	X	X	X	X
Product-country fixed effects	X	X	X	X	X	X
R&D intensity × *North* × Year dummies	X	X	X	X	X	X
Skill intensity × *North* × Year dummies	X	X	X	X	X	X
TFP ratio × *North* × Year dummies	X	X	X	X	X	X
log (number of suppliers) × *North*	X	X	X	X	X	X
Industry composition × *North*	X	X	X	X	X	X
New × log (K/L)	X	X	X	X	X	X
New × log GDPpc	X	X	X	X	X	X
Tariffs	X	X	X	X	X	X
Observations	215,440	243,269	156,653	206,672	209,964	209,964

Note: Dependent variable is the share of FDI-based offshoring. *New* is measured as the percentage of HS 10-digit new products within an HS 6-digit product category. *North* is a dummy for north country. *T* is the turning point from declining to increasing in the share of FDI-based offshoring. R&D intensity is measured as the average ratio of R&D investment to value added of each industry. Skill intensity is measured as the ratio of high-skilled employment of each industry. TFP ratio is measured as the relative ratio of the average TFP by foreign firms over that of domestic firms of each industry. # suppliers is measured as the number of suppliers of each industry. Industry composition is measured as the composition of capital and labor of each industry. K/L is measured as the capital-labor ratio of each country. GDPpc is measured as the GDP per capita of each country. Tariffs is a control for export tariffs. The regressions are weighted by total exports in each product. Standard errors are clustered at the product level. ***, ** and * denote significance at the 1, 5 and 10% level respectively.

Table 3 Heterogeneous effects across contractibility

	High contractibility	Medium contractibility	Low contractibility
Dependent variable: share of FDI-based offshoring	(1)	(2)	(3)
New × *North* × t	0.0148	−0.0508*	−0.0385***
	(0.0203)	(0.0265)	(0.0140)
New × *North* × t^2	−0.00183	0.00642*	0.00640***
	(0.00350)	(0.00365)	(0.00221)
New × *North* × t^3	0.0000816	−0.000245*	−0.000264***
	(0.000135)	(0.000145)	(0.0000935)
T	−	6.06	4.00
Product-year fixed effects	X	X	X
Country-year fixed effects	X	X	X
Product-country fixed effects	X	X	X
R&D intensity × *North* × Year dummies	X	X	X
Skill intensity × *North* × Year dummies	X	X	X
TFP ratio × *North* × Year dummies	X	X	X
log (number of suppliers) × *North*	X	X	X
Industry composition × *North*	X	X	X
New × log (K/L)	X	X	X
New × log GDPpc	X	X	X
Tariffs	X	X	X
Observations	68,460	69,234	71,954

Note: Dependent variable is the share of FDI-based offshoring. *New* is measured as the percentage of HS 10-digit new products within an HS 6-digit product category. *North* is a dummy for north country. *T* is the turning point from declining to increasing in the share of FDI-based offshoring. R&D intensity is measured as the average ratio of R&D investment to value added of each industry. Skill intensity is measured as the ratio of high-skilled employment of each industry. TFP ratio is measured as the relative ratio of the average TFP by foreign firms over that of domestic firms of each industry. # suppliers is measured as the number of suppliers of each industry. Industry composition is measured as the composition of capital and labor of each industry. K/L is measured as the capital-labor ratio of each country. GDPpc is measured as the GDP per capita of each country. Tariffs is a control for export tariffs. The regressions are weighted by total exports in each product. Standard errors are clustered at the product level. ***, ** and * denote significance at the 1, 5 and 10% level respectively.

Appendix Table A1 Country list

List of North countries						
Antigua and Barbuda	Argentina	Australia	Austria	Bahamas	Bahrain	Barbados
Belgium	Bermuda	Brunei Darussalam	Canada	Cayman Islands	Chile	Hong Kong
Macao	Croatia	Cyprus	Czech Republic	Denmark	Estonia	Finland
France	Germany	Greece	Hungary	Iceland	Ireland	Israel
Italy	Japan	Kuwait	Latvia	Lithuania	Luxembourg	Malaysia
Malta	Mauritius	Mexico	Montserrat	Netherlands	New Zealand	Norway
Oman	Poland	Portugal	Qatar	Korea	Saudi Arabia	Seychelles
Singapore	Slovakia	Slovenia	Spain	Sweden	Switzerland	Taiwan
Trinidad and Tobago	Turkey	United Arab Emirates	United Kingdom	United States		
List of South countries						
Albania	Algeria	Angola	Armenia	Azerbaijan	Bangladesh	Belarus
Belize	Benin	Bolivia	Bosnia and Herzegovina	Brazil	Bulgaria	Burkina Faso
Cambodia	Cameroon	Central African	Chad	Colombia	Congo	Costa Rica
Côte d'Ivoire	Djibouti	Dominica	Dominican Republic	Ecuador	Egypt	El Salvador
Equatorial Guinea	Ethiopia	Fiji	Gabon	Gambia	Georgia	Ghana
Grenada	Guatemala	Guinea	Guinea-Bissau	Haiti	Honduras	India
Indonesia	Iran	Iraq	Jamaica	Jordan	Kazakhstan	Kenya
Kyrgyzstan	Laos	Lebanon	Lesotho	Liberia	Madagascar	Malawi
Maldives	Mali	Mauritania	Moldova	Mongolia	Morocco	Mozambique
Myanmar	Namibia	Nepal	Nicaragua	Niger	Nigeria	Pakistan
Panama	Paraguay	Peru	Philippines	Romania	Russia	Rwanda
Saint Lucia	Sao Tome and Principe	Senegal	Serbia	Sierra Leone	South Africa	Sri Lanka
St. Vincent and the Grenadines	State of Palestine	Sudan	Suriname	Swaziland	Syrian Arab Republic	Tanzania
TFYR of Macedonia	Tajikistan	Thailand	Togo	Tunisia	Turkmenistan	Turks and Caicos Islands
Uganda	Ukraine	Uzbekistan	Venezuela	Viet Nam	Yemen	Zambia
Zimbabwe						

Appendix Table A2 Examples of new and old products

HS 6-digit	Product name
Panel A: New product examples	
540231	Textured yarn nes, nylon, polyamide <50dtex not retai
670210	Artificial flowers foliage fruit, articles, plastic
701710	Laboratory, hygienic or pharmaceutical glassware
842831	Mine conveyors/elevators, continuous action
900820	Microfilm, microfiche or other microform readers
Panel B: Old product examples	
070110	Potatoes seed, fresh or chilled
250510	Silica sands and quartz sands
400211	Styrene-butadiene rubber (SBR/XSBR) latex
611610	Gloves impregnated or coated with plastic, rubber, knit
700510	Float glass etc sheets, absorbent or reflecting layer