Multinational Production and Innovation in Tandem

Jin Liu
Princeton University

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Abstract

Multinational firms colocate production and innovation by offshoring them to the same host country or region. In this paper, I examine the determinants of multinational firms' production and innovation locations. Exploiting plausibly exogenous variations in tariffs, I find complementarities between production and innovation within host countries and regions. To evaluate manufacturing reshoring policies, I develop a quantitative multicountry offshoring location choice model. I allow for rich colocation benefits and cross-country interdependencies and prove supermodularity of the model to solve this otherwise NP-hard problem. I find the effects of manufacturing reshoring policies are nonlinear, contingent upon firm heterogeneity, and they accumulate dynamically.

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Keywords: multinational firms, colocation of production and innovation, offshoring

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I Introduction

Multinational firms account for a large share of global production and innovation.[1] These firms produce and innovate in various countries, choosing the optimal locations for each activity. Whether a firm should produce and innovate in the same host country or region turns on the size of the colocation benefits for these activities relative to the force separating them. This separating force arises from the fact that countries with low production costs are usually not countries with high returns to innovation (Antras, Fort and Tintelnot, 2017; Arkolakis, Ramondo, Rodríguez-Clare and Yeaple, 2018). Nevertheless, in the data, the former force dominates, and firms tend to colocate production and innovation. As Figure 1 shows, large destinations of offshore production are often also large destinations of offshore innovation for U.S. firms.

The colocation benefits are twofold. First, synergy exists between production and innovation, as direct interactions between the manufacturing and R&D teams reduce communication and coordination costs, spur new ideas, and increase innovation efficiencies (Bahar, 2020; Fort, Keller, Schott, Yeaple and Zolas, 2020). For instance, to invent new medicines, product designers at biotechnology companies must deeply understand feasible manufacturing processes, as changes in product design often directly impact the production methods to be used and their technical specifications (Ketokivi, 2006; Pisano and Shih, 2012). Hewlett-Packard and Texas Instruments operate laboratories in Singapore close to their manufacturing facilities to promote interactions between plant engineers and product development teams during trial runs of new chips (Kuemmerle, 1997). Second, having local production can reduce the costs of innovation. Firms often locate their innovation lab and manufacturing plant at the same place to save on overhead expenses in terms of rent, utilities, insurance, and supportive infrastructure (Alcácer and Delgado, 2016). Some of the overhead cost sharing, such as for the management team and legal and accounting services, can happen not only within a country but also across borders within a region (ASEAN, 2017).[2]

I first use microdata to show that multinational firms offshore more innovation to a host country if they have more production there and if they produce more in other countries within the region. This pattern could be explained by inherent connections between pro-

[1]Multinational firms constitute nearly 80% of U.S. imports and exports in the year 2000 (Bernard, Jensen and Schott, 2009). Sales from foreign affiliates of U.S. manufacturing multinationals exceeded double the value of total U.S. exports. Furthermore, multinational firms are among the most innovation-intensive firms and account for the majority of innovation investment worldwide (see UNCTAD, 2015). They account for 91% of the innovation investment performed by firms in the U.S. (National Science Board, 2014).

[2]For example, Deloitte provides auditing and accounting services to multiple Samsung affiliates, including Samsung Electronics in South Korea and various subsidiaries in China. Nissan has set up a regional R&D hub in Thailand to support operations in Indonesia, the Philippines, Malaysia, and Vietnam.

duction and innovation, as well as by unobserved affiliate traits and correlation in country characteristics (the reflection problem in Manski (1993)). To isolate the former, I exploit plausibly exogenous variation in tariffs to establish a causal impact of production on innovation. I find that an increase in the U.S. import tariff for a host country reduces the firm's offshored production and innovation both within that country and in the surrounding region.

Motivated by the empirical findings, I develop a dynamic framework of offshoring location choices to answer several key questions. On a micro level, to what extent do colocation benefits shape the impact of multinational firms' production relocations on their choices of innovation locations? On an aggregate level, how do recent reshoring policies aimed at bringing back U.S. manufacturing affect the global allocation of innovation?[3] In particular, when production is reshored, will innovation continue to stay in the host country, return to the U.S., or flow to third-party countries?

Bilateral trade policies can have significant third-country effects. For instance, as a result of recent trade tensions between the U.S. and China, many multinational firms have relocated activities from China to other East Asian countries, such as Vietnam (see Table 1.11 in ASEAN, 2021, for examples of such firms). Allowing for cross-country interdependencies in firm decisions is necessary for understanding these third-country effects. However, this creates a hard permutation problem, as optimal choices in one country affect payoffs in other countries. Firms simultaneously choose the set of countries in which to produce and another set of countries in which to innovate. The number of possible country combinations, $2^{2\mathcal{L}}$, grows exponentially with the number of countries, $\mathcal{L}$, and quickly becomes intractable when the model includes more than a few countries. I establish a supermodularity property of the model and leverage it to efficiently solve this combinatorial problem in a dynamic setting.

To measure *firm-level* offshore production and innovation in each foreign country, I use administrative data from the U.S. Census Bureau and explore a previously underused survey module in their Business R&D Survey. This module collects information on firms' annual R&D expenditure and provides a comprehensive breakdown of that expenditure by foreign countries. I combine these rich data with two identification strategies to establish a causal link between production and innovation. In the first strategy, I construct a shift-share style, firm-country-year specific tariff rate and use it as an instrument for the firm's offshore production. In the second strategy, I exploit plausibly exogenous origin-by-product tariff changes during the Trump Tariffs policy.

The underlying identification argument for both empirical strategies is that U.S. import

[3] Examples of U.S. reshoring policies include the Tax Cuts and Jobs Act, which lowered the domestic corporate tax rate from 35% to 21%, and the CHIPS and Science Act, which allocated $280 billion to enhance domestic research and semiconductor manufacturing (White House, 2022).

tariff shocks affect firms' production offshoring to the host country by affecting the cost of shipping goods across borders. However, these tariff shocks would only impact firms' innovation efforts in that country if there is an interaction between production and innovation. For both identification strategies, I find that increasing tariffs for a host country lead to declining production and innovation both within that country and the surrounding region, indicating a positive causal impact of production on innovation.

In my modeling framework, multinational firms choose offshoring destinations for production and innovation, taking into account colocation benefits and how decisions in one country impact payoffs in others. Their productivity is endogenously affected by the offshore innovation investment and its proximity to production activities. The optimal choice of offshoring locations is contingent upon countries' production costs and returns to R&D, and most importantly, the magnitude of synergies and cross-country interdependencies between production and innovation. These decisions are dynamic and also influenced by individual firm characteristics and their history of activities.

The model is estimated using a three-step procedure. First, I estimate countries' production costs based on their respective shares in firms' overall offshore production, following the method in Antras, Fort and Tintelnot (2017). Next, I draw from the production function estimation literature and employ a control function approach to back out input elasticities and parameters that govern the returns to offshore R&D.

The estimated colocation forces and interdependencies from the first two steps ensure that the firm's lifetime objective function is supermodular. This property is particularly advantageous, allowing me to adapt a recently developed algorithm by Alfaro-Ureña, Castro-Vincenzi, Fanelli and Morales (2023) to solve the firm's dynamic combinatorial discrete choice problem. With the model solutions in hand, the final step involves applying the method of simulated moments to estimate the dynamic costs associated with offshoring production and innovation, targeting moments informed by firms' average offshoring probabilities.

The synergy effect in the model is identified by measuring how firm productivity responds to offshoring colocation choices. This effect can vary over time and depending on host country's characteristics. Residual colocation patterns reflect the cost-sharing effect. I find that offshoring innovation alongside production results in 0.06% to 0.2% greater productivity gains compared to offshoring innovation alone. The magnitude of the synergy effect is large enough to explain more than 95% of the colocation pattern, and thus, the cost-sharing mechanism has a relatively minor impact.

I validate my model by simulating the Trump Tariffs and comparing its predictions to the IV estimates obtained from Census microdata. The IV estimates suggest that the Trump Tariffs led to a 7.2% decrease in imports from China and a 0.1 percentage point reduction in the likelihood of innovating there. In comparison, my model predicts a 6.5% decline in imports and a 0.06 percentage point decrease in the probability of offshoring innovation.

Next, I apply my model to assess the impact of counterfactual bilateral trade policies that negatively affect U.S. firms' production offshoring to China. While these policies successfully reshore production back to the U.S., the associated reshoring of innovation is modest. There are two reasons why innovation in the U.S. does not significantly increase. First, some of the innovation leaving China is redirected to alternative countries like Brazil and France, which offer a competitive mix of low production costs and relatively high returns on innovation. Second, because China is estimated to have the highest potential for offshore production but relatively smaller returns on innovation, many firms choose to produce in China while conducting R&D in the U.S. When these firms face a negative shock, they scale down global operations, reducing their U.S. innovation as well.

Consistently, I find that third-country effects are significant for these bilateral trade policies. For example, when the U.S. raises tariffs on China by 14% (resulting in a 30% reduction in China's production-offshoring potential), the likelihood of U.S. firms offshoring R&D to China decreases by 0.13 percentage points, while the probability for the rest of the world declines by 0.15 percentage points.

I also examine the roles of firm heterogeneity and dynamics in my model. Firm heterogeneity introduces nonlinearity in the effects of trade policies: many small firms, despite colocation benefits, choose to produce in China due to its low costs but innovate in other countries with higher R&D returns. Moderate trade shocks primarily impact these firms, resulting in a counterintuitive increase in China's share of global R&D. However, larger shocks, including the extreme case of decoupling, impact even the most productive firms that innovate in China, thus leading to a decline in China's share of global R&D.

Finally, by incorporating an endogenous innovation process, my model speaks to the dynamic effects of trade policies that are absent in previous static models. I find, for instance, that a 30% increase in trade costs with China decreases U.S. firms' productivity only slightly at first but by 0.45% over a decade.

Related Literature. My primary contribution is to provide causal evidence and an empirical framework for analyzing the sources and policy implications of colocation benefits and cross-country interdependencies. The synergy effect, where colocating innovation with production leads to greater productivity growth, is identified as the key driver of colocation benefits. My estimate of the synergy effect adds to the literature on endogenous innovation and firm performance. Previous studies have empirically estimated the general returns of R&D on productivity gains (Doraszelski and Jaumandreu, 2013), the returns when R&D is pursued alongside exporting (Aw, Roberts and Xu, 2011), and the returns when domestic

R&D is combined with immigrant researchers and imported R&D services (Fan, Lee and Smeets, 2022). My framework extends this by incorporating multi-country R&D choices and explicitly accounting for the direct colocation benefits between production and innovation.

This paper closely relates to the relatively nascent empirical literature on the colocation of production and innovation. Studies by Tecu (2013), Lan (2019), Delgado (2020), and Fort, Keller, Schott, Yeaple and Zolas (2020) provide evidence of the benefits of colocating production and innovation in the same localized area. While my study is consistent with the presence of localized colocation benefits, its primary focus is on establishing the colocation pattern on an international scale by analyzing multi-country location choices. I also contribute to this literature by leveraging plausibly exogenous tariff variations across a wide range of countries to provide causal evidence for both within-location and cross-location complementarities between production and innovation.[4] My findings that higher tariffs reduce innovation within the host country are consistent with the observations of Branstetter, Chen, Glennon and Zolas (2021). Furthermore, I show that higher tariffs in the host country also reduce innovation in other countries within the same region, suggesting the presence of cross-country colocation benefits. Lastly, I offer an empirical framework that quantifies the mechanisms and policy implications of these colocation benefits.

My context of firms' global location choices engages with a vibrant research area on multinational production, sourcing, and innovation (Rodríguez-Clare, 2010; Arkolakis, Ramondo, Rodríguez-Clare and Yeaple, 2018; Fan, 2019). Antras, Fort and Tintelnot (2017) develop a framework for global sourcing and establish conditions under which sourcing from different countries becomes complementary. I integrate their framework with elements from the R&D literature, enabling a simultaneous treatment of foreign production and innovation. Bilir and Morales (2020) provide a thorough treatment of multinational innovation by distinguishing between the different scopes of headquarter and affiliate R&D. Bøler, Moxnes and Ulltveit-Moe (2015) explore the complementarity between R&D and imports driven by scale effects. My model, while accounting for the scale effect, primarily introduces direct interactions between production and innovation through synergy and cost-sharing effects. Furthermore, my study distinguishes itself by solving the dynamic location choice problem faced by multinational firms—an aspect often overlooked due to technical complexities, but crucial for generating rich implications for offshoring and reshoring policies.

Methodologically, since firms in my model choose a set of production and innovation locations rather than making independent offshoring decisions in each country, this paper

[4]By leveraging tariff variations from the recent trade war, this paper contributes to the expanding literature on its effects, including works such as Amiti, Redding and Weinstein (2020), Flaaen, Hortaçsu and Tintelnot (2020), Monarch (2022), and Handley, Kamal and Monarch (Forthcoming).

joins the literature on large interdependent discrete choice problems. Three main approaches have been employed to handle models with this problem. The first uses the Euler method or moment inequalities to estimate parameters without fully solving the model (Holmes, 2011; Aguirregabiria and Magesan, 2013, 2016; Morales, Sheu and Zahler, 2019; Hsiao, 2021). The second combines value function approximation with restrictions on the decision-making process to manage large state and action spaces (Sweeting, 2013; Aguirregabiria and Vicentini, 2016). Most closely related to my work is the third approach that leverages complementarities and lattice theory. Jia (2008) pioneered this approach in studying the expansion game between two chain stores. Arkolakis, Eckert and Shi (2021) formalize a general solution method for combinatorial discrete choice problems with either supermodularity or submodularity. However, these models are static and do not face the large state space challenge inherent in dynamic models. My solution method builds primarily on the novel work by Alfaro-Ureña, Castro-Vincenzi, Fanelli and Morales (2023), who propose the first algorithm to solve dynamic combinatorial discrete choice problems with supermodularity.

The rest of the paper is organized as follows: Section II describes the data sources and presents descriptive facts. Section III outlines two empirical identification strategies and discusses the causal evidence. Section IV provides the details of the model and proves its supermodularity property. Section V describes the solution algorithm, estimation procedure, and results. Section VI presents the counterfactual exercises. Section VII concludes.

II Data and Descriptive Facts

I introduce data sources, descriptive patterns, and two stylized facts in this section.

II.A Data Sources

Firm-level data on R&D investment in each foreign country is scarce. To overcome this challenge, I use administrative records from the U.S. Census Bureau, specifically exploring a previously underutilized survey module from the Business Research and Development and Innovation Survey (BRDIS).[5] This module, with its questionnaire snapshotted in Appendix Figure A3, gathers information on firms' annual R&D expenditure and provides a detailed breakdown of that expenditure by foreign country.[6] This measure of R&D expenditure

[5]The BRDIS is an annual survey conducted by the Census Bureau and sponsored by the National Science Foundation and the National Center for Science and Engineering Statistics. It employs a representative sample of for-profit, nonfarm firms in the United States. The survey focuses on firms with five or more paid employees and at least one establishment (see Foster, Grim and Zolas, 2020, for more details).

[6]In this survey module, 40 countries and regions are individually included. Additionally, there is a category labeled "others," which encompasses countries grouped together due to their relatively smaller

captures both direct costs, such as researchers' salaries, and administrative and overhead costs clearly associated with the company's R&D activities. It includes expenditures for both basic and applied R&D, as well as for both product and process innovation. It excludes spending on capital inputs, routine product testing and quality control, and market research.

I use several restricted-use micro datasets from the Census Bureau to obtain information on trade transactions and other firm characteristics for the manufacturing sector. In particular, I access import transactions at U.S. customs through the Longitudinal Firm Trade Transactions Database (LFTTD). This database furnishes a detailed record for each custom transaction, including a firm identifier, product categories based on the 10-digit Harmonized System (HS10) code, value and quantity of goods, origin and destination countries, duties collected for imports, and whether the transaction occurs at arm's length or with related parties.[7] With this dataset, I generate a measure of firm imports by country and calculate firm-country-year specific tariff rates based on which products the firm imports. Furthermore, I draw on the Census of Manufacturing (CMF) and the Annual Survey of Manufactures (ASM) for data on firms' industry classification, employment, shipments, materials, and energy usage.[8] Additional country-level data on human capital index and capital services are obtained from the Penn World Tables.

There are three data caveats. Due to the lack of information on the operations of foreign affiliates—except for their trade with U.S. plants—I resort to using a firm's imports from a specific country as a proxy for its offshore production in that country. Although imports represent only approximately half of offshore production,[9] there is a strong correlation between the trends of imports and offshore production, both in terms of absolute value and growth rate (Figure 2). This suggests that the proxy strategy provides accurate insights, particularly when relative variations are used in regression analyses. Alternatively, I can proxy within-firm offshore production using only related-party imports. The reduced-form results remain robust to this alternative measure.

The sales recorded in the CMF and ASM capture shipments from all U.S. plants but miss

contributions, together representing less than 5% of the total foreign R&D expenses.

[7]Exporting parties are defined to be related when they own 10 percent or more of the other party. For imports, 19 CFR §152.102(g) defines related persons as (i) members of the same family, (ii) shared officers or directors, (iii) partners, (iv) employers and employees, and (v) a party having a 5% controlling interest in the other. A similar definition of multinationals is used in Bernard and Fort (2015), Antras, Fort and Tintelnot (2017), and Boehm, Flaaen and Pandalai-Nayar (2020).

[8]The CMF is conducted in years ending in 2 and 7, covering the entire population of manufacturing establishments. The ASM is conducted annually, excluding years ending in 2 or 7, and covers a representative sample of manufacturing establishments with at least one paid employee. Appendix A provides more details on how I use the raw data to construct the firm-level variables necessary for production function estimation.

[9]In 2019, the total import value of U.S. multinational firms was $2.5 trillion, while the total value of offshore production was $5.3 trillion. Thus, imports amounted to about 47 percent of the total offshore production in that year. These numbers are calculated based on data from the Bureau of Economic Analysis.

shipments from foreign affiliates to local foreign customers if they are not rerouted through the U.S. These direct sales from foreign affiliates account for about 30% of the firm's global sales (Antràs, Fadeev, Fort and Tintelnot, 2023). In light of this, I focus on the colocation of production for products shipped back to the U.S. and innovation activities serving the U.S. parent. Appendix B details how my empirical strategies identify this specific form of colocation. I leave the interesting topic of the colocation between local production and local customization-driven innovation for future research.[10]

Finally, an important distinction between the Census data I use and the alternative data on U.S. multinational firms from the Bureau of Economic Analysis is that the latter restricts its sample to only multinationals, whereas my sample also includes many domestic firms. This allows me to study the extensive-margin decision of when a domestic firm chooses to become multinational by establishing its first foreign affiliate. The Census data also enables me to distinguish between imports from related parties and those at arm's length,[11] which differentiates outsourcing from within-firm offshoring. I use the sum of the two as my main measure. However, the reduced-form results are robust when focusing solely on related-party imports, and I found suggestive evidence that within-firm offshore production is associated with greater colocation benefits with innovation compared to outsourced production.

II.B Descriptive Patterns

The final data sample comprises about 36,000 manufacturing firms covering the period from 2008 to 2019. Although the panel is unbalanced, large firms, which account for a substantial share of total sales, are surveyed nearly every year (Appendix Table A2). The sample is not fully representative of the entire population of U.S. manufacturing firms and is biased towards larger firms, covering approximately 65% of total annual manufacturing shipments. Table 1 presents summary statistics. The average firm has an annual sales of $500 million. Among firms investing in R&D, offshore innovation accounts for 23% of total R&D expenditure.

It is important to consider firms' choices of multiple locations, rather than assuming a single location, when studying their offshoring of production and innovation offshoring. Firms conducting R&D in just one foreign country represent a mere 2.4% of total offshore R&D. Similarly, those importing from only one origin country account for just 0.1% of the

[10]This source of colocation is more closely associated with horizontal and platform FDIs, whereas the data and model in my paper are better suited for analyzing vertical FDI. Anecdotally, many multinationals firms establish foreign R&D labs near their factories to customize products for local consumer preferences (Håkanson and Nobel, 1993; Krishna, Patra and Bhattacharya, 2012). Therefore, I hypothesize a strong incentive for colocation in the context of horizontal and platform FDIs.

[11]According to Lakatos and Ohnsorge (2017), a substantial 57% of total U.S. trade occurs at arm's-length between unrelated firms. Specifically, arm's-length trade constitutes 50% of U.S. imports and 70% of exports.

overall import value. In contrast, although firms conducting R&D in more than five foreign countries make up only 3% of the observations, they contribute to 36% of total sales, 70% of worldwide R&D, and 87% of the total offshore R&D (Appendix Table A3). Additionally, firms importing from over ten countries capture 95% of the total import value.

I now present two descriptive patterns that suggest a positive linkage between offshore production and innovation at both the aggregate and micro levels. Table 2 lists the top five destinations for offshore production and innovation for U.S. firms. Germany stands out as the largest destination for offshore R&D, accounting for 15% of U.S. firms' foreign R&D expenditure. Mexico is the largest origin country for imports, representing 20% of the total import value. Notably, Germany, China, and Canada appear on both lists. When examining the complete global distributions of U.S. imports and offshore R&D across all countries, I find they have similar geographical patterns, indicating that major destinations for offshore innovation also serve as major destinations for offshore production (Figure 3). This reveals a positive correlation between offshore production and innovation at the aggregate level.

The same holds true at the micro level. Table 3 groups firm-country-year observations into four categories based on whether they are associated with positive R&D and import values. Strikingly, 94% of foreign R&D is conducted in countries from which the firm imports.[12] This suggests that the return on offshoring only R&D without production may be minimal, whereas offshoring both activities can yield substantial benefits.

II.C Firm-Level Facts on Offshoring Activities

To better establish the micro-level linkage between offshore production and innovation, I present two facts based on firm-country level regressions, which suggest a correlation between these activities both within a host country and across countries within the same region. The regressions control for firm and country-industry fixed effects, ruling out the confounding factors that larger firms are more likely to offshore both production and innovation, as well as that certain destination countries may be more attractive for both activities in a given industry. Instead, the observed positive correlation is driven by variation across different affiliates within the same firm, as well as variation across affiliates of different firms within the same destination country and industry.

Fact 1. *(Within-Country Colocation) Firms engage in more offshore R&D activities in countries from which they import more, and vice versa.*

Fact 2. *(Cross-Country Interdependence) Production and R&D offshoring decisions are*

[12] This significant proportion of foreign R&D accompanied by offshore production remains consistent across various minimum cutoffs (instead of zeros) used to define offshoring modes.

interdependent across countries: firms engage in more offshore R&D activities in a host country if they import more from other countries within the region, and vice versa.

The regressions that establish these facts analyze the relationship between R&D and imports in a cross-sectional sample from the year 2017, regressing each variable on the other:

$$y_{il} = \beta_1 \cdot x_{il} + \beta_2 \cdot x_{iR} + \gamma_i + \gamma_{jl} + \varepsilon_{il}. \tag{1}$$

x_{iR} represents the total value of the independent variable for firm i in the region R surrounding country l, excluding country l itself. To illustrate with an example, if we consider l as China and use x and y to represent imports and R&D, respectively, the regression investigates whether there is a correlation between firm i's R&D activities in China and its imports from China, as well as its imports from other East Asian countries. Furthermore, the firm and country-industry fixed effects are denoted by γ_i and γ_{jl}.

The regression results are reported in Table 4. Various combinations of the extensive and intensive margins of imports and R&D are considered across different columns. Panel A regresses R&D on imports, while Panel B does the opposite. In both panels, the coefficient estimate $\hat{\beta}_1$ is significant and positive, indicating that a firm is more likely to have R&D activities in countries where it has more production, and vice versa. Specifically, β_1 is estimated to be 0.0195 in Column (1) of Panel A, implying that the probability of a firm conducting R&D in a host country increases by 1.95 percentage points if the firm also engages in production there. Given that the baseline probability of conducting R&D in a host country is only 1.3 percentage points, the presence of production more than doubles the likelihood of conducting R&D in the same host country.[13]

Another observation is the robust and positive estimate of β_2, which establishes the second fact. A firm's offshore innovation in a particular host country is positively correlated not only with its offshore production in that same country but also with its production in other neighboring countries within the region. Specifically, after controlling for whether the firm engages in production in the focal host country, the probability of conducting R&D in the focal host country increases by 0.15 percentage points if the firm also produces in neighboring countries. This represents a 12% increase in the probability of offshoring R&D relative to its baseline level. This second fact implies that firms' offshoring decisions for production and innovation in different countries are interconnected.

Industry Heterogeneity. The intensity of colocation can vary across industries, depending on the complexity of the product and process and the degree of knowledge spillover

[13] The estimate of β_1 remains robust without the regional terms, as shown in Table A4, which reports regressions with only x_{ilt}. The estimates for both β_1 and β_2 are robust to a panel version of the regression with firm-year and country-industry-year fixed effects (Appendix Table A5). Furthermore, when separating related-party imports from arm's length imports in this regression, the coefficient for the former is significantly larger (Appendix Table A6).

from engineering to innovation (Ketokivi, 2006). While causal analysis is limited by sample size and cannot fully explore industry heterogeneity, I provide suggestive evidence based on correlations between production and innovation. When splitting the sample by industry, I find that coefficient estimates vary significantly across industries, and this variation remains substantial even when comparing 6-digit NAICS industries within the same 3-digit industry category (Appendix Figure A4). Although exploring how the magnitude of colocation benefits changes with different types of manufacturing activities is beyond the scope of this paper, it presents an interesting avenue for future research.

III Evidence: Colocation and Interdependencies

The two facts highlight positive correlations between offshore production and innovation within countries and across countries within regions. These correlations may be attributed to a fundamental linkage between production and innovation, as well as to unobserved affiliate traits, such as management skills, and correlation in country characteristics. To disentangle the former, I now introduce two identification strategies. The first strategy leverages a firm-country-year specific tariff rate, constructed in a shift-share style based on the firm's import product bundle, as an instrument for production offshoring. The second strategy exploits origin-product level tariff line changes that occurred during the Trump Tariffs policy as plausible exogenous shifters of offshore production.

III.A Shift-Share Style Tariff Rate—IV Strategy

Firms import different products from different countries. The firm-country-specific import product bundle combined with country-product-specific tariff lines implies that firms face different tariff rates in each country. I design a firm-country-year level tariff rate T_{ilt} to reflect the effective tariff rate firm i would face in country l if it had continued to import the same bundle of products from a fixed prior period t_0:

$$T_{ilt} = \sum_g s_{igt_0} T_{glt}.$$

This is a weighted average of product-country-level tariff rates T_{glt}, with the weights being the firm's initial import value shares across products (s_{igt_0}) from all origin countries during the prior time period.[14] Products g are defined at the 10-digit HS code level. I use the initial five years of my sample, spanning from 2008 to 2012, to compute s_{igt_0}. The subsequent years from 2013 to 2019 constitute the study period.

[14] T_{glt} is calculated by averaging transaction-level import data from the LFTTD.

The validity of using T_{ilt} as an instrument for firm i's offshore production in country l in year t rests on the assumption that the import tariff affects the firm's cost of shipping goods across borders, thereby influencing production offshoring. However, the tariff should not affect the firm's foreign R&D expenditures, unless there is an interaction between production and innovation. By holding the import product bundle constant across countries and time periods, I exclude variations in T_{ilt} that stem from the endogenous selection of import bundle across countries and its potential adjustment over time in response to tariff changes.

Another useful variable to construct is the average tariff rate within the region, excluding the host country itself. This variable, T_{iRt}, will serve as the instrument for the firm's offshore production to the surrounding region and is calculated as follows:

$$T_{iR(l)t} = \frac{1}{\sum_{l' \neq l} c_{ll'} M_{l'}} \sum_{l' \neq l} c_{ll'} M_{l'} T_{il't}, \tag{2}$$

where $c_{ll'}$ is a dummy variable that equals one if countries l and l' are in the same region, and $M_{l'}$ is the aggregate import value from country l' over all sample years. For instance, when l represents China, T_{ilt} represents firm i's average tariff rate in China, while T_{iRt} represents its (weighted) average tariff rate in other East Asian countries excluding China.

I estimate a reduced-form specification, regressing offshore production and innovation on the instrument to examine how these offshoring activities respond to tariffs:

$$y_{ilt} = \beta_1 \cdot T_{ilt} + \gamma_{it} + \gamma_{lt} + \nu_{ilt}. \tag{3}$$

I also estimate a two-stage least squares (2SLS) specification. In the first stage, I regress imports on the tariff rate, and in the second stage, I regress R&D on the predicted imports:

$$\begin{aligned} \text{R\&D}_{ilt} &= \beta \cdot \widehat{\text{Imp}}_{ilt} + \gamma_{it} + \gamma_{lt} + \varepsilon_{ilt}, \\ \text{Imp}_{ilt} &= \kappa \cdot T_{ilt} + \gamma_{it} + \gamma_{lt} + \nu_{ilt}, \end{aligned} \tag{4}$$

Both specifications include firm-year and country-year fixed effects.

III.B Trump Tariffs as a Quasi-Experiment

In an effort to tackle the trade deficit, the U.S. implemented a series of tariff increases on specific goods and countries in 2018 and 2019.[15] Consequently, major trading partners of the U.S. retaliated with their own tariffs, escalating trade tensions. As estimated by Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020), these U.S. tariff changes led to an overall increase in the average tariff rate from 2.6% to 16.6% for a total of 12,043 goods. These goods accounted for about $303 billion (12.7%) of the annual imports into the U.S.

[15] Refer to Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020); Fajgelbaum, Goldberg, Kennedy, Khandelwal and Taglioni (2022) for information on various stages of Trump tariffs until 2019, and Bown (2020) for an up-to-date chart of US-China Trade War tariffs.

The Trump Tariffs provide a compelling quasi-experiment to study the effect of offshore production on offshore innovation. The unexpected tariff shocks at the country-product level are plausibly uncorrelated with affiliate-specific unobservables, such as management skill, that influence the growth rate of R&D. To leverage this quasi-experiment, I first obtain data on tariff line changes by 10-digit HS code and country, compiled by Fajgelbaum, Goldberg, Kennedy and Khandelwal (2020); Fajgelbaum, Goldberg, Kennedy, Khandelwal and Taglioni (2022) from U.S. International Trade Commission schedules. In total, the tariff increases affected 116 countries, with approximately 26 thousand tariff lines targeting Chinese goods and 19 thousand tariff lines targeting goods from other countries (see Figure 4 for the log number of affected goods and the average effective tariff increase among affected goods by country).[16] While China had the highest number of affected products, its effective tariff increase on those goods did not rank among the highest.

To assign firm-country pairs to the treatment and control groups, I use data from the LFTTD to compile a list of goods that firm i imported from country l during the five-year period preceding the Trump Tariffs. If any of these imported goods were affected by tariff changes in 2018 and 2019, the firm-country pair is designated as treated. Conversely, if none of the goods were impacted, the pair is classified as untreated. For robustness checks, I also explore alternative measures of treatment intensity, such as the fraction and value share of affected products and the effective amount of tariff rate increases on affected goods. It is worth noting that the event study sample is limited to firm-country pairs where the firm had imported from the country during the prior period.

I estimate an event study specification as follows:

$$y_{ilt} = \sum_{t=2014:2019} \beta_t \cdot \text{Treat}_{il} \times \text{Year}_t + \gamma_{il} + \gamma_{lt} + z_{it} + \varepsilon_{ilt}, \tag{5}$$

where z_{it} is a control vector that includes firm sales and employment to account for the scale effect. I also estimate a difference-in-differences specification:

$$y_{ilt} = \beta \cdot \text{Treat}_{il} \times \text{Post}_t + \gamma_{il} + \gamma_{lt} + z_{it} + \varepsilon_{ilt}, \tag{6}$$

which focuses on comparing baseline and endline outcomes, with Post set to one in 2019 and zero between 2014 and 2017.[17] Both specifications include firm-country and country-year fixed effects, with standard errors clustered at the firm level.

Section 301 Investigation. In March 2018, the U.S. government concluded a Section 301 investigation, asserting that China was engaging in forced technology transfers and

[16] A tariff line is defined as a combination of a country, a ten-digit HS code, and a year.

[17] Excluding 2018 ensures a clean comparison between baseline and endline outcomes. This choice is motivated by the fact that R&D decisions typically take time to respond to shocks, and it avoids the complications from intermediate stages of tariff increases.

intellectual property theft. This led to multiple rounds of tariffs on Chinese goods starting in July 2018, under the broader Trump Tariffs policy. Given the legal basis for these tariffs, they were likely imposed disproportionately on more innovation-intensive goods. A potential concern is that this selective application could bias the treatment effect by introducing a correlation between the treatment dummy and unobserved affiliate characteristics.

However, two arguments suggest that this issue may not be particularly concerning. First, the inclusion of firm-country fixed effects means that the event study relies on the parallel trend assumption that the *growth rates* of R&D for products with high versus low initial R&D intensity would have been the same in the absence of the Trump tariffs. This assumption is supported by Appendix Table A7, which shows no statistically significant difference in R&D growth rates between the treated and control groups prior to the tariff policy. Second, even if the U.S. deliberately targeted industries with rapid innovation growth, such as semiconductor, the direction of the bias in the treatment effect would likely be towards zero, meaning I would be estimating a lower bound of the actual effect.

III.C Comparison of Two Strategies

The sample size for the event study on the Trump Tariffs is limited to 0.2 million firm-country-year observations, as the treatment dummy is defined only for firms that imported from the country in the prior period. In contrast, the instrumental strategy is not subject to these restrictions and includes a much larger sample of 1.5 million observations.

Despite the larger sample size, two potential validity concerns arise for the instrumental strategy. Firms may anticipate tariff changes years in advance and respond endogenously by adjusting their investments. Additionally, tariff schedule changes—especially those from Free Trade Agreements—might include Intellectual Property (IP) provisions that directly affect innovation incentives (Santacreu, 2021). However, the latter concern is mitigated by the absence of new trade agreements or major revisions to existing U.S. trade agreements during the study period. Moreover, this issue would only threaten the validity of the instrument if the confounding IP factor varies at the *product* level, as the instrument is constructed using product-level tariff variations and the regressions control for country-year fixed effects that account for any country-level IP term changes. These concerns are less relevant for the Trump Tariffs event study strategy, where tariff changes at the country-product level were unexpected and less linked to IP issues.

The event study strategy relies on tariff increases from the Trump Tariffs policy, while the instrumental strategy leverages additional tariff variations dating back to 2013, mainly from pre-established reduction schedules in U.S. Free Trade Agreements with countries like

Chile, the Dominican Republic, Morocco, Peru, and Singapore. It would be reassuring if both identification strategies, despite using different sources of variations, produce consistent and robust estimates of the impact of production on innovation.

III.D Results

Evidence from the Instrumental Strategy

Table 5 reports estimates from the reduced-form specification in Panel A and the two-stage least squares specification in Panel B. The main result is that higher tariffs lead to a decrease in both offshore production and innovation in the host country, and that offshore production positively affects offshore innovation. Columns (1) and (4) of Panel A reveal that a 10 percentage points increase in the tariff rate (i.e., $\Delta T_{ilt} = 0.1$) is associated with a 19% decrease in imports and a 2.4% decrease in R&D expenditure within the host country.[18] Column (3) of Panel B suggests that when firm i doubles its imports from country l, its R&D expenditure in the same country increases by 12.5%.[19] This positive effect of production on innovation indicates the presence of colocation benefits between these two activities.

To further explore empirical evidence for cross-country interdependence in offshoring activities, I pose the following question: Do import tariffs for neighboring countries within the region also impact innovation offshored to the host country? To answer this question, I extend the previous reduced-form regression in Equation (3) by introducing an additional independent variable, T_{iRt}, which is the regional average tariff rate constructed in Subsection III.A. To illustrate this generalized regression, consider China as the focal host country; the regression then investigates whether offshored activities in China are influenced not only by the tariff rate that firm i faces in China (T_{ilt}) but also by the tariff rate in the broader East Asian region excluding China (T_{iRt}).

Panel C of Table 5 presents estimates from the generalized regression. The average leave-one-out regional tariff also negatively affects a firm's offshored production and innovation within the host country. The estimated effect of the host country's tariff rate remains robust, and the estimated coefficient for the regional tariff rate is significant and negative. These results collectively indicate that offshored production and innovation are adversely affected not only by tariff shocks in the host country but also by those in other countries within the host region. The findings that these offshoring decisions in one country are influenced by exogenous shocks occurring in other countries provide compelling causal evidence for

[18] The coefficient estimates for imports correspond to a trade elasticity between 1.98 and 2.93, which falls within the plausible range of estimates found in the literature.

[19] The first-stage F statistic is above 60.

cross-country interdependence in production and innovation offshoring.

Evidence from the Trump Tariffs Quasi-Experiment

As introduced in Section III.B, the Trump Tariffs provide exogenous country-product level tariff shocks that affect production offshoring without directly influencing innovation offshoring. Therefore, if offshore innovation also responds to these tariff changes, it serves as evidence for the intermediary causal effect of production on innovation.

Figure 5 presents estimates from Equation (5). The tariff increases adversely affect both offshore production and innovation in the host country. Treated units experience a 9.8% decrease in imports and a 1.4 percentage point decrease in the probability of conducting R&D. Among firms that continue performing R&D in the host country, the amount of R&D expenditure decreases by 15.4%. Consistent with these results, Table 6 reports difference-in-differences estimates, showing robust negative treatment effects. The second to fourth rows confirm this finding using alternative continuous measures of treatment intensity.

Robustness

Given that China has been the primary target of U.S. manufacturing reshoring policies, one might wonder whether U.S. firms' offshoring decisions to China significantly drive the observed reduced-form results. Similarly, the semiconductor industry has been a key focus in policy discussions surrounding the revival of U.S. manufacturing. However, despite their policy relevance, when I repeat the event study on the Trump Tariffs and exclude China and the semiconductor industry from the sample individually, I find that neither is the main driver of the observed patterns of colocation and interdependencies. Appendix Figures A5 and A6 show that the estimated effects remain highly robust.

My measure of R&D expenditure captures all innovation activities performed by the firm but does not include potential outsourced R&D, such as those contracted to external organizations. Therefore, it is useful to check the robustness of the causal effects when imports are also restricted to within-firm imports. To do this, I repeat both the instrumental and event study strategies, focusing exclusively on *related-party* imports. For the instrumental strategy, I calculate the effective tariff rate the firm faces in each country based solely on the goods it imports from related parties and use it to instrument for related-party imports in examining its effect on R&D. The coefficient estimates, reported in Appendix Table A8, are similar to those in Panel B of Table 5. For the event study strategy, I define a firm-country pair as treated if any products the firm previously imported from related parties in that country were subject to the tariff increase. Reassuringly, within-firm imports drop significantly after treatment, while arm's length imports do not. The estimated responses in R&D remain robust (see Appendix Figure A7).

I focus on the colocation between offshore production and innovation that serve U.S. plants, due to data limitations. Import serve as a good proxy for the production of goods shipped back to the U.S. However, R&D expenditure may include a potential measurement error from local innovation efforts, such as product customization for heterogeneous consumer preferences. I address this issue by leveraging the idea that while U.S. import tariffs affect production and innovation for products destined for the U.S., they arguably do not influence incentives for local production and innovation, as the locally produced and innovated products are typically sold directly to the host or neighboring countries (see Appendix B for a thorough explanation). Thus, the reduced-form analyses are immune to this measurement error since tariff shocks isolate variations relevant to activities serving U.S. plants.

Discussion. The analyses in Section III provide evidence on the extent of colocation and cross-country interdependence, showing that a firm's offshore innovation in a host country is positively affected not only by its offshore production in that country but also by production in neighboring countries within the same region. However, estimating the mechanisms driving colocation and interdependence, as well as analyzing their policy implications, requires a quantitative framework, which I develop in the next section.

IV A Model of Dynamic Offshoring Location Choice

This section presents a dynamic partial-equilibrium framework that characterizes firms' joint decisions on offshoring production and innovation locations. The primary goal is to incorporate two key empirical features: colocation benefits and cross-country interdependencies.

In the model, firms import parts from foreign countries, either manufactured by their foreign affiliates or external suppliers. These imported goods, combined with domestically produced goods, are aggregated using a CES function to form the firm's intermediates, which are then used to produce the final product sold to the global market.

Firms solve an infinite-horizon combinatorial discrete choice problem, selecting location bundles for production and innovation in each period. They face sunk and fixed costs of offshoring, with the fixed cost of offshore innovation affected by whether the firm has production in the region. The production location bundle determines the price index of intermediates, reflecting countries' relative cost advantages. This, along with the innovation location bundle, influences the firm's future productivity. Firms take into account cross-country interdependencies, recognizing how decisions in one country can affect optimal choices elsewhere.

My model highlights three mechanisms that generate colocation benefits. First, it accounts for spillovers from local production to innovation, allowing for a higher return on innovation when paired with production in the host country. Second, it enables production and innovation to share overhead costs, reducing the fixed cost of innovation when production exists in the surrounding region. Third, an additional complementarity between production and innovation arises from a scale effect: conducting R&D in a host country increases productivity and firm size, leading to a greater payoff for producing in that country.[20]

My model also introduces three sources of cross-country interdependencies. First, imported goods from different countries substitute for each other in the cost function, reflecting the firm's flexibility in choosing among production locations based on relative costs. Second, production and innovation in different countries are complementary due to firm-level scale effect. For example, adding a new production location lowers intermediate costs, increasing demand and raising payoffs for producing and innovating in other locations. Third, I incorporate a region-specific force that allows for reduced innovation costs in a host country when the firm produces in neighboring countries. These interdependencies enable the model to capture third-country effects of bilateral trade policies, setting it apart from models that have traditionally assumed independence across countries for technical simplicity.

IV.A Static Demand and Production

Each firm is denoted by i, location (or country, interchangeably) by l, industry by j, and time period by t.

Market Demand. The final goods market is monopolistically competitive. The demand for firm i is given by

$$q_{it} = Q_{jt} \cdot \left(\frac{p_{it}}{P_{jt}}\right)^{-\eta} = \Phi_{jt} \cdot (p_{it})^{-\eta},$$

where η is the elasticity of substitution between products offered by different firms, and Φ_{jt} captures the market conditions for the industry in which firm i operates.

Production. The short-run unit production cost is independent of output levels and is specified as a function of cost shifters (Berry, Levinsohn and Pakes, 1995; Aw, Roberts and Xu, 2011; Piveteau, 2021):

$$\ln c_{it} = \beta_0 + \beta_k \cdot \ln k_{it} + \beta_w \cdot \ln w_{jt} + \beta_m \cdot \ln p^m_{it} - \omega_{it}.$$

The log of marginal cost depends on the firm's exogenous capital stock (k_{it}), the wage rate in the industry (w_{jt}), the price index of intermediate goods (p^m_{it}), and the unobserved Hicks neutral productivity (ω_{it}). Both the intermediate price index and productivity are endogenously affected by the firm's choice of production and innovation locations.

[20]This scale effect works through the firm's productivity and the import price index, thereby generating consistent impacts across all affiliates within the firm rather than being specific to one location.

The firm's profit optimization under this demand structure and marginal cost function implies the following revenue function:

$$\ln R_{it} = (1-\eta)\ln\left(\frac{\eta}{\eta-1}\right) + \ln\Phi_{jt} + (1-\eta)\left(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_{jt} + \beta_m \ln p^m_{it} - \omega_{it}\right).$$

The firm's profit, π_{it}, is proportional to its revenue, R_{it},, with a constant markup equal to $\eta/(\eta-1)$. That is,

$$\pi_{it} = \frac{1}{\eta}\cdot R_{it}\left(\omega_{it}, k_i, w_{jt}, p^m_{it}, \Phi_{jt}\right).$$

Foreign Production. Given the observed data pattern that all firms in my sample purchase domestic materials, I assume that they always produce or source intermediates in the home country. In the static problem, the firm takes the set of production locations as given and decides how to allocate production across these locations. Intermediates from different locations are aggregated using a CES structure.

$$m_{it} = \left(\sum_{l\in\mathcal{L}} y_{ilt}\cdot m_{ilt}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}},$$

where y_{ilt} is a dummy variable that equals one if firm i produces in country l in period t, and ρ is the elasticity of substitution between goods from different countries.

The unit cost of goods from a specific location, $p_{m,ilt}$, is determined by the host country's wage level (w_{lt}), the shipping cost between the U.S. and the host country (τ_{lt}), and the U.S. import tariff rate for the host country (T_{lt}). Specifically, $p_{m,ilt} = w_{lt}\tau_{lt}(1+T_{lt})$. The CES structure implies that the price index for the aggregated intermediates is given by

$$p^m_{it} = \left(\sum_{l\in\mathcal{L}} y_{ilt}\left[w_{lt}\tau_{lt}(1+T_{lt})\right]^{1-\rho}\right)^{\frac{1}{1-\rho}}.$$

It varies with the set of production locations and the unit cost of goods at each location.[21]

I define $\theta_{lt} = [w_{lt}\tau_{lt}(1+T_{lt})]^{1-\rho}$ as country l's "production-offshoring potential" in period t, as it represents the country's average cost advantage in manufactured goods. I also define $\Theta_{it} = (p^m_{it})^{1-\rho}$ as firm i's "production-offshoring capability" in period t, which captures the firm's ability to produce more cheaply when it has established more production locations.

IV.B Dynamic Location Choices

Firms' offshoring location choices incur dynamic costs and affect future productivity.

Innovation Effort and Productivity Evolution. A firm's productivity is governed by a Markov process that depends on its past productivity, an i.i.d. shock, and its production

[21] This CES aggregation of intermediates can be microfounded by considering a continuum of goods varieties and assuming a Fréchet distribution of production efficiencies across countries (Antras, Fort and Tintelnot, 2017). The equivalence of these two approaches is demonstrated in Appendix C.1.

and innovation at each location:

$$\omega_{it} = \alpha_0 + \alpha_1 \omega_{it-1} + \sum_l \left[1 + \boldsymbol{X}'_{lt-1}\boldsymbol{\mu}\right] \cdot \left[\beta_1 r_{ilt-1} + \beta_2 y_{ilt-1} r_{ilt-1} + \beta_3 y_{ilt-1}\right] + \xi_{it}, \qquad (7)$$

where r_{ilt} is a dummy indicating whether the firm conducts R&D in country l at time t, and y_{ilt} indicates whether the firm produces in country l at time t. β_1 captures the stand-alone return on R&D, while β_2 captures the additional return from the synergy effect, where local production enhances innovation efficiency. β_3 accounts for the learning-by-doing effect. The effective return on R&D varies by country and depends on specific country characteristics included in the vector $\boldsymbol{X}_{lt}$. The innovation shock, ξ_{it}, follows a normal distribution with mean zero and variance σ_ξ^2, capturing the randomness in innovation.

Sunk and Fixed Costs. Firms incur sunk costs ϕ_s^p for production and ϕ_s^r for innovation when they begin offshoring these activities to a foreign country for the first time. If they have previously engaged in such offshoring, they instead pay fixed costs: ϕ_f^p for production and $\phi_{f,ilt}^r$ for innovation. The fixed cost for innovating in country l can be reduced if the firm has production within the region:

$$\phi_{f,ilt}^r = \phi_f^r - \lambda_1 \max_{l'}\{c_{ll'} y_{il't}\}.$$

$c_{ll'}$ is a dummy variable that indicates whether countries l and l' are in the same region. The degree of the cost reduction is determined by the parameter λ_1.

Timing Assumption. (1) At the beginning of period t, the firm observes its state vector, which includes the location bundles for production and innovation from the previous period, the current-period productivity, and other exogenous demand and cost shifters: $\boldsymbol{s}_{it} = \left(\{y_{ilt-1}\}_l, \{r_{ilt-1}\}_l, \omega_{it};\ k_{it}, \Phi_{jt}\right)$. The value function $V_{it}(\boldsymbol{s}_{it})$ is defined at this stage. (2) Productivity shocks are realized, and the firm chooses the quantities of labor, intermediate inputs, and energy consumption. (3) The firm is aware of the fixed and sunk costs associated with each offshoring choice and selects its optimal location bundles $\boldsymbol{y}_{it}$ and $\boldsymbol{r}_{it}$. (4) Static profits $\pi_{it}(\boldsymbol{y}_{it}, \omega_{it})$ are realized, and dynamic offshoring costs are paid. (5) The new state is formed at the end of this period: $\boldsymbol{s}_{it+1} = \left(\boldsymbol{y}_{it}; \boldsymbol{r}_{it}; \omega_{it+1}|\omega_{it}, \boldsymbol{y}_{it}, \boldsymbol{r}_{it}; k_{it+1}, \Phi_{jt+1}\right)$.

Dynamic Problem. The firm's dynamic programming problem is characterized by the following Bellman equation:

$$\begin{aligned} V_{it}\left(\boldsymbol{s}_{it}\right) = \max_{\boldsymbol{y}_{it}, \boldsymbol{r}_{it}} \Bigg\{ & \pi_{it}(\boldsymbol{y}_{it}, \omega_{it}) - \sum_l y_{ilt}\left[(1 - y_{ilt-1}) \cdot \phi_s^p + y_{ilt-1} \cdot \phi_f^p\right] \\ & - \sum_l r_{ilt}\left[(1 - r_{ilt-1}) \cdot \phi_s^r + r_{ilt-1} \cdot \phi_{f,ilt}^r\left(\boldsymbol{y}_{it}\right)\right] + \zeta \mathbb{E}_\xi V_{it+1}\left(\boldsymbol{s}_{it+1}|\omega_{it}, \boldsymbol{y}_{it}, \boldsymbol{r}_{it}\right) \Bigg\}. \end{aligned} \qquad (8)$$

The firm's objective is to maximize the present value, which depends on current-period profit, dynamic offshoring costs, and the discounted expected value of future periods. Regarding the state transition rule, next period's productivity ω_{it+1} is determined by the current-period productivity ω_{it} and the firm's location choices $(\boldsymbol{y}_{it}, \boldsymbol{r}_{it})$. The optimal choices of location bundles, $(\boldsymbol{y}_{it}, \boldsymbol{r}_{it})$, also directly serve as components of the new states.

IV.C Supermodularity Property

The dynamic programming problem characterized by the Bellman Equation (8) is NP-hard, with prohibitively large state and action spaces covering all possible country combinations. To tackle this computational challenge, I first derive a condition under which the complementarities in the model dominate the substitutabilities, ensuring that the firm's lifetime objective function is supermodular. This condition holds empirically given the estimates of static parameters. Since maximizing a supermodular function is feasible in polynomial time, I can then adapt a cutting-edge algorithm to effectively solve this otherwise unsolvable dynamic location choice problem.

To introduce the supermodularity property, let us reframe the recursive dynamic programming problem as a lifetime planning problem. Defining Π_t as the variable profit net of fixed and sunk costs, the firm's expected lifetime payoff can be expressed as

$$\Pi_0\left(\boldsymbol{o}_i|\boldsymbol{y}_{i,-1}, \boldsymbol{r}_{i,-1}, \omega_{i,-1}\right) = \mathbb{E}_{\boldsymbol{z}} \sum_{t=0}^{\infty} \zeta^t \Pi_t\left(\omega_{it}\left(z^t, \left\{\boldsymbol{o}_{i\tau}\left(z^\tau\right)\right\}_{\tau=0}^{t-1}\right), \boldsymbol{o}_{it}\left(z^t\right), \boldsymbol{o}_{it-1}\left(z^{t-1}\right)\right),$$

where $z^t = (\xi_1, \xi_2, \ldots, \xi_t)$ represents the history of productivity shocks up to period t and $z = \{\xi_t\}_{t=0}^{\infty}$ represents the full history. Define Ω as the space of all possible shock histories, $\mathcal{L}$ as the set of locations, and $\mathcal{T}$ as the set of time periods. The firm's production offshoring decisions, $\boldsymbol{y}_i$, are represented as a point in $\{0,1\}^{\mathcal{L}\mathcal{T}\Omega}$, specifying choices across locations and periods for all possible shock histories. Similarly, $\boldsymbol{r}_i$ represents innovation offshoring decisions in the same space. Let $\boldsymbol{o}_i = (\boldsymbol{y}_i, \boldsymbol{r}_i)$ compactly represent the firm's full decision rule. Without loss of generality, I consider a fixed initial state and occasionally omit notations $(\boldsymbol{y}_{i,-1}, \boldsymbol{r}_{i,-1}, \omega_{i,-1})$. The firm's problem is to select the optimal $\boldsymbol{o}_i$ that maximizes $\Pi_0(\boldsymbol{o}_i)$.

Next, I establish a proposition that the firm's lifetime payoff function exhibits supermodularity with respect to its decision rules under an empirically valid inequality condition. This proposition ensures the effectiveness of the solution algorithm used later.

Proposition 1. *Assume that sunk costs are greater than or equal to fixed costs, and that $\beta_1, \beta_2, \beta_3$ and λ_1 are non-negative. If $(\eta-1)\beta_m > \rho - 1$, then $\Pi_0\left(\boldsymbol{o}_i|\boldsymbol{y}_{i,-1}, \boldsymbol{r}_{i,-1}, \omega_{i,-1}\right)$ is supermodular in $\boldsymbol{o}_i$ on $\{0,1\}^{2\mathcal{L}\mathcal{T}\Omega}$.*

The proof of Proposition 1 is provided in Appendix C.3. Mathematically, supermodularity requires that if an item adds value to a decision set, it continues to add value in any subset of the original decision set. Intuitively, it corresponds to rich static and dynamic complementarities in the model, which I now elaborate on.

Under the inequality condition, production offshoring decisions across locations, y_{ilt} and $y_{il't}$, are complementary, meaning that production at one location increases the return from production at other locations. This condition ensures that the static profit function is supermodular in y_{ilt} and $y_{il't}$. A larger value of $(\eta - 1)\beta_m$ indicates a stronger revenue response to a decrease in the marginal production cost (elasticity η) and a greater sensitivity of marginal production cost to changes in intermediate prices (elasticity β_m). The condition also requires a small substitution effect between goods from different countries, characterized by the elasticity of substitution ρ, similar to the condition in Antras, Fort and Tintelnot (2017).

The regularity conditions imply additional complementarities. Over time, y_{ilt} is complementary to y_{ilt+1} if sunk costs are greater than or equal to fixed costs, as offshoring production today lowers the cost of offshoring in future periods. Similarly, r_{ilt} complements r_{ilt+1} for the same reason. There is complementarity between y_{ilt} and r_{ilt} because local production increases the return to innovation (β_2) and decreases its cost (γ_1). Lastly, complementarity exists between y_{ilt} and $r_{il't}$ because having a production plant in neighboring countries can also reduce innovation cost (γ_1). These complementarities together imply the supermodular nature of the model, which is crucial for the solution algorithm.

V Solution Algorithm and Model Estimation

The lattice structure of the dynamic programming problem can be leveraged to form a squeezing algorithm, whereby one starts from the highest and lowest points in the lattice and gradually narrows down the range to reach the optimal solution. This section first presents the solution algorithm adapted from Alfaro-Ureña, Castro-Vincenzi, Fanelli and Morales (2023) and then discusses the estimation steps and results.

V.A Solution Algorithm

I begin by assuming that the model is non-stationary until a terminal period T, beyond which all exogenous determinants of payoffs, such as market demand and countries' production-offshoring potentials, remain constant (as in Eaton, Kortum, Neiman and Romalis, 2016; Caliendo, Dvorkin and Parro, 2019; Igami and Uetake, 2020; Alfaro-Ureña, Castro-Vincenzi, Fanelli and Morales, 2023). This implies that the value and policy functions become stationary for $t \geq T$. Let $\underline{t}_I$ represent the initial sample period.

The first computational challenge in solving the Bellman Equation (8) is the large state space, especially when coupled with the non-stationarity of the model. Essentially, one needs to solve $2^{2\mathcal{L}N_\omega\mathcal{T}}$ distinct choice problems, and for each of these problems, there are $2^{2\mathcal{L}}$ options to evaluate. The idea to tackle this issue is to design the algorithm in such a way that we only need to compute the policy function at selective states rather than at all possible states. In particular, this is done only at states $\{\check{\boldsymbol{y}}_{it}, \check{\boldsymbol{r}}_{it}, \check{\omega}_{it}\}_{t_I}^{t_F}$ that the firm would reach if it chooses the optimal location bundles at each period and all exogenous determinants follow specific paths of interest $\{\check{\xi}_{it}, \check{\Phi}_{jt}\}_{t_I}^{t_F}$—e.g., observed or simulated paths. This approach significantly reduces the number of problems that need to be solved.

The second insight of the solution algorithm is that solving the optimization problem at a given state does not require full knowledge of the optimal choices in all states that may be subsequently reached (Alfaro-Ureña, Castro-Vincenzi, Fanelli and Morales, 2023). For instance, if a firm's return to establishing an R&D lab in the current state is sufficiently high, its optimal decision may be to do so regardless of what its optimal choices might be at any other states. As a result, the algorithm is able to track only the upper and lower bounds on the optimal choices, sparing the need to store the entire policy function. The last idea in the solution algorithm is to break down a complex problem with a large choice set into many simpler problems, by solving single-country problems each at a time while fixing choices in other countries at their bounds (Jia, 2008; Arkolakis, Eckert and Shi, 2021).

The algorithm updates an upper and lower bound on the firm's optimal choices along specific paths of interest. If these bounds coincide, they must also coincide with the solution. However, if they narrow but do not converge, additional refinement is needed to further tighten the bounds. Now, consider a specific firm i and, without loss of generality, assume it is born in period one.

Step 1. To initiate the algorithm, I set an initial constant upper bound as a vector of ones, i.e. $\bar{b}_i^{[0]} = \{\bar{y}_{ilt}, \bar{r}_{ilt}\}_{l,t} = \mathbf{1}^{2TL}$, so that $\bar{b}_{ilt} \geq o_{ilt}\left(y_{it-1}, r_{it-1}, \omega_{it}\right)$ for all $(y_{it-1}, r_{it-1}, \omega_{it})$. In words, this is an upper bound on the firm's optimal production and innovation choices in each country l and period $t \geq 1$, regardless of the path of productivity shocks and concurrent decisions in other countries.

Step 2. I define single-country problems and solve them one at a time to derive an upper bound policy function $\bar{o}_i^{[0]}$, where $\bar{o}_{ilt}^{[0]}(y_{ilt-1}, r_{ilt-1}, \omega_{it}) \geq o_{ilt}\left(y_{it-1}, r_{it-1}, \omega_{it}\right)$ for all $y_{i(-l)t-1}$ and $r_{i(-l)t-1}$. This upper bound policy function is distinct from the full policy function, which is a mapping from the entire state space to the entire action space and requires storage of a prohibitively large size. In contrast, the upper bound policy function pertains to the problem for a specific country where actions in other countries are fixed at the initial constant bound.[22] As a result, it bounds the firm's optimal choices regardless of concurrent decisions in other countries but remains dependent on the path of productivity shocks.

The single-country problem is solved by backward induction. For a specific country l, I first consider its optimization in the final period T:

$$\bar{V}_{ilT}\left(y_{ilT-1}, r_{ilT-1}, \omega_{iT}\right) = \max_{y_{ilT}\in\{0,1\}, r_{ilT}\in\{0,1\}} \left\{ \pi_{iT}\left(\omega_{iT}, y_{iT}|\bar{b}^{[0]}_{i,-l,T}\right) - y_{ilT}\left[\left(1-y_{ilT-1}\right)\phi^p_s + y_{ilT-1}\phi^p_f\right] \right.$$
$$\left. - r_{ilT}\left[\left(1-r_{ilT-1}\right)\phi^r_s + r_{ilT-1}\phi^r_{f,ilT}\left(y_{ilT}|\bar{b}^{[0]}_{i,-l,T}\right)\right] + \zeta\mathbb{E}_{\xi}\bar{V}_{ilT}\left(s_{iT+1}|y_{ilT}, r_{ilT}, \omega_{iT}, \bar{b}^{[0]}_{i,-l,T}\right)\right\}.$$

This is a simple optimization problem with a small state space and action space. I use standard value function iterations to solve it and obtain $\bar{V}_{ilT}$ and $\bar{o}_{ilT}$. Similarly, I solve the same problem from period $T-1$ to 1 and obtain $\{\bar{V}_{ilt}\}_{t=1}^{T-1}$ and $\{\bar{o}^{[0]}_{ilt}\}_{t=1}^{T-1}$.

I then repeatedly solve the single-country problem for countries 1 to L to get the entire upper bound value function $\bar{V}_i$ and the entire upper bound policy function $\bar{o}^{[0]}_i$. The supermodularity property of the model guarantees that the upper bound policy function obtained through this process is indeed an upper bound on the firm's optimal choices.

Step 3. The next step is to update the constant upper bound using the obtained upper bound policy function $\bar{o}^{[0]}_i$. This is achieved by evaluating the upper bound policy function at the most favorable path of productivity shocks, i.e. when firm i receives the highest shock in every period. This step gives us the highest choices among all possible histories:

$$\bar{b}^{[n]}_{it'} = \bar{o}^{[n-1]}_{it'}\left(\bar{b}^{[n]}_{it'-1}, \omega_{it}\left(\omega_{i0}, \bar{\xi}\right)\right), t' = 1, \ldots, T$$

with the initial condition equal to $\mathbf{0}_{2J}$ and ω_{i0}. In contrast to the firm-country level shocks in Alfaro-Ureña, Castro-Vincenzi, Fanelli and Morales (2023), the unobserved shocks in my model are at the firm level, so the updating procedure also operates at the firm level.

Step 4. I iterate over the previous steps until the constant upper bound converges, i.e. $\bar{b}^{[n]}_{it} = \bar{b}^{[n-1]}_{it}, \forall t \in [\underline{t}_i, T]$, and denote the resulting upper bound policy function as $\bar{o}^*_i$. Similarly, if we start with an initial constant lower bound equal to $\underline{b}^{[0]}_i = \mathbf{0}^{2TL}$, obtain the lower bound policy function, and update the constant lower bound by evaluating the lower bound policy function at the least favorable path of shocks, we obtain the converged lower-bound policy function $\underline{o}^*_i$. Convergence in this step is always achieved because the constant upper (lower) bound always decreases (increases) and there are only finitely many values it can take.

Step 5. The final step is to derive bounds on the firm's optimal choices along the "path of interest" using the converged upper and lower bound policy functions. The path of interest,

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[22] For comparison, the upper bound policy function $\bar{o}^{[0]}_i$ is a point in the $\{0,1\}^{2TL\times 4\mathbb{R}}$ space. The full policy function, on the other hand, is a mapping from the state space $\{0,1\}^{2L}\times\mathbb{R}$ to the action space $\{0,1\}^{2L}$ in every period, thereby existing in the $\{0,1\}^{2TL\times 4^L\mathbb{R}}$ space.

typically the simulated path of productivity shocks, is denoted as $\left\{\check{\xi}_{it}\right\}_t$. The upper bound $\bar{\check{y}}_i$ (lower bound $\underline{\check{y}}_i$) consists of the decisions made by the firm if it receives the simulated shocks and follows the upper bound policy function $\bar{o}_i^*$ (lower bound policy function $\underline{o}_i^*$):

$$\bar{\check{y}}_{it'} = \bar{o}_{it'}^* \left(\bar{\check{y}}_{it'-1}, \check{\xi}_{it'}\right), \quad \underline{\check{y}}_{it'} = \underline{o}_{it'}^* \left(\underline{\check{y}}_{it'-1}, \check{\xi}_{it'}\right), \quad t' = \underline{t}_i, \ldots, t,$$

with initial condition equal to $\mathbf{0}_{2J}$ and ω_{i0}. If $\bar{\check{y}}_{it}$ and $\underline{\check{y}}_{it}$ coincide for all sample periods, they represent the firm's optimal choices along the path of interest. However, they differ for at least one period, additional refinement steps are needed to further tighten the bounds.

Refinement. I begin the refinement step with the period τ where the upper and lower bounds on the firm's optimal choices along the path of interest differ for the first time; that is, $\tau = \min\{t \in [t_I, T] : \bar{\check{y}}_{it} > \underline{\check{y}}_{it}\}$. Using the knowledge about the firm's optimal choices along the path of interest up to period $\tau - 1$, I can refine the bounds at period τ by solving for the same problem as in the main steps, but only for the truncated periods $[\tau, T]$ with the initial state $(\check{\boldsymbol{y}}_{i\tau-1}, \check{\boldsymbol{r}}_{i\tau-1}, \check{\omega}_{i\tau-1})$. The idea behind this refinement step is that convergence is easier to achieve when a shorter time period is involved and initial bounds are more accurate.

One difference in this refinement step compared to the main steps is how I initialize the constant bounds. For the constant upper bound, instead of using a vector of ones, I evaluate the converged upper bound policy function, $\bar{o}_{it}^*$, at the state firm i reaches if it (1) starts from $(\check{\boldsymbol{y}}_{i\tau-1}, \check{\boldsymbol{r}}_{i\tau-1}, \check{\omega}_{i\tau-1})$ at period τ, (2) receives the highest shock for all $t' \in [\tau, T]$, and (3) chooses location bundles according to $\bar{o}_{it}^*$. The constant lower bound is initialized similarly.

Solving the truncated problem gives us upper and lower bounds on the firm's optimal choices at period τ along the path of interest, denoted by $\bar{\check{y}}_{i\tau|\tau}$ and $\underline{\check{y}}_{i\tau|\tau}$. If these bounds coincide, we obtain the optimal choice at τ. In this case, I proceed to the next $\tau' > \tau$ where the bounds differ and apply the refinement procedure again to tighten the bounds at τ'. Otherwise, I assume the firm follows the lower bound policy function. This assumption has minimal impact on estimation results and counterfactuals, as more than 99% of the individual problems are solved accurately.

It is worth reiterating that the supermodularity property is responsible for ensuring that $\bar{b}_i^{[n]}$ ($\underline{b}_i^{[n]}$) is an upper (lower) bound on the firm's optimal choice at any feasible history, changes monotonically with each iteration n, and converges after a finite number of iterations. My setting differs from that of Alfaro-Ureña, Castro-Vincenzi, Fanelli and Morales (2023) in several ways: it incorporates two interrelated dynamic choices with rich complementarities, allows for a more general context where the static profit function is supermodular but not additively separable across countries, and permits the unobserved state to be endogenously affected by choices. Nonetheless, the algorithm is effective as a result of Proposition 1.

V.B Estimation Steps and Results

I now turn to model estimation. Table 7 summarizes the parameters to be estimated and their sources of identification. Further details on each parameter's identification will be discussed in the corresponding estimation steps. The estimation strategy follows three steps. First, I estimate the countries' production-offshoring potentials, θ_{lt}, firms' production offshoring capabilities, Θ_{it}, and the elasticity of substitution, ρ, based on firms' production shares across countries. I also estimate η using the average markup. Second, I apply the control function approach to estimate the unit cost function and the productivity evolution process, recovering parameters $\beta_k, \beta_m, \alpha_0, \alpha_1, \boldsymbol{\mu}, \beta_1, \beta_2$, and σ_ξ. Finally, I use the method of simulated moments (MSM) to estimate the fixed and sunk cost parameters: $\phi_s^p, \phi_s^r, \phi_f^p, \phi_f^r$, and λ_1.

V.B.1 Step 1—Production-Offshoring Potentials

In this step, I take the firm's production locations as given and focus on the variation in its product value shares across countries. Given the CES aggregation of intermediates, firm i's value share of imported goods from country l in period t is given by

$$\chi_{ilt} = \left(\frac{w_{lt}\tau_{lt}(1+T_{lt})}{p_{it}^m}\right)^{1-\rho} = \frac{\theta_{lt}}{\Theta_{it}},$$

which represents the contribution of the country's production-offshoring potential to the firm's production-offshoring capability.

After taking logs of this equation and normalizing the foreign product shares by the firm's domestic product share (i.e. setting $\theta_{0t} = 1$ where location 0 represents the U.S.), I obtain the following expression:

$$\ln \chi_{ilt} - \ln \chi_{i0t} = \ln \theta_{lt} + \ln \epsilon_{ilt}. \tag{9}$$

A firm-country-year-level measurement error, ϵ_{ilt}, is added to turn the model's equilibrium condition into an empirical specification. The left-hand side of Equation (9) is the difference between a firm's share of goods imported from country l and its share of goods made domestically. I estimate Equation (9) via Ordinary Least Squares (OLS) and employ country-year fixed effects to capture the $\ln \theta_{lt}$ terms. A country's production-offshoring potential is identified by how much firms import from that country relative to other countries.

I cross-validate the estimates of production-offshoring potentials, $\hat{\theta}_{lt}$, by comparing them to the number of firms importing from each country. Panel A of Figure 6 shows the overtime correlation for China, and Panel B shows the cross-sectional correlation for all countries in 2017. Both graphs indicate that a host country's production-offshoring potential is highly correlated with the number of U.S. firms importing from that country. In 2017, China had the highest production-offshoring potential, largely due to its competitive production cost.

Canada was a close second, likely benefiting from its low trade costs with the U.S.

Using the estimated production-offshoring potentials, $\hat{\theta}_{lt}$, I calculate each firm's production-offshoring capability as $\hat{\Theta}_{it} = \sum_{l \in \mathcal{L}} y_{ilt} \hat{\theta}_{lt}$. The estimates of $\hat{\Theta}_{it}$ imply that a firm importing from all countries in the sample has a production-offshoring capability that is 10.3 percent larger than a firm obtaining intermediates solely from the domestic market.

The effect of a firm's production-offshoring capability on its marginal cost is determined by the parameter ρ. To estimate ρ, I run the following regression derived from the definition of production-offshoring potentials:

$$\widehat{\ln \theta_{lt}} = -(\rho - 1) \cdot \ln(1 + T_{lt}) + \nu_{lt}. \tag{10}$$

Here, T_{lt} is the ad valorem tariff rates, and ν_{lt} captures other determinants of offshore production costs such as wage and shipping costs. I project the estimated production-offshoring potentials on changes in tariffs instead of alternative cost shifters like wages and shipping costs because tariffs are more likely to be exogenous to firm characteristics.

Table 8 reports coefficient estimates for Equation (10). Column (1) serves as the baseline without any controls, while column (2) includes controls for population, common language, and colonial relationships. In column (3), I further control for human capital and the level of corruption in the country. The coefficient estimate of tariffs remains consistent across different sets of controls. Using column (1) as the baseline, I estimate ρ to be 3.739.

I then construct the intermediate price index for each firm as $p^m_{it} = \left(\sum_l y_{ilt} \cdot \hat{\theta}_{lt}\right)^{\frac{1}{1-\hat{\rho}}}$. The intermediate price that a firm faces when it imports from all countries is approximately 3.52 percent lower compared to a firm that only obtain intermediates domestically.

Finally, I recover the demand elasticity η from markups. With CES preferences and monopolistic competition, the ratio of sales to total variable cost is $\eta/(\eta - 1)$, implying that $\eta = \frac{R_{it}/\text{tvc}_{it}}{R_{it}/\text{tvc}_{it} - 1}$, where R_{it} and tvc_{it} are the firm's revenue and total variable cost. The median markup in the sample is 1.237, suggesting an estimate of $\hat{\eta} = 5.217$. Appendix A presents further information on the construction of total variable cost using census data variables.

V.B.2 Step 2—Cost Function and Productivity Evolution

To allow revenue to be measured with error, I augment the original revenue function with an independently and identically distributed error term u_{it}:

$$\ln R_{it} = (1-\eta) \ln\left(\frac{\eta}{\eta - 1}\right) + \ln \Phi_{jt} + (1-\eta)\left(\beta_0 + \beta_k \ln k_{it} + \beta_w \ln w_{jt} + \beta_m \ln p^m_{it} - \omega_{it}\right) + u_{it}. \tag{11}$$

The composite error term $u_{it} - (1-\eta)\omega_{it}$ correlates with firm's input choices due to its inclusion of firm productivity. As a result, a simple OLS regression for this equation would yield biased estimates for the coefficients of input factors.

Building on insights from Olley and Pakes (1996) and Ackerberg, Caves and Frazer (2015), I assume there is a fully flexible energy input n_{it} that, conditioning on other factor inputs, strictly increases with the firm's realized productivity. Strict monotonicity guarantees inversion, allowing me to express productivity as a conditional function of the variable energy input; that is, $\omega_{it}(n_{it}; k_{it}, p_{it}^m)$. Using this and combining industry-year level terms, Equation (11) can be written as

$$\ln R_{it} = \psi_0 + \psi_{jt} + \underbrace{(1-\eta)\left(\beta_k \ln k_{it} + \beta_m \ln p_{it}^m - \omega_{it}\right)}_{\phi_{it}} + u_{it}, \tag{12}$$

$$\psi_0 = (1-\eta)\ln\left(\eta/(\eta-1)\right) + (1-\eta)\beta_0, \quad \psi_{jt} = \ln \Phi_{jt} + (1-\eta)\beta_w \ln w_{jt},$$

where $\hat{\phi}_{it}$ is estimated as a second-order polynomial function $h\left(k_{it}, p_{it}^m, n_{it}\right)$. Identification of h comes from mean independence of u_{it}. ψ_{jt} will be absorbed by industry-year fixed effects.

By plugging the estimate $\hat{\phi}_{it}$ into the productivity evolution process in Equation (7), I obtain the following nonlinear equation:

$$\begin{aligned}\hat{\phi}_{it} =& \beta_k^* \cdot \ln k_{it} + \beta_m^* \cdot \ln p_{it}^m - \alpha_0^* + \alpha_1 \cdot \left(\hat{\phi}_{it-1} - \beta_k^* \cdot \ln k_{it-1} - \beta_m^* \cdot \ln p_{it-1}^m\right) \\ &- \sum_l \left[1 + \boldsymbol{X}_{lt-1}' \boldsymbol{\mu}\right] \cdot \left[\beta_1^* r_{ilt-1} + \beta_2^* r_{ilt-1} y_{ilt-1} + \beta_3^* y_{ilt-1}\right] - \xi_{it}^*,\end{aligned} \tag{13}$$

where the transformation $x^* = (1-\eta)x$. I estimate this equation using Nonlinear Least Squares, where the identification of parameters comes from the mean independence of the innovation in productivity, i.e. ξ_{it}, and the timing assumptions. Once the coefficients are estimated, a firm's productivity can be computed as follows:

$$\omega_{it} = -\frac{\hat{\phi}_{it}}{1-\hat{\eta}} + \hat{\beta}_k \cdot \ln k_{it} + \hat{\beta}_m \cdot \ln p_{it}^m.$$

Table 9 presents estimates of Equation (13). In the baseline specification, Column (1), the elasticity of capital is estimated at -0.164, indicating that doubling a firm's capital stock reduces its marginal production cost by 16.4%. The positive coefficient for intermediate price confirms that unit production costs increase as intermediates become more expensive.

The estimates of β_1 to β_3 indicate that the contribution of stand-alone offshore R&D to productivity is not statistically significant.[23] However, offshore R&D accompanied by offshore production significantly increases the firm's future productivity. Additionally, offshore

[23] The result that $\hat{\beta}_1$ is not significantly different from zero partly reflects the fact that stand-alone offshore R&D is typically on a small scale. In host countries where the firm has R&D but no production, the average R&D expenditure is less than 20% of that in host countries where the firm has both R&D and production (which is also a reflection of colocation). A model that accounts for both the extensive margin and the intensive margin of offshore R&D investment can "micro-found" the small magnitude of the return to stand-alone R&D.

production itself contributes positively to productivity, likely due to the learning-by-doing effect. These findings emphasize the importance of the synergy effect, where the proximity between production and innovation is crucial for enhancing innovation efficiency.

To test the robustness of these estimates, Column (2) of Table 9 includes only firms with foreign employees, likely multinationals, in contrast to the full sample, which includes many domestic firms that have not offshored. Column (3) excludes countries typically considered tax havens in order to address the potential concern that R&D expenditures may reflect tax evasion incentives rather than genuine innovation activities.[24] The known tax havens in the sample include Hong Kong, Ireland, Luxembourg, the Netherlands, Switzerland, and Singapore (Gravelle, 2015).[25] Column (4) excludes China, showing that the estimated synergy effect is not mainly driven by offshoring to China. Additionally, Appendix B uses a two-step control function approach to address potential measurement error in the R&D indicator from local innovation incentives, confirming robust estimates in Appendix Table A1.

For easier interpretation of the magnitude of the synergy effect, Table 9 also reports the mean, standard deviation, and maximum of $(1 + \boldsymbol{X}'\hat{\boldsymbol{\mu}})\hat{\beta}_2$ across countries. On average, colocating R&D with production in a foreign country increases firm productivity by 0.05% to 0.07% in the following year. In countries with the highest synergy effect, the return is 0.17% to 0.21%. Figure 7 shows the annual average of $1 + \boldsymbol{X}'\hat{\boldsymbol{\mu}}$ for each country, indicating that the synergy effect is strong for Mexico and India, but weak for Australia and Russia.[26]

V.B.3 Step 3—Dynamic Parameters

The elasticity estimates obtained from Steps 1 and 2 confirm that the inequality condition required by Proposition 1 is satisfied, i.e. $(\eta - 1)\beta_m > \rho - 1$. This provides additional evidence supporting the model's supermodularity, alongside the reduced-form evidence on positive cross-country interdependence.

The supermodularity property ensures that the model can be solved using the algorithm

[24] However, the specification that examines *discrete* R&D and production decisions is already less susceptible to misreporting concerns compared to a continuous analog because firms might hide part of the R&D revenue at a location but are unlikely to hide the entire presence of an R&D lab.

[25] This list is based on the U.S. Congressional Research Service and aligns with those from the Organization for Economic Cooperation and Development (OECD) and the U.S. Government Accountability Office (GAO).

[26] The estimates suggest a larger synergy effect in countries farther from the U.S. with less human and physical capital. Several factors may explain this. First, the initial obstacles of innovating without producing are higher in poorer countries. For instance, new product testing that requires communication with the U.S. headquarter is more difficult in a stand-alone lab in South Africa than in Canada. Second, immersion in an exotic culture can spark new ideas and provides differentiated innovation. Third, higher fixed costs of offshoring to poorer countries may lead firms to produce more there to justify these costs, thus boosting the return to R&D. Finally, the specialization of countries in different industries introduces heterogeneity that is not accounted for. This paper does not provide further evidence for which explanations are more relevant.

outlined in Section V.A. However, the dynamic model does not yield a closed form solution for firms' location choices given market observables and parameter values. Therefore, I use simulation methods to estimate the dynamic cost parameters. Commonly used simulation methods include the method of simulated log likelihood (MSL) and the method of simulated moments (MSM). Implementing MSL is difficult because the cross-country and cross-period dependencies in the location choices imply that the log-likelihood of the sample is no longer the sum of the log-likelihood of each country and period, and one needs an exceptionally large number of simulations to get a reasonable estimate. Consequently, I use the MSM method to estimate five dynamic parameters, $\phi_s^p, \phi_s^r, \phi_f^r, \phi_f^p$ and λ_1.

As shown in Table 10, six moments are used to identify these five parameters. The first two moments, $\mathbb{E}[y_{ilt}]$ and $\mathbb{E}[r_{ilt}]$, reflect the fraction of firms offshoring production and R&D to foreign countries, respectively, and help identify the fixed costs ϕ_f^r and ϕ_f^p. The third and fourth moments, $\mathbb{E}[y_{ilt}\,(1 - y_{ilt-1})]$ and $\mathbb{E}[r_{ilt}\,(1 - r_{ilt-1})]$, capture the frequency at which non-offshoring firms begin offshoring production and innovation, providing information about the sunk costs ϕ_s^p and ϕ_s^r. The last two moments, $\mathbb{E}[y_{ilt}y_{il't}|c_{ll'} = 1] - \mathbb{E}[y_{ilt}y_{il't}|c_{ll'} = 0]$ and $\mathbb{E}[r_{ilt}r_{il't}|c_{ll'} = 1] - \mathbb{E}[r_{ilt}r_{il't}|c_{ll'} = 0]$, measure the disparity in the frequency of firms offshoring production and innovation to both country l and l' when they are in the same region compared to when they are not. A higher value of the parameter λ_1 results in a larger disparity in this frequency.

The estimates of cost parameters are reported in Panel A of Table 10. The sunk and fixed costs of offshoring production to a foreign country are approximately \$5 million and \$3.3 million. For offshoring R&D, these costs are estimated at around \$69.2 million and \$41.2 million, comparable to the conditional mean R&D expenditures of the large multinational firms in my sample, as shown in Table 1. The cost-sharing parameter λ_1 is estimated at \$1.1 million, representing only 2.6% of the fixed cost of R&D. This indicates that firms colocate production and innovation primarily to improve innovation efficiency rather than to save on overhead costs, a hypothesis I further verify through counterfactual analysis.

VI Counterfactual Exercises

This section presents four counterfactual exercises. The first is a model validation, where I simulate the model-implied effects of the Trump Tariffs on China and show their alignment with reduced-form predictions. Next, I quantify the relative importance of the two colocation mechanisms—synergy and cost-sharing—by individually shutting them down. Then, I simulate counterfactual policies that make it harder for U.S. firms to offshore production to China and analyze their impact on global production and innovation reallocation. I find nontrivial third-country effects and nonlinear effects, contingent on firm heterogeneity and the magnitude of the shocks. Finally, I highlight my model's prediction of dynamic losses from trade policies, distinct from static models of global production and sourcing.

VI.A Model Validation Based On Trump Tariffs

Between 2017 and 2019, the U.S. tariff rate on Chinese goods increased by 3.8 percentage points on average, rising from 4.07% to 7.87% (based on the Trade Analysis Information System data). The estimates in Table 5 suggest that this tariff increase will result in a 7.2% decline in imports and a 0.1 percentage point reduction in the likelihood of offshoring R&D.

In my model, implementing an identical tariff increase corresponds to a 10% reduction in China's production-offshoring potential. The model predicts a 6.5% decrease in imports and a 0.06 percentage point decline in the likelihood of offshoring R&D to China over the two-year period. This exercise underscores the model's ability to generate effects of the right magnitude, aligning well with the reduced-form estimates.

VI.B Quantifying Colocation Mechanisms

I conduct two exercises in this subsection to assess the relative importance of two key mechanisms in the model. In the first exercise, I gradually weaken the synergy effect between production and innovation by reducing the value of β_2 from its baseline estimate to zero. The simulation results are presented in Panel A of Table 11. When β_2 is reduced by half, the probability of offshoring production declines by less than 1% but the probability of offshoring R&D drops by 86.2% (third column). The probability of offshoring R&D to a foreign country, conditional on having offshore production in that country, decreases by more than 85%. These results demonstrate that the synergy effect is a crucial driver of firms' decisions to conduct R&D, particularly in countries where they already have production sites.

The second exercise involves reducing the cost-sharing parameter λ_1 from its baseline estimate to zero, effectively shutting down the mechanism where local production lowers the fixed cost of conducting R&D. The results of this analysis are presented in Panel B of Table 11. As a consequence of the higher effective offshoring costs, the first two rows show that the probability of a firm offshoring R&D to a foreign country decreases by 3.3%. The within-country colocation pattern is also weakened: the probability of a firm conducting R&D in a foreign country, conditional on having offshore production there, decreases by 3.4%. Additionally, the cross-country colocation within the same region is negatively affected. In the third row, given that a firm has production in country l, the probability that it conducts R&D in other countries within the same region decreases from 7.54 to 7.29 percentage points.

The fact that these colocation measures are reduced by less than 5% when the cost-sharing mechanism is eliminated suggests that over 95% of the observed colocation pattern is driven by the synergy effect (along with implicit scale effects). Coupled with the large impacts observed in the first exercise, I conclude that the synergy effect is the primary factor behind firms' incentives to colocate production and innovation.

VI.C Effects of Bilateral Trade Policies

In recent years, the trade relationship between the world's two largest economies, the U.S. and China, has become increasingly contentious. China has been a major target of the U.S. in the trade war since 2018 and recent trade policies of both the Trump and Biden administrations. The increased tariffs and U.S. government's reshoring efforts together made it more costly for U.S. firms to offshore production to China.

My framework is particularly well-suited for analyzing such policies for three main reasons. First, it considers that trade policies affecting the production locations of multinational firms will also influence their R&D locations due to colocation incentives. Second, it accounts for third-country effects by incorporating cross-country interdependencies. Third, it captures not only the static losses from trade shocks but also the dynamic losses that arise from endogenous innovation.

In this exercise, I simulate two sets of policy shocks that negatively impact U.S. firms' production offshoring to China after 2017. The first set of shocks involves tariff increases, represented as a reduction in China's production-offshoring potential by 30% to 100%. The second set of shocks pertains to rising fixed and sunk costs for production offshoring in China, increasing by 5 to 300 million dollars. I examine how these shocks of varying magnitudes affect the global distribution of production and innovation.

The results show that worsening offshoring conditions in China lead to some reshoring of production to the U.S., but the corresponding reshoring of innovation remains limited. For example, when China's sunk and fixed production costs increase by $50 million, the U.S. share of global production rises by 1.07 percentage points (10.6%), while its innovation share increases by only 0.008 percentage points (0.6%). This modest uptick in U.S. innovation is driven by two factors. First, some innovation leaving China is redirected to countries like Brazil and France, which offer a favorable combination of low production costs and relatively high innovation returns. Second, a scale effect partially offsets the reshoring of innovation to the U.S.: Many firms choose to produce in China to take advantage of its low production costs while innovating in the U.S. for higher returns. When these firms face rising offshoring costs, they scale down operations globally, including reducing innovation in the U.S.

The second observation is the importance of third-country effects from bilateral trade policies. When the U.S. raises tariffs on China by 14%, equivalent to reducing China's production-offshoring potential by 30%, the likelihood of a firm offshoring production to China over the next two years decreases by 5.9 percentage points (23%), with the corresponding decline for other regions of the world (ROW) at 0.8 percentage points (5.5%). The probability of offshoring R&D to China falls by 0.13 percentage points (9.7%), with an even larger decrease of 0.15 percentage points (11.4%) for ROW. These non-trivial third-country effects consistently appear across all counterfactual policy shocks and are driven by the cross-country interdependencies embedded in my framework—an element often overlooked in previous models that assume independent decisions in each country.

The changes in the innovation shares of China, the U.S., and ROW reveal interesting nonlinear patterns, as shown in Figure 8.[27] For moderate shocks (e.g. when production costs rise by less than 150 million dollars), innovation shares increase for both China and the U.S., while they decrease for ROW. However, under larger shocks, innovation shares decline in China but rise in both the U.S. and ROW.

Firm heterogeneity plays a key role in driving these nonlinear effects on innovation shares. Figure 9 shows the fraction of firms offshoring production and innovation to China and other countries, categorized by deciles of firm productivity and capital stock. It reveals that many firms with relatively low productivity and capital stock tend to produce in China without conducting innovation there, instead performing R&D in other countries. This pattern arises because China is estimated to have the highest production-offshoring potential (see Figure 6) but a relatively low synergy between production and innovation (see Figure 7).

When a moderate trade shock occurs, smaller and less efficient firms are the first to be affected. Due to the firm-level scale effect, they reduce offshoring activities globally, particularly cutting down production in China and innovation in the ROW. This results in a relative *increase* in China's share of globa innovation. However, as the shock intensifies (e.g., in the case of full U.S.-China decoupling), even firms in the top decile (upper-right blocks in the figure) that also innovate in China are impacted. At this point, innovation shares shift away from China towards the U.S. and ROW.

Taking stock, I find that U.S. reshoring policies effectively bring production back to the U.S., though the impact on innovation reshoring is more moderate. There are significant third-country effects resulting from U.S.-China bilateral policies, along with nonlinear shifts in innovation shares that depend on firm heterogeneity and the intensity of the policy.

[27] ROW refers to the sum of individual third-party countries. Country-specific results from the counterfactual exercises are detailed in Appendix Figure A8.

VI.D Dynamic Effects of Trade Policies

One important distinction between my framework and previous static models of global production and sourcing is that it incorporates endogenous productivity that is affected by firms' R&D investments. As a result, my framework can evaluate not only the static losses from adverse trade shocks, which are standard in traditional models, but also the dynamic losses that arise as offshoring decisions and endogenous productivity interact. The final counterfactual exercise illustrates this by simulating a permanent 50% reduction in China's production-offshoring potential, while holding all other environmental factors—such as other countries' offshoring potentials and industry demand—constant across years.

The simulation results indicate a 1.8 percentage point decline in the probability of offshoring production and a 0.26 percentage point reduction in the probability of offshoring innovation to a host country, immediately following the shock. Panel A of Figure 10 presents additional outcome measures related to static losses: the distributions of log intermediate prices and log marginal production costs both shift rightward, indicating rising costs. Correspondingly, the distribution of log profits shifts leftward. These changes reflect the static losses from reduced production offshoring opportunities, aligning with the findings of earlier static global production and sourcing models.

Furthermore, this adverse trade shock generates dynamic losses, as shown in Panel B of Figure 10. With the decline in China's production-offshoring potential, firms immediately reduce their offshore production and innovation, which subsequently diminishes their future productivity. Lower productivity and a smaller operational scale make it more difficult for firms to overcome the sunk and fixed costs of offshoring, further reducing their likelihood of engaging in production and innovation abroad. Additionally, firms face rising intermediate prices and marginal production costs due to the reduced scale of offshore production during this process. These negative effects accumulate over time: initial average productivity losses begin at zero but gradually build up to around 0.45% over a decade, while average annual firm profits drop by 3.7% in the first year and intensify to a 6.5% decline after ten years.

VII Conclusion

In this paper, I study the location choices of multinational firms regarding the offshoring of production and innovation. I show empirically the importance of colocation benefits between production and innovation, as well as the interdependence of these decisions across countries. Causal evidence shows that an increase in a host country's tariff not only reduces production and innovation within that country but also affects neighboring countries in the region.

I contribute to the literature on multinational production and innovation by developing a dynamic framework that allows for direct interaction between production and innovation while accounting for cross-country interdependence. My model incorporates rich static and dynamic complementarities in offshoring decisions. Additionally, I establish conditions for the model's supermodularity and apply a new algorithm to effectively solve this otherwise NP-hard problem. The quantification exercises reveal that the synergy effect between production and innovation is the primary driver for firms to colocate these activities.

I apply the model to assess the impact of U.S. trade policies that negatively affect production offshoring to China. The results reveal significant third-country effects and nonlinear effects in innovations shares, which are contingent upon firm heterogeneity and the scale of the policy shocks. Moreover, I highlight the importance of dynamic effects that are absent in previous static frameworks of global production and sourcing. These findings suggest that policymakers must consider the interplay between production and innovation, as well as the complex and potentially unintended consequences that offshoring and reshoring policies may have on the global geography of innovation.

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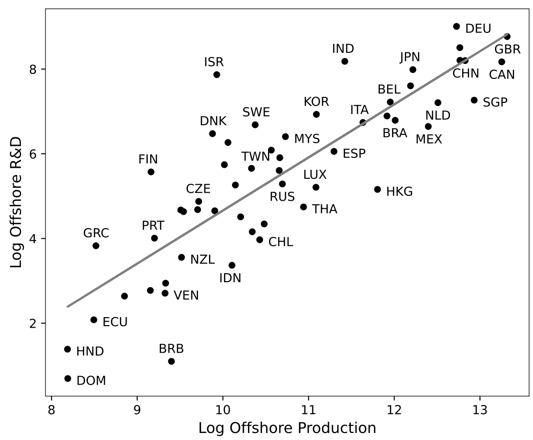
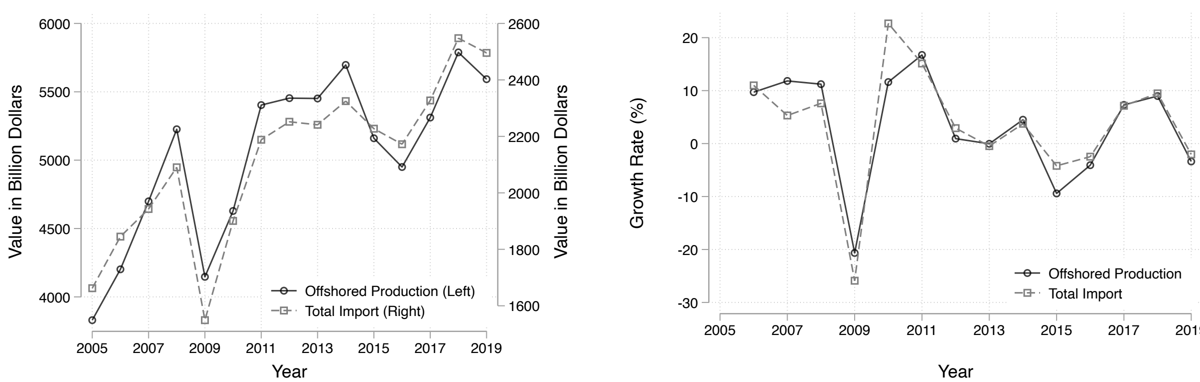
Figures and Tables

Figure 1: U.S. Offshore Production and R&D in 2017



Notes: This figure plots the offshore production and R&D activities of U.S. multinational firms across destination countries and regions for the year 2017. The data is sourced from the Bureau of Economic Analysis's Survey of U.S. Direct Investment Abroad (USDIA), which gathers information on the activities of all U.S. multinational parent firms and their foreign affiliates. Offshore Production is measured by the dollar value of goods supplied by foreign affiliates. Offshore R&D refers to the research and development activities performed by foreign affiliates. Each observation is a country or region.

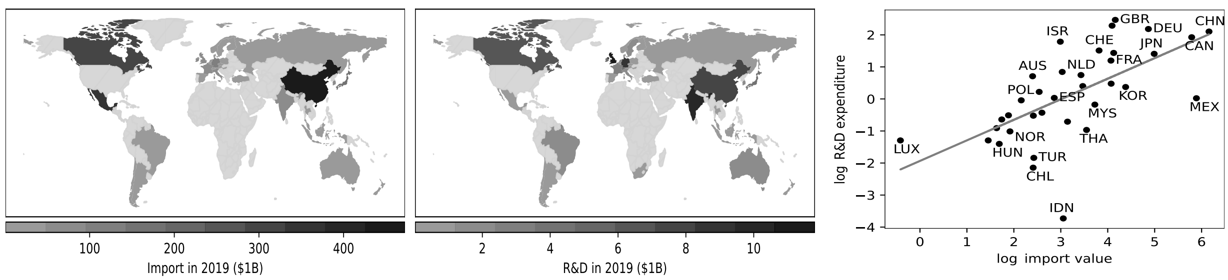
Figure 2: Correlation between Offshored Production and Imports



Notes: This figure compares the amount and growth rate of offshored production and imports from 2005 to 2019 to evaluate the strategy of using imports as a proxy for offshore production. The values of annual offshored production are sourced from the BEA. Total imports are calculated from the LFTTD.

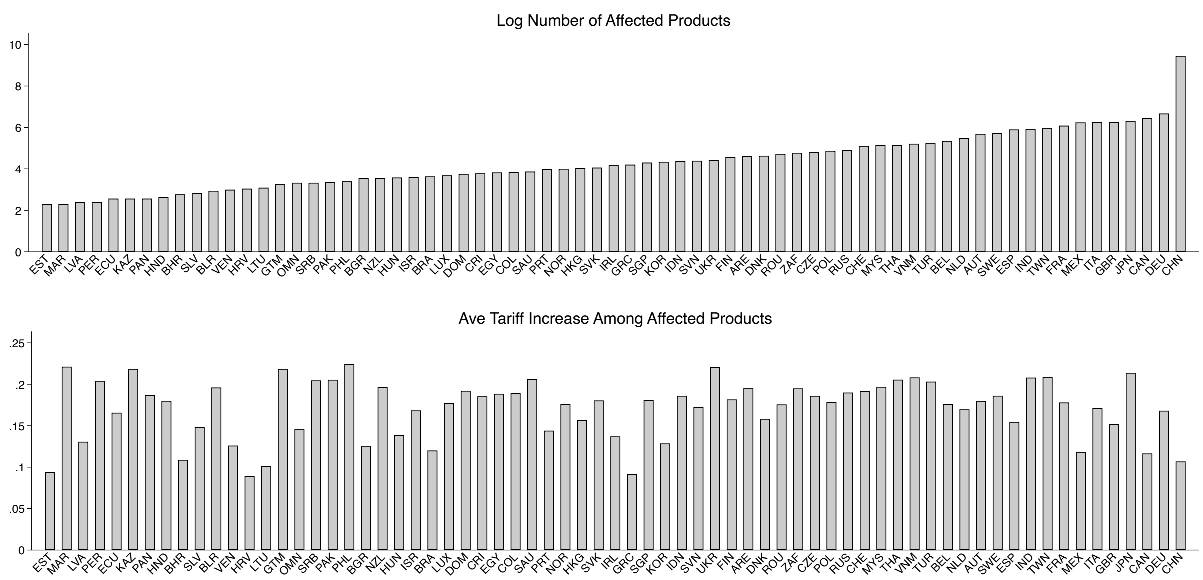
Figure 3: Spatial Distribution of U.S. Offshore Activities

Panel A. Imports Panel B. Offshore R&D Panel C. Correlation



Notes: This figure illustrates the spatial distribution of U.S. offshore innovation and production. Panel A displays U.S. imports from each origin country, using data from the World Trade Organization (WTO). Panel B plots U.S. offshore R&D expenditure in each foreign country, with data sourced from the BRDIS. Panel C shows the correlation between these two offshore activities by plotting the log of R&D expenditure against the log of import value across countries. All data is from the year 2019. The gray color in the first two panels indicates missing data. Countries not surveyed in the BRDIS are grouped into a residual categories, which account for less than 5% of total U.S. offshore R&D.

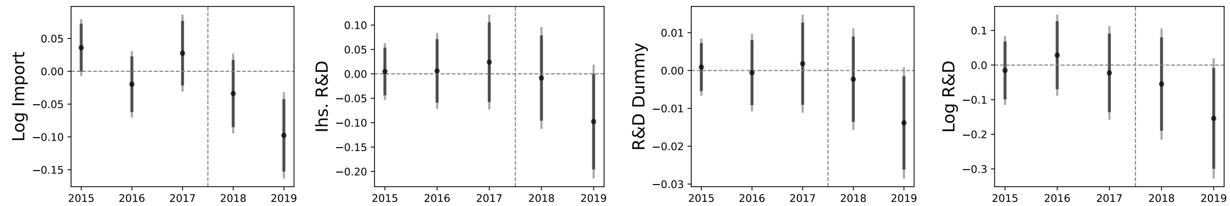
Figure 4: Coverage of Trump Tariffs by Country



Notes: This figure presents the coverage of the Trump Tariffs policy by country. The top panel displays the log number of products affected by the tariff increases in 2018 and 2019. The bottom panel shows the average effective tariff rate increase during this period for the affected products. The raw data is obtained from Fajgelbaum et al. (2020) and Fajgelbaum et al. (2022). The "effective tariff rate increase" for a product refers to the raw tariff increase scaled by the number of months in a year that the increase was in effect. For example, if a 10 percentage points tariff increase was implemented in July 2018 and lasted until the end of 2019, the scaled tariff increase for this period would be 6.67 percentage points, calculated as $10 \times 18/24$.

Figure 5: The Effect of Trump Tariffs on Offshoring

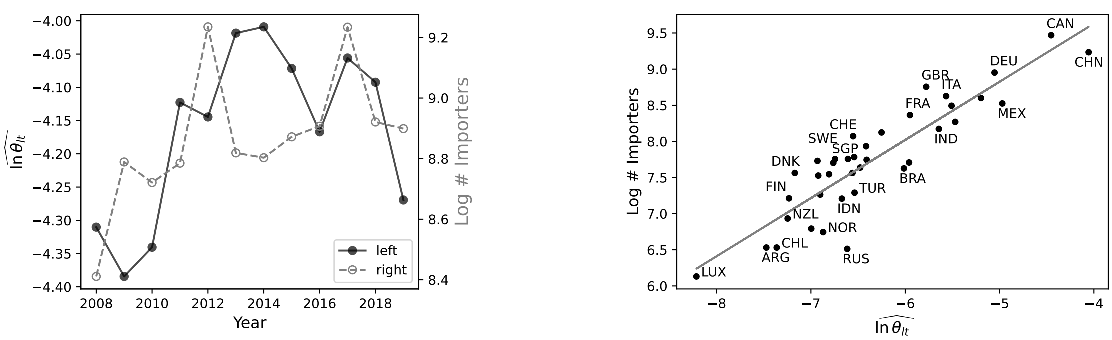
Panel A. Log Import   Panel B. Ihs. R&D   Panel C. R&D Dummy   Panel D. Log R&D



Notes: This figure presents coefficient estimates from Equation (5). Each panel corresponds to a different outcome variable. Dummy variables capture the extensive margin, log values capture the intensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. The regressions include firm-country fixed effects, country-year fixed effects, and firm sales and employment as control variables. Standard errors are clustered at the firm level. 90% and 95% confidence intervals are plotted as error bars. Coefficient estimates and statistics are rounded to four effective digits in accordance with Census data disclosure requirements.

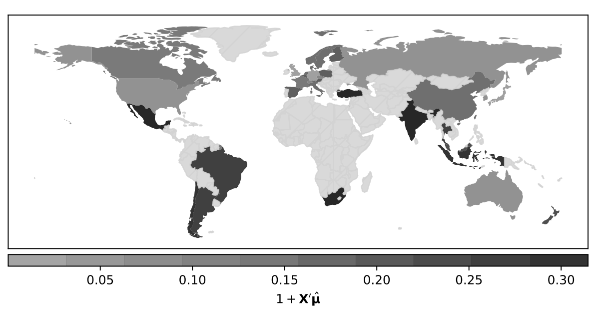
Figure 6: Validation of Estimated Production Offshoring Potentials

Panel A. China, 2008-2019   Panel B. All Countries, 2017



Notes: This figure plots the log of estimated production-offshoring potential ($\log \hat{\theta}_{lt}$) against the number of importing firms to cross-validate the estimates. Panel A displays China's production-offshoring potentials for U.S. firms between 2008 and 2019. Panel B shows the production-offshoring potentials of all countries for U.S. firms in the census year 2017. For details on the definition of production-offshoring potentials, see Section IV. The estimation methodology is discussed in Section V.B.1.

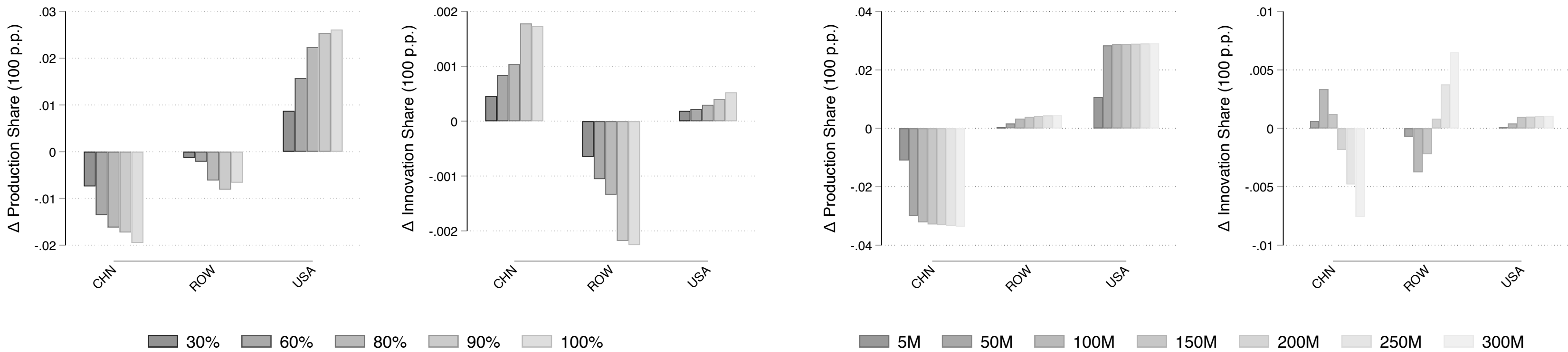
Figure 7: Estimated Synergies Between Production and Innovation



Notes: This figure plots the yearly average of the estimated coefficients $(1 + \boldsymbol{X}'_{lt}\hat{\boldsymbol{\mu}})$ from Equation (7), reflecting countries' heterogeneity in the synergy between production and innovation. $\mathbf{X}$ is a vector of country characteristics, including human capital stock, log distance to the U.S., and capital services. $\hat{\boldsymbol{\mu}}$ represents the coefficient estimates from Column (1) of Table 9. Countries in gray are not surveyed in the BRDIS and thus are not included in the study sample. These countries are categorized into residual groups such as "Other African Countries," collectively accounting for a small fraction of U.S. offshore R&D.

Figure 8: Simulated Effects of Bilateral Policy Shocks

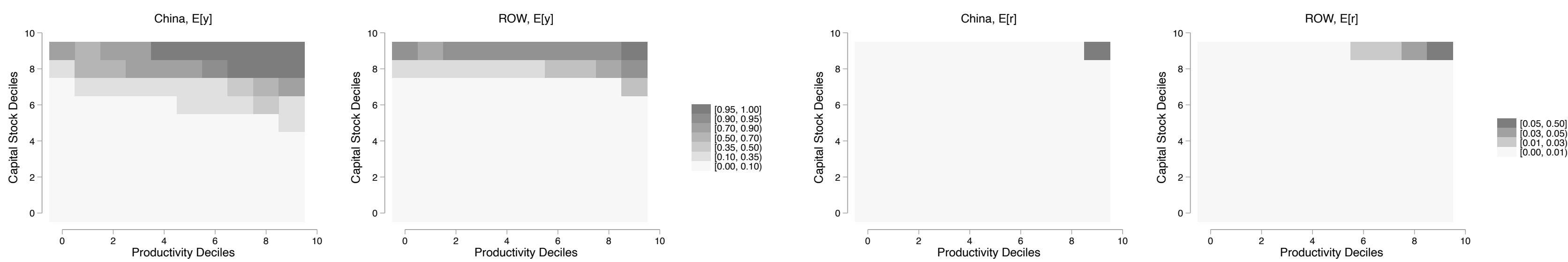
Panel A. Increasing Import Tariffs Panel B. Increasing Production Costs



Notes: This figure presents the changes in production and innovation shares for China, the USA, and the rest of the world (ROW) under various counterfactual scenarios. The production share for l is computed as $\sum_i y_{il} / \sum_{il} y_{il}$, and the innovation share is computed similarly as $\sum_i r_{il} / \sum_{il} r_{il}$. Panel A shows how these shares adjust in response to increases in U.S. import tariffs on China, with tariff increases reflected as percentage decreases in China's offshoring potential (30%, 60%, 80%, 90%, and 100%). Panel B illustrates how these shares shift when the sunk and fixed costs of producing in China rise by different amounts, ranging from 5 to 300 million dollars.

Figure 9: Firm Heterogeneity in Offshoring Patterns

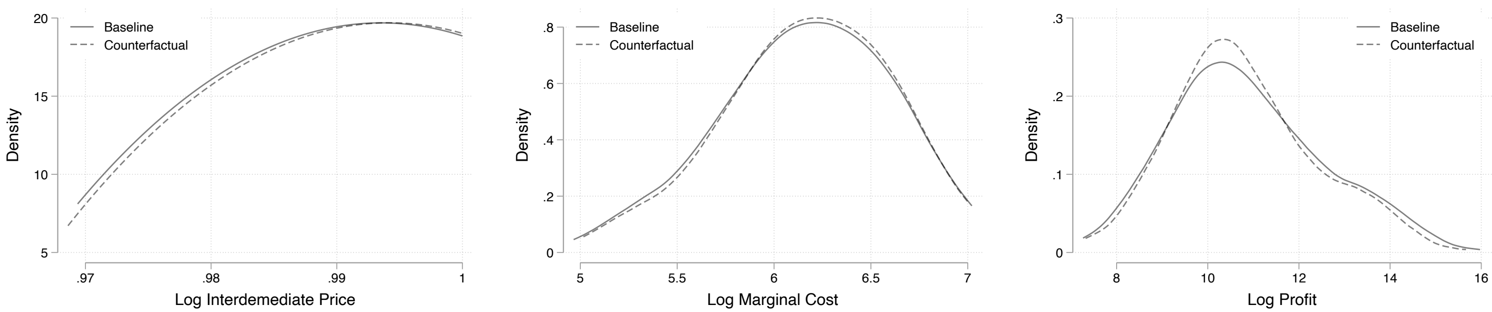
Panel A. Production Offshoring, $E[y]$ Panel B. Innovation Offshoring, $E[r]$



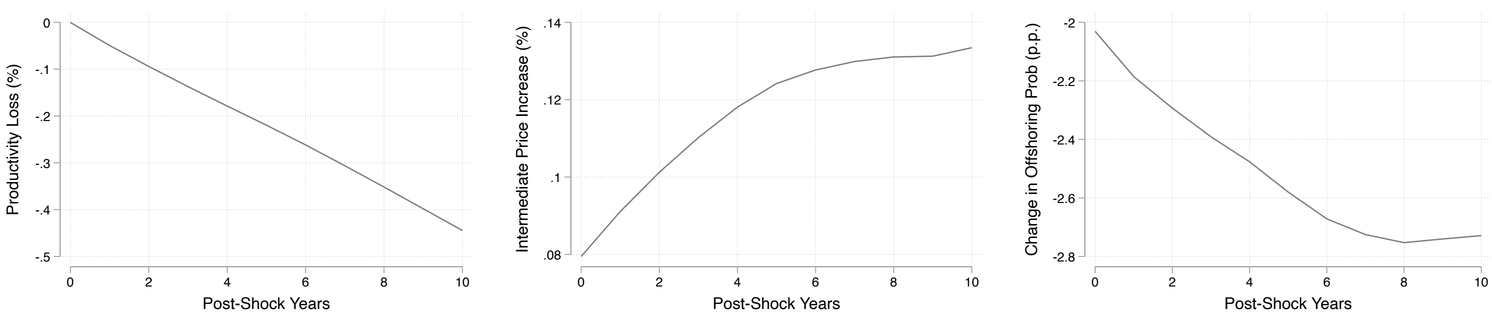
Notes: This figure shows the fraction of firms engaging in production offshoring (Panel A) and innovation offshoring (Panel B) to China and the rest of the world (ROW) from 2015 to 2017, based on simulated data from the baseline model. Firms are grouped by productivity deciles on the x-axis and capital stock deciles on the y-axis.

Figure 10: Dynamic Effects of Trade Policies

Panel A: Static Losses



Panel B: Dynamic Losses



Notes: This figure presents static losses (Panel A) and dynamic losses (Panel B) resulting from a permanent shock that reduces China's production-offshoring potential by half. Panel A displays the distributions of log marginal production cost, log intermediate price, and log profit one year after the shock, along with their baseline counterparts. Panel B illustrates the changes in productivity, log intermediate price, and the probability of offshoring over several years following the shock.

Table 1: Summary Statistics

Panel A. Firm-Year Level	
Mean Sales ($K)	497700
Mean Employment	2945
Mean Domestic Employment	1797
Mean Foreign Employment	1145
Observations	85000
% Importing	83.40
Conditional on Importing	
# Import Countries	8.007
Mean Import Value ($K)	142800
% Performing R&D	57.95
Conditional on Performing R&D	
Mean R&D Expenditure ($K)	49400
Mean Domestic R&D Expenditure ($K)	38030
Mean Foreign R&D Expenditure ($K)	11380
% Performing Foreign R&D	19.65
Conditional on Performing Foreign R&D	
# Foreign R&D Countries	5.63
Mean Foreign R&D Expenditure ($1K)	61970
Panel B. Firm-Country-Year Level	
Observations	3475000
% Importing	16.06
Conditional Imporot Value ($1K)	17840
% Performing Foreign R&D	1.303
Conditional Foreign R&D Expenditure ($1K)	11010

Notes: This table presents summary statistics of firms in the study sample, which is constructed by combining three census micro datasets—the BRDIS, LFTTD, and CFM/ASM. Statistical values are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. Panel A provides statistics at the firm-year level. Panel B details the firm-country-year level.

Table 2: Top Five Offshoring Destinations

Top R&D Locations (1)	Share R&D Expenditure (%) (2)	Top Import Locations (3)	Share Import Value (%) (4)
Germany	14.76	Mexico	19.51
UK	11.32	Canada	17.76
China	8.25	China	12.58
India	6.78	Japan	8.18
Canada	5.38	Germany	7.16

Notes: This table lists the top five destination countries for U.S. offshore R&D and the origin countries for U.S. imports between 2010 and 2019. Statistical values are rounded up to four effective digits in accordance with Census data disclosure requirements. Column (2) shows each country's share of total U.S. foreign R&D expenditure. Column (4) shows each country's share of total U.S. import value. The R&D expenditure data is from the BRDIS and import data from the LFTTD.

Table 3: Offshoring Modes of Production and Innovation

Mode	Fraction of observations (1)	Share import Value (%) (2)	Share R&D Expenditure (%) (3)
None	83.75	0	0
Import Only	14.94	62.26	0
R&D Only	0.19	0	6.17
Both	1.12	37.74	93.83
Total	100	100	100

Notes: This table summarizes four offshoring modes and their respective shares in the number of observations, import value, and R&D expenditure. Observations are at the firm-country-year level. Offshoring modes are defined based on whether R&D expenditure and import value in an observation are positive or zero. Statistical values are rounded to four effective digits in accordance with Census data disclosure requirements. Data on R&D expenditure is obtained from the BRDIS. Data on import value is obtained from the LFTTD.

Table 4: OLS Coefficient Estimates for Two Facts

Panel A. Regress R&D on Import

	R&D Dummy (1)	R&D Dummy (2)	Log R&D (3)	Log R&D (4)	Ihs. R&D (5)
Import Dummy	0.0195***		0.322***		
	(0.00109)		(0.119)		
Region Import Dummy	0.00147***		-0.00580		
	(0.000338)		(0.143)		
Log Import		0.0150***		0.212***	
		(0.000761)		(0.0191)	
Log Region Import		0.00167***		0.0105	
		(0.000626)		(0.0211)	
Ihs. Import					0.0217***
					(0.00102)
Ihs. Region Import					0.000936***
					(0.000233)
N	499000	41000	4100	3100	499000
R-squared	0.392	0.486	0.569	0.592	0.419
Firm FE	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes

Panel B. Regress Import on R&D

	Import Dummy (1)	Import Dummy (2)	Log Import (3)	Log Import (4)	Ihs. Import (5)
R&D Dummy	0.210***		1.763***		
	(0.00909)		(0.0546)		
Region R&D Dummy	0.0591***		0.239***		
	(0.00634)		(0.0498)		
Log R&D		0.00498		0.325***	
		(0.00329)		(0.0308)	
Log Region R&D		0.000284		0.106***	
		(0.00428)		(0.0403)	
Ihs. R&D					0.576***
					(0.0161)
Ihs. Region R&D					0.126***
					(0.0100)
N	499000	2800	57000	2300	499000
R-squared	0.421	0.608	0.476	0.681	0.471
Firm FE	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates from equation (1) using data from 2017. Panel A regresses R&D measures on import measures, while Panel B does the opposite. Observations are at the firm-country level. "Region Import" and "Region R&D" refer to the firm's total import value and R&D expenditure in all countries of the host region, excluding the focal host country itself. Dummy variables capture the extensive margin, log values capture the intensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. Industries are classified by 3-digit NAICS codes. Standard errors are clustered at the firm level and reported in parentheses. Coefficient estimates and regression statistics are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Instrumental Strategy Coefficient Estimates

Panel A. Reduced-Form Regression

	Ihs. Import (1)	Import Dummy (2)	Log Import (3)	Ihs. R&D (4)	R&D Dummy (5)	Log R&D (6)
T_{ilt}	-1.906***	-0.0643*	-5.163***	-0.239***	-0.0281***	-0.728
	(0.504)	(0.0357)	(0.712)	(0.0811)	(0.0104)	(1.531)
N	1516000	1516000	317000	1516000	1516000	27500
R-sq	0.491	0.440	0.396	0.401	0.384	0.475
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. 2SLS Regression

	Ihs. Import (1)	Ihs. R&D (2)	Ihs. R&D (3)	R&D Dummy (4)	R&D Dummy (5)
Ihs. Import		0.0252***	0.125**	0.00315***	0.0147**
		(0.00111)	(0.0493)	(0.000131)	(0.00616)
T_{ilt}	-1.906***				
	(0.504)				
Method	OLS	OLS	IV	OLS	IV
1st-stage F	61.93				
N	1516000	1516000	1516000	1516000	1516000
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes

Panel C. Reduced-Form Regression for Interdependence

	Ihs. Import (1)	Import Dummy (2)	Log Import (3)	Ihs. R&D (4)	R&D Dummy (5)	Log R&D (6)
T_{ilt}	-2.817***	-0.124***	-5.689***	-0.226**	-0.0240**	-1.108
	(0.531)	(0.0373)	(0.723)	(0.0890)	(0.0113)	(1.590)
T_{iRt}	-1.666***	-0.119***	-1.638*	-0.461***	-0.0612***	1.985
	(0.555)	(0.0398)	(0.886)	(0.135)	(0.0182)	(2.395)
N	1238000	1238000	272000	1238000	1238000	23500
R-sq	0.504	0.452	0.410	0.402	0.383	0.481
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents results from the instrumental strategy. Panel A contains coefficient estimates for the reduced-form specification in equation (3). Panel B provides coefficient estimates for the 2SLS specification in equation (4). Panel C mirrors Panel A but includes the additional regressor T_{iRt}. Observations are at the firm-country-year level. Dummy variables capture the extensive margin, log values capture the intensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. Standard errors are clustered at the firm level and reported in parentheses. Coefficient estimates and regression statistics are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Difference-in-Differences Coefficient Estimates

	Log Import (1)	Ihs. R&D (2)	R&D Dummy (3)	Log R&D (4)
Treat × Post	-0.106***	-0.0945*	-0.0130**	-0.151**
	(0.0263)	(0.0494)	(0.00637)	(0.0659)
Share Affected Products × Post	-0.258*	-0.189***	-0.0207***	-0.250
	(0.137)	(0.0567)	(0.00757)	(0.518)
Share Affected Product Value × Post	-0.161*	-0.160***	-0.0175**	-0.243
	(0.0861)	(0.0596)	(0.00772)	(0.250)
Product-Count Weighted Effective Tariff Increase × Post	-1.686**	-0.758**	-0.101**	3.031
	(0.845)	(0.318)	(0.0421)	(2.958)
Product-Value Weighted Effective Tariff Increase × Post	-1.098**	-0.642**	-0.0807**	0.119
	(0.540)	(0.313)	(0.0394)	(1.760)
N	187000	187000	187000	16500
R-squared	0.889	0.877	0.838	0.893
Firm-Country FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates from equation (6). Each row represents a different regression with varying measures of treatment. The dummy variable "Treat" equals one for firm-country pairs affected by the Trump Tariffs. The "Post" dummy equals one for the year 2019 and zero for the years 2014-2017. Four additional continuous measures of treatment are considered in the second to fourth rows: "Share Affected Products" is the fraction of product counts affected by the Trump Tariffs among all products the firm used to import; (2) "Share Affected Product Value" is the value share of affected products defined similarly; (3) "Product-Count Weighted Effective Tariff Increase" is the simple average of the effective tariff increase across the firm's imported products; (4) "Product-Value Weighted Effective Tariff Increase" is the weighted average of the effective tariff increase across the firm's imported products, with weights being the import value shares in the prior period. Dummy variables capture the extensive margin, log values capture the intensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. Standard errors are clustered at the firm level and reported in parentheses. Coefficient estimates and regression statistics are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Model Parameters and Sources of Identification

Parameter	**Source of Identification**
η	Average markup.
ρ	Response of country production-offshoring potential to tariff change.
β_k, β_m	Relationship between output and input factors.
$\alpha_0, \alpha_1, \sigma_\xi$	Persistence and variation in firm productivity.
$\beta_1, \beta_2, \beta_3, \boldsymbol{\mu}$	Relationship between productivity change and innovation efforts in each country.
$\phi_s^p, \phi_s^r, \phi_f^p, \phi_f^r$	Fraction of firms offshoring production and innovation (unconditional and conditional on past choices).
λ_1	Colocation of production and innovation in and out of the region.

Notes: This table lists the model parameters and their primary sources of identification. Refer to the model setup in Section IV for their definitions.

Table 8: Production-Offshoring Potentials and Tariffs

	$\ln \hat{\theta}_{lt}$ (1)	(2)	(3)
$\ln(1 + T_{lt})$	-2.739*	-2.952***	-3.697***
	(1.567)	(1.123)	(1.110)
Log Population		0.358***	0.580***
		(0.0203)	(0.0252)
Common Language Dum		0.0246	-0.109*
		(0.0820)	(0.0601)
Colony Dum		0.0622	-0.210***
		(0.0712)	(0.0535)
Human Capital Index			0.657***
			(0.0840)
Control of Corruption Index			0.230***
			(0.0467)
N	450	450	450

Notes: This table presents coefficient estimates from equation (10). Observations are at the country-year level. T_{lt} is the ad valorem tariff rate. Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Estimation of Production Function and Productivity Evolution Process

	Full Sample (1)	Firms with Foreign Employmees (2)	Excluding Tax Havens (3)	Excluding China (4)
Capital Coefficient, β_k	-0.164***	-0.172***	-0.164***	0.164***
	(0.0017)	(0.0027)	(0.0017)	(0.0017)
Intermediate Price Coefficient, β_m^F	0.435***	0.412***	0.435***	0.435***
	(0.0049)	(0.0075)	(0.0049)	(0.0049)
Constant in AR(1): α_0	-0.0433***	-0.0521***	-0.0431***	-0.0433***
	(0.0027)	(0.0048)	(0.0027)	(0.0027)
Slope in AR(1): α_1	0.909***	0.907***	0.909***	0.909***
	(0.0038)	(0.0056)	(0.0038)	(0.0038)
Return to Innovation: β_1	-0.000803	-0.00095	-0.001	-0.000624
	(0.0021)	(0.0028)	(0.0019)	(0.0022)
Return to Colocation: β_2	0.0064**	0.0072*	0.0058**	0.0064**
	(0.0031)	(0.0038)	(0.0029)	(0.0031)
Return to Production: β_3	0.00463***	0.00666***	0.00418***	0.00491***
	(0.0010)	(0.0014)	(0.0011)	(0.0010)
ρ: Human Capital	-0.214***	-0.163***	-0.240***	-0.209***
	(0.038)	(0.0285)	(0.0514)	(0.0356)
ρ: Log Distance	-0.0409***	-0.0587***	-0.0318*	-0.0407***
	(0.0137)	(0.0098)	(0.0182)	(0.0136)
ρ: Capital Services	-0.0509***	-0.0397***	-0.0604***	-0.0443***
	(0.0132)	(0.0112)	(0.0183)	(0.0132)
N	28500	12500	28500	28500
Mean Elasticity	0.0006	0.0005	0.0007	0.0006
SD of Elasticity	0.0006	0.0005	0.0006	0.0006
Max of Elasticity	0.002	0.0017	0.0021	0.002
RMSE	0.126	0.113	0.126	0.126

Notes: This table presents coefficient estimates from Equation (1) using non-linear least squares. Column (1) leverages the full sample. Column (2) restricts to firms that report to have foreign employees. Column (3) excludes countries known as tax havens. Column (4) excludes China. β_m^F is the elasticity of log unit production cost with respect to log foreign intermediate price index (Appendix C.2). Log Distance is the log of the country's geographical distance to the U.S. Human capital and capital services are indices obtained from Penn World Tables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the firm level and reported in parentheses. The table also reports the mean, standard deviation, and max of R&D elasticities implied by the coefficient estimates across countries. The last row reports the root mean squared errors to form an estimate of σ_ξ.

Table 10: Estimates of Dynamic Offshoring Costs

Panel A: Parameter Estimates

ϕ_s^p	ϕ_f^p	ϕ_s^r	ϕ_f^r	λ_1
5039.31	3304.68	69196.30	41213.89	1058.63
(572.63)	(77.11)	(16403.78)	(4359.88)	(352.64)

Panel B: Matched Moments

Moment	Data	Model
$E[y_{ilt}]$	0.16059	0.1601
$E[r_{ilt}]$	0.01303	0.01297
$E[y_{ilt}y_{ilt-1}]$	0.01901	0.01797
$E[r_{ilt}r_{ilt-1}]$	0.00182	0.00150
$E[y_{ilt}y_{il't}\|c_{ll'}=1] - E[y_{ilt}y_{il't}\|c_{ll'}=0]$	0.01115	0.01166
$E[r_{ilt}r_{il't}\|c_{ll'}=1] - E[r_{ilt}r_{il't}\|c_{ll'}=0]$	0.00048	0.00039

Notes: This table presents the estimated dynamic costs of offshoring. Panel A provides the point estimates, expressed in thousands of dollars, with standard errors shown in parentheses. Panel B displays the six moments used in the MSM, comparing their empirical values from the data to the corresponding simulated values from the model.

Table 11: Relative Importance of Colocation Mechanisms

Panel A: Significance of Synergy Effect

	(1) $\beta_2 = \hat{\beta}_2$	(2) $\beta_2 = \frac{3}{4}\hat{\beta}_2$	(3) $\beta_2 = \frac{1}{2}\hat{\beta}_2$	(4) $\beta_2 = \frac{1}{4}\hat{\beta}_2$	(5) $\beta_2 \approx 0$
$\mathbb{E}[y_{ilt}]$	0.1601	0.1593	0.1593	0.1593	0.1593
	(100)	(99.50)	(99.50)	(99.50)	(99.50)
$\mathbb{E}[r_{ilt}]$	0.013	0.0065	0.0018	0.0	0.0
	(100)	(50.00)	(13.85)	(0.0)	(0.0)
$\mathbb{E}[r_{ilt}\|y_{ilt}=1]$	0.081	0.0406	0.0116	0.0	0.0
	(100)	(50.12)	(14.32)	(0.0)	(0.0)

Panel B: Significance of Cost Sharing Effect

	(1) $\lambda_1 = \hat{\lambda}_1$	(2) $\lambda_1 = 0$	(3) Δ
$\mathbb{E}[r_{ilt}]$	0.0130	0.0125	0.0004
	(100)	(96.70)	(3.30)
$\mathbb{E}[r_{ilt}\|y_{ilt}=1]$	0.0810	0.0783	0.0028
	(100)	(96.59)	(3.41)
$\mathbb{E}[r_{il't}\|y_{ilt}=1, c_{ll'}=1, l' \neq l]$	0.0754	0.0729	0.0025
	(100)	(96.67)	(3.33)
$\mathbb{E}[r_{iRt}\|y_{iRt}=1]$	0.0773	0.0736	0.0037
	(100)	(95.20)	(4.80)

Notes: This table compares the relative importance of two colocation mechanisms: the synergy effect and the cost-sharing effect. In Panel A, the synergy parameter, β_2, is gradually reduced from its baseline estimate to zero, and the resulting model statistics are reported. In Panel B, the cost-sharing parameter, λ_1, is reduced from its baseline estimate to zero, and the corresponding model statistics are presented similarly. The last column of Panel B shows the difference between the first two columns. The variables y_{iRt} and r_{iRt} are dummy variables equal to one if the firm has production and innovation in region R, respectively. For both panels, relative percentage changes are reported in parentheses.

Online Appendix for "Multinational Production and Innovation in Tandem"

Jin Liu (Princeton University)

October 2024

A Data Appendix

This appendix details the construction of firm-level variables in the Census. The total output R_{it} is measured by the total value of shipments adjusted for inventories and the cost of resales:

$$R_{it} = \begin{cases} \left(\mathrm{TVS}_{it} + \mathrm{FIE}_{it} - \mathrm{FIB}_{it} + \mathrm{WIE}_{it} - \mathrm{WIB}_{it} - \mathrm{CR}_{it}\right)/\mathrm{PISHIP}_{jt}, & \text{if positive;} \\ \mathrm{TVS}_{it}/\mathrm{PISHIP}_{jt}, & \text{otherwise.} \end{cases}$$

TVS represents the total value of shipments. FIE and FIB denote the total value of finished goods inventories at the end and beginning of the year, respectively. WIE and WIB are the work-in-progress inventories at the end and beginning of the year, respectively. CR stands for the cost of resales. All these raw variables are measured in nominal dollars. They are deflated using PISHIP, the four-digit industry-level shipments deflator from the NBER-CES Manufacturing Database.

Domestic materials (excluding energy) is defined as the real value of non-energy material inputs:

$$\mathrm{M}_{it} = \left(\mathrm{CP}_{it} + \mathrm{CR}_{it} + \mathrm{CW}_{it}\right)/\mathrm{PIMAT}_{jt}.$$

CP is the total cost of materials and parts, CW is the total cost of contract work done by others, and PIMAT is the NBER-CES 4-digit industry level materials deflator.

Energy cost primarily includes expenses on electricity and fuels:

$$E_{it} = \left(\mathrm{EE}_{it} + \mathrm{CF}_{it}\right)/\mathrm{PIEN}_{jt}.$$

EE is the cost of purchased electricity, CF is the cost of fuels, and PIEN is the NBER-CES 4-digit industry level energy deflator.

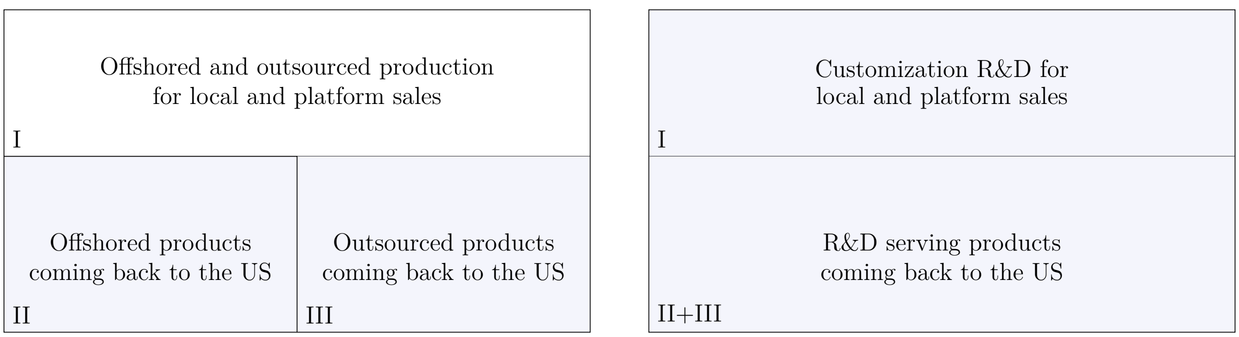
Capital stock K_{it} is not directly available in the ASM and CMF, so it is constructed using the Perpetual Inventory method for equipment and structures separately. The detailed procedures for estimating initial values and discounting are described in Cunningham, Foster, Grim, Haltiwanger, Pabilonia, Stewart and Wolf (2021).

The total variable cost TVC_{it} is computed as the sum of wages (SW_{it}), material cost (M_{it}), energy cost (E_{it}), and total capital expenditures (raw variable TCE).

B Discussing Measurement Error in R&D

Offshore activities can be categorized into three types based on whether they are organized within or outside the firm and whether the products are used for U.S. plants or local sales. Figure A1 illustrates these three types: area I represents within-firm offshored and externally outsourced activities related to products sold directly in the host country or its neighboring countries; areas II and III represent within-firm offshored activities and externally outsourced activities related to products used in the U.S., respectively. The data and model in this paper are best suited to analyze the colocation of production and innovation in areas II and III, as imports serve as a good proxy for the production of products shipped back to the U.S. However, the R&D measure captures the firm's expenditure on all types of innovation, potentially including customization efforts in area I for products tailored to the local region. The inclusion of potential local R&D incentives introduces measurement error in r_{ilt}.

Figure A1: Scope of Production and Innovation Measures



Notes: This figure illustrates the potential source of measurement error in R&D. This paper focuses on the colocation of production and innovation for products returning to the U.S. (areas II and III). Imports accurately capture offshored production serving the U.S. plants. However, the R&D measure also includes customization R&D efforts for products sold locally (area I).

To address this issue, I leverage the idea that while U.S. import tariffs affect production and innovation for products shipped back to the U.S., they arguably do not influence incentives for local production and innovation, as these locally produced and innovated products are typically sold directly in the host or neighboring countries. As a result, the reduced-form analyses are immune to this measurement error because, in both the instrumental variable and event study strategies, tariff shocks have been employed to isolate the relevant variations in activities that serve the U.S. plants, as local activities are not directly impacted by these shocks.

A remaining question is whether the structural estimates from equation (13) are robust to potential measurement error in innovation. Let us start with $r^o_{ilt} = r_{ilt} + \iota_{ilt}$, where r_{ilt}

Table A1: Structural Estimates—With Measurement Error

	$\hat{\phi}_{it}$
Capital Coefficient, β_k	-0.161***
	(0.0024)
Intermediate Price Coefficient, β_m^F	0.439***
	(0.0074)
Constant in AR(1): α_0	-0.0409***
	(0.0055)
Slope in AR(1): α_1	0.926***
	(0.0058)
Return to Innovation: β_1	0.168
	(0.1870)
Return to Colocation: β_2	0.0186*
	(0.0107)
Return to Production: β_3	0.00755***
	(0.0019)
ρ: Human Capital	-0.0540***
	(0.0200)
ρ: Log Distance	-0.0810***
	(0.0076)
ρ: Capital Services	0.0226*
	(0.0130)
Control for Measurement Error: $\hat{\iota}_{it}$	-0.181
	(0.1880)
N	12000
Mean Elasticity	0.0008
SD of Elasticity	0.0012
Max of Elasticity	0.0045
RMSE	0.12

Notes: This table presents coefficient estimates from equation (1) using the two-step control function approach. β_m^F is the elasticity of log unit production cost with respect to log foreign intermediate price index (Appendix C.2). Log Distance is the log of the country's geographical distance to the U.S. Human capital and capital services are indices obtained from Penn World Tables. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the firm level and reported in parentheses. The table also reports the mean, standard deviation, and max of R&D elasticities implied by the coefficient estimates for different countries. The last row reports the root mean squared errors to form an estimate of σ_ξ.

is the true value of innovation in areas II and III, r_{ilt}^o is the observed value, and ι_{ilt} is the measurement error that potentially arises from local innovation activities. Assume that ι_{ilt} is orthogonal to the tariff rate T_{ilt}.

The estimation equation that takes into account the measurement error is

$$\begin{aligned}\hat{\phi}_{it} =& \beta_k^* \cdot \ln k_{it} + \beta_m^* \cdot \ln p_{it}^m - \alpha_0^* + \alpha_1 \cdot \left(\hat{\phi}_{it-1} - \beta_k^* \cdot \ln k_{it-1} - \beta_m^* \cdot \ln p_{it-1}^m\right) \\ &- \sum_l \left[1 + X_{lt-1}\rho\right] \cdot \left[\beta_1^* r_{ilt-1}^o + \beta_2^* r_{ilt-1}^o y_{ilt-1} + \beta_3^* y_{ilt-1}\right] + \kappa_{it}. \end{aligned} \tag{1}$$

The new error term κ_{it} is a function of the original innovation shock ξ_{it}^* and the measurement errors $\{\iota_{ilt}\}_l$. Given that ι_{ilt} is uncorrelated with the tariff rate T_{ilt}, I employ a control function approach to address the potential measurement error issue. There are two steps.

In the first step, I regress r_{ilt} on T_{ilt} to obtain the residual $\hat{\iota}_{ilt}$. This residual captures the variations in innovation that stem from local R&D incentives, which are uncorrelated with import tariffs. In the second step, I estimate equation (1) with the additional control variable $\hat{\iota}_{it}$ that proxies for the measurement error. The parameter estimates are reported in Appendix Table A1, and they remain close to their counterparts in Table 9.

C Model Appendix

C.1 Microfoundation of CES Input Aggregation

Consider a framework of input sourcing as in Antras, Fort and Tintelnot (2017). Each firm sources a continuum of intermediate varieties, $v \in [0,1]$. The varieties aggregate to the firm's intermediate accroding to CES,

$$m_{it} = \left[\int_0^1 q_i\left(v\right)^{\frac{\sigma-1}{\sigma}} dv\right]^{\frac{\sigma}{\sigma-1}}.$$

Let v_{it} denote the optimal price for sourcing input v. The price index of intermediate is then

$$p_{it}^m = \left[\int_0^1 z_{it}\left(v\right)^{1-\sigma} dv\right]^{\frac{1}{1-\sigma}}.$$

The firm always sources variety v from the cheapest location, therefore,

$$z_{it}\left(v\right) = \min_{l \in \mathcal{L}_{it}} \left\{w_{lt}\tau_{lt}(1+T_{lt}) \cdot a_{lt}\left(v\right)\right\},$$

where $a_{lt}\left(v\right)$ is the unit labor requirement for producing v in country l at time t. Assume Fréchet distribution such that

$$\Pr\left(a_{lt}\left(v\right) \geq a\right) = e^{-S_{lt} \cdot a^{\theta}},$$

with $S_{lt} > 0$ capturing the technology level of country l and $\theta > 0$ capturing the dispersion in productivity. Then it can be shown that the price for intermediate is

$$p_{it}^m = \left[c_0 \cdot \underbrace{\sum_{l \in \mathcal{L}_{it}} S_{lt}\left(w_{lt}\tau_{lt}(1+T_{lt})\right)^{-\theta}}_{\Theta_{it}\text{:sourcing capability}}\right]^{-\frac{1}{\theta}}$$

where

$$c_0 = \left[\Gamma\left(\frac{\theta+1-\rho}{\theta}\right)\right]^{\frac{\theta}{1-\rho}}.$$

The share of sourcing for each country is

$$\chi_{il}\left(\varphi\right) = \frac{S_{lt}\left(w_{lt}\tau_{lt}(1+T_{lt})\right)^{-\theta}}{\Theta_{it}}.$$

This is equivalent to a CES aggregation with elasticity of substitution being $1+\theta$ and unit labor productivity varying by country as $(c_0 S_{lt})^{-\frac{1}{\theta}}$.

C.2 Deriving β_m^F from β_m

The overall price index for intermediate goods is defined to be

$$p_{it}^m = \left(1 + \sum_{l>0} y_{ilt}\theta_{lt}\right)^{1/(1-\rho)},$$

and that for foreign intermediate goods is

$$p_{it}^{m,F} = \left(\sum_{l>0} y_{ilt}\theta_{lt}\right)^{1/(1-\rho)}.$$

Combining these two equations leads to the following relationship between two price indices:

$$(p_{it}^m)^{1-\rho} = 1 + \left(p_{it}^{m,F}\right)^{1-\rho},$$

or equivalently,

$$\ln p_{it}^m = \frac{\ln\left(1 + e^{(1-\rho)\cdot \ln p_{it}^{m,F}}\right)}{1-\rho}.$$

Next, let's define a function

$$y = f(x) = \ln\left(1 + e^{(1-\rho)x}\right).$$

Taking the first-order approximation of $f(x)$ around x_0 implies

$$f(x) \approx \frac{1}{1-\rho}\left[\ln\left(1 + e^{(1-\rho)x_0}\right) - \frac{e^{(1-\rho)x_0}\cdot(1-\rho)}{1+e^{(1-\rho)x_0}}x_0\right] + \frac{e^{(1-\rho)x_0}}{1+e^{(1-\rho)x_0}}\cdot x.$$

Plugging in $y = \ln p_{it}^m$ and $x = \ln p_{it}^{m,F}$ to achieve the first-order approximation of the relationship between the two price indices:

$$\ln p_{it}^m \approx C + \frac{1}{1+e^{(\rho-1)x_0}}\cdot \ln p_{it}^{m,F},$$

where

$$C = \frac{1}{1-\rho}\left[\ln\left(1 + e^{(1-\rho)x_0}\right) - \frac{e^{(1-\rho)x_0}\cdot(1-\rho)}{1+e^{(1-\rho)x_0}}x_0\right].$$

It follows that

$$\partial \ln p_{it}^m = \frac{1}{1+e^{(\rho-1)x_0}}\cdot \partial \ln p_{it}^{m,F}$$

and thus

$$\beta_m^F \equiv \frac{\partial \ln c_{it}}{\partial \ln p_{it}^{m,F}} = \frac{1}{1+e^{(\rho-1)x_0}}\frac{\partial \ln c_{it}}{\partial \ln p_{it}^m} = \frac{1}{1+e^{(\rho-1)x_0}}\beta_m$$

where

$$\beta_m \equiv \frac{\partial \ln c_{it}}{\partial \ln p_{it}^m}.$$

Finally, evaluating x_0 at the mean value of $\ln p_{it}^{m,F}$, 1.0274, implies

$$\hat{\beta}_m^F = \frac{\hat{\beta}_m}{1 + e^{(\hat{\rho}-1)\times 1.0274}} = 0.435.$$

C.3 Proof of Proposition 1

C.3.1 Lifetime Payoffs

The expected lifetime payoff function Π_0 can be decomposed as

$$\Pi_0 \left(\boldsymbol{o}_i\right) = \sum_{\boldsymbol{z}\in\Omega} \Pr\left(\boldsymbol{z}\right) \Pi^\dagger \left(\boldsymbol{o}_i | \boldsymbol{z}\right),$$

where $\Pi^\dagger \left(\boldsymbol{o}_i|\boldsymbol{z}\right)$ is the deterministic lifetime payoff following decision rule $\boldsymbol{o}_i$ under history $\boldsymbol{z}$. In particular,

$$\Pi^\dagger \left(\boldsymbol{o}_i|\boldsymbol{z}\right) = \sum_{t=0}^{\infty} \zeta^t \Pi_t \left(\omega_{it}\left(z^t, \left\{\boldsymbol{o}_i\left(z^\tau\right)\right\}_{\tau=0}^{t-1}\right), \boldsymbol{o}_i\left(z^t\right), \boldsymbol{o}_i\left(z^{t-1}\right)\right).$$

Since payoff in one history is independent of decisions rules along other histories, we can define $\tilde{\Pi}^\dagger \left(\boldsymbol{o}_{\boldsymbol{z}}|\boldsymbol{z}\right) = \Pi^\dagger \left(\boldsymbol{o}_i\left(\boldsymbol{z}\right)|\boldsymbol{z}\right)$, which is a function from $\{0,1\}^{2\mathcal{L}\mathcal{T}}$ to $\mathbb{R}$. Note that $\tilde{\Pi}^\dagger \left(\cdot|\boldsymbol{z}\right)$ is identical to $\Pi^\dagger \left(\cdot|\boldsymbol{z}\right)$, but written as only a function of the subvector of choices for all countries and periods in a given history $\boldsymbol{z}$.

C.3.2 Lemmas and Proofs

Lemma 2.6.1 from Topkis (1998) will be used in the proof, and I state it below:

Lemma 1. *Suppose X is a lattice. Then,*

1. *If $f(x)$ is supermodular on X and $\alpha > 0$, then $\alpha f(x)$ is supermodular on X.*
2. *If $f(x)$ and $g(x)$ are supermodular on X, then $f(x) + g(x)$ is supermodular on X.*

I then state the second lemma that will be proved at the end of this section.

Lemma 2. *$\tilde{\Pi}^\dagger \left(\boldsymbol{o}_{\boldsymbol{z}}|\boldsymbol{z}\right)$ has increasing differences in $\{0,1\}^{2\mathcal{L}\mathcal{T}}$.*

Now, let's repeat and prove the main proposition here.

Proposition. *$\Pi_0 \left(\boldsymbol{o}_i|\boldsymbol{y}_{i,-1}, \boldsymbol{r}_{i,-1}, \omega_{i,-1}\right)$ is supermodular in $\boldsymbol{o}_i$ on $\{0,1\}^{2\mathcal{L}\mathcal{T}\Omega}$.*

Proof of Proposition. From Lemma 2, $\tilde{\Pi}^\dagger \left(\boldsymbol{o}_{\boldsymbol{z}}|\boldsymbol{z}\right)$ has increasing differences in $\{0,1\}^{2\mathcal{L}\mathcal{T}}$. Using Corollary 2.6.1 in Topkis (1998), $\tilde{\Pi}^\dagger \left(\boldsymbol{o}_{\boldsymbol{z}}|\boldsymbol{z}\right)$ is supermodular in $\boldsymbol{o}_{\boldsymbol{z}}$ on $\{0,1\}^{2\mathcal{L}\mathcal{T}}$.

I then show that $\Pi^{\dagger}(\boldsymbol{o}_i|\boldsymbol{z})$ is supermodular in $\boldsymbol{o}_i$ on $\{0,1\}^{2\mathcal{L}\mathcal{T}\Omega}$. Consider two decision rules $\boldsymbol{o}_i, \boldsymbol{o}_i' \in \{0,1\}^{2\mathcal{L}\mathcal{T}\Omega}$, the following must hold for any history $\boldsymbol{z}$:

$$\begin{aligned}
\Pi^{\dagger}(\boldsymbol{o}_i|\boldsymbol{z}) + \Pi^{\dagger}(\boldsymbol{o}_i'|\boldsymbol{z}) &= \tilde{\Pi}^{\dagger}(\boldsymbol{o}_i(\boldsymbol{z})|\boldsymbol{z}) + \tilde{\Pi}^{\dagger}(\boldsymbol{o}_i'(\boldsymbol{z})|\boldsymbol{z}) \\
&\leq \tilde{\Pi}^{\dagger}(\boldsymbol{o}_i(\boldsymbol{z}) \vee \boldsymbol{o}_i'(\boldsymbol{z})|\boldsymbol{z}) + \tilde{\Pi}^{\dagger}(\boldsymbol{o}_i(\boldsymbol{z}) \wedge \boldsymbol{o}_i'(\boldsymbol{z})|\boldsymbol{z}) \\
&= \tilde{\Pi}^{\dagger}(\boldsymbol{o}_i \vee \boldsymbol{o}_i'(\boldsymbol{z})|\boldsymbol{z}) + \tilde{\Pi}^{\dagger}(\boldsymbol{o}_i \wedge \boldsymbol{o}_i'(\boldsymbol{z})|\boldsymbol{z}) \\
&= \Pi^{\dagger}(\boldsymbol{o}_i \vee \boldsymbol{o}_i'|\boldsymbol{z}) + \Pi^{\dagger}(\boldsymbol{o}_i \wedge \boldsymbol{o}_i'|\boldsymbol{z}),
\end{aligned}$$

where the first and last equality follow from the relationship between the functions $\tilde{\Pi}^{\dagger}(\cdot|\boldsymbol{z})$ and $\Pi^{\dagger}(\cdot|\boldsymbol{z})$, the inequality in the second line follows from the supermodularity of the function $\tilde{\Pi}^{\dagger}(\boldsymbol{o}_{\boldsymbol{z}}|\boldsymbol{z})$, and the equality in the third line follows from basic linear algebra rules. The "join" $\vee$ takes the maximum element by element, and the "meet" $\wedge$ takes the minimum element by element.

Recall that

$$\Pi_0(\boldsymbol{o}_i) = \sum_{\boldsymbol{z}\in\Omega} \Pr(\boldsymbol{z}) \Pi^{\dagger}(\boldsymbol{o}_i|\boldsymbol{z}).$$

Since from Lemma 1 we know that the finite sum of supermodular functions is supermodular, $\Pi_0(\boldsymbol{o}_i)$ is supermodular in $\boldsymbol{o}_i$ on $\{0,1\}^{2\mathcal{L}\mathcal{T}\Omega}$. □

What remains to be proved is Lemma 2.

Proof of Lemma 2. For a given history $\boldsymbol{z}$, unpack the decision rule vector as

$$\boldsymbol{o}_{\boldsymbol{z}} = \left(\{y_{ilt}\}_{l\in\mathcal{L},t\in\mathcal{T}}, \{r_{ilt}\}_{l\in\mathcal{L},t\in\mathcal{T}}\right).$$

Note that I omit the notation of $\boldsymbol{z}$ in y_{ilt} since we are looking at a fixed $\boldsymbol{z}$ throughout this proof. The goal is to show that $\tilde{\Pi}^{\dagger}(\boldsymbol{o}_{\boldsymbol{z}}|\boldsymbol{z})$ has increasing difference along y_{ilt} and r_{ilt} for any l and any t in the given history $\boldsymbol{z}$.

Increasing difference along y_{ilt}. Consider two decision rules $\boldsymbol{o}_{\boldsymbol{z}}, \boldsymbol{o}_{\boldsymbol{z}}' \in \{0,1\}^{2\mathcal{L}\mathcal{T}}$ where the only difference between them is that $y_{ilt} = 0$ and $y_{ilt}' = 1$ for a specific l and t. The difference between $\tilde{\Pi}^{\dagger}(\boldsymbol{o}_{\boldsymbol{z}}'|\boldsymbol{z})$ and $\tilde{\Pi}^{\dagger}(\boldsymbol{o}_{\boldsymbol{z}}|\boldsymbol{z})$ has the following components:

- An increase in variable profit π_{it} due to higher sourcing capability:

$$\begin{aligned}
\Delta\pi_{it} &= \frac{1}{\eta} \cdot \left(\frac{\eta}{\eta-1}\right)^{1-\eta} \cdot \Phi_{jt} \cdot \left(\frac{e^{\beta_0}}{e^{\omega_{it}}} \cdot k_i^{\beta_k} \cdot w_{it}^{\beta_w}\right)^{1-\eta} \\
&* \left[\left((w_{lt}\tau_{lt})^{1-\rho} + \sum_{l'\neq l} y_{il't} \cdot (w_{l't}\tau_{l't})^{1-\rho}\right)^{\frac{(1-\eta)\beta_m}{1-\rho}} - \left(\sum_{l'\neq l} y_{il't} \cdot (w_{l't}\tau_{l't})^{\frac{\rho-1}{\rho}}\right)^{\frac{(1-\eta)\beta_m}{1-\rho}}\right].
\end{aligned}$$

- A change in the cost paid in period t:

$$-\phi_s^p + y_{ilt-1}\left(\phi_s^p - \phi_f^p\right) + \lambda_1 \sum_{l_1} r_{il_1t-1} r_{il_1t}\left(\max_{l_2}\{c_{l_1l_2}y_{il_2t}|y_{ilt}=1\} - \max_{l_2}\{c_{l_1l_2}y_{il_2t}|y_{ilt}=0\}\right).$$

- A change in the cost paid in period $t+1$: $\zeta^{t+1} \cdot y_{ilt+1} \cdot \left(\phi_s^p - \phi_f^p\right)$.

- All future productivities, holding $\{\xi_{it}\}_t$ fixed, change by
$$\Delta\omega_{it+\tau} = \zeta^{t+\tau}\alpha^{\tau-1}\left[1 + X_{lt}\rho\right] \cdot \left[\beta_2 r_{ilt} + \beta_3\right], \tau \geq 1.$$
This leads to changes in variable profit for all periods after t, the sum of which has the following first-order approximation:
$$\sum_{\tau=1}^{\infty} \zeta^{t+\tau} \cdot \frac{1}{\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta} \cdot \Phi_{jt+\tau} \cdot \left(e^{\beta_0} \cdot k_{it+\tau}^{\beta_k} \cdot w_{it+\tau}^{\beta_w} \cdot \left(p_{it+\tau}^m\right)^{\beta_m}\right)^{1-\eta}$$
$$* \alpha^{\tau-1}\left[1 + X_{lt}\rho\right] \cdot \left[\beta_2 r_{ilt} + \beta_3\right] \cdot \exp\left((\eta - 1) \cdot \omega_{it+\tau}\left(y_{ilt} = 0\right)\right).$$

Combining the four components, the first-order change from $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o_z}|\boldsymbol{z}\right)$ to $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o'_z}|\boldsymbol{z}\right)$ is thus
$$\begin{aligned}\tilde{\Pi}^{\dagger}\left(\boldsymbol{o'_z}|\boldsymbol{z}\right) - \tilde{\Pi}^{\dagger}\left(\boldsymbol{o_z}|\boldsymbol{z}\right) = {} & \frac{1}{\eta} \cdot \left(\frac{\eta}{\eta-1}\right)^{1-\eta} \cdot \Phi_{jt} \cdot \left(\frac{e^{\beta_0}}{e^{\omega_{it}}} \cdot k_i^{\beta_k} \cdot w_{it}^{\beta_w}\right)^{1-\eta} \\
& * \left[\left(\left(w_{lt}\tau_{lt}\right)^{1-\rho} + \sum_{l' \neq l} y_{il't} \cdot \left(w_{l't}\tau_{l't}\right)^{1-\rho}\right)^{\frac{(1-\eta)\beta_m}{1-\rho}} - \left(\sum_{l' \neq l} y_{il't} \cdot \left(w_{l't}\tau_{l't}\right)^{\frac{\rho-1}{\rho}}\right)^{\frac{(1-\eta)\beta_m}{1-\rho}}\right] \\
& - \phi_s^p + y_{ilt-1} \cdot \left(\phi_s^p - \phi_f^p\right) + \zeta^{t+1} y_{ilt+1} \cdot \left(\phi_s^p - \phi_f^p\right) \\
& + \lambda_1 \sum_{l_1} r_{il_1t-1} \cdot r_{il_1t} \cdot \left(\max_{l_2}\left\{c_{l_1l_2} y_{il_2t} | y_{ilt} = 1\right\} - \max_{l_2}\left\{c_{l_1l_2} y_{il_2t} | y_{ilt} = 0\right\}\right) \\
& + \sum_{\tau=1}^{\infty} \zeta^{t+\tau} \cdot \frac{1}{\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta} \cdot \Phi_{jt+\tau} \cdot \left(e^{\beta_0} \cdot k_{it+\tau}^{\beta_k} \cdot w_{it+\tau}^{\beta_w} \cdot \left(p_{it+\tau}^m\right)^{\beta_m}\right)^{1-\eta} \\
& * \alpha^{\tau-1}\left[1 + X_{lt}\rho\right] \cdot \left[\beta_2 r_{ilt} + \beta_3\right] \cdot \exp\left((\eta - 1) \cdot \omega_{it+\tau}\left(y_{ilt} = 0\right)\right).\end{aligned}$$
If $\frac{(1-\eta)\beta_m}{1-\rho} > 1$, then the first component is increasing in $\sum_{l' \neq l} y_{il't} \cdot \left(w_{l't}\tau_{l't}\right)^{1-\rho}$ and thus $y_{il't}$; vice versa if $\frac{(1-\eta)\beta_m}{1-\rho} < 1$. When $\phi_s^p > \phi_f^p$, the second and third components are increasing in $y_{ilt-1}, y_{ilt+1}, r_{ilt}, r_{ilt-1}, r_{il't}, r_{il't-1}$. The last component is increasing in r_{ilt} when $\beta_2\left(1 + X_{lt}\rho\right) > 0$. Therefore, $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o_z}|\boldsymbol{z}\right)$ has increasing differences along y_{ilt} for any l and t.

Increasing difference along r_{ilt}. Consider two decision rules $\boldsymbol{o_z}, \boldsymbol{o'_z} \in \{0,1\}^{2\mathcal{LT}}$ where the only difference between them is that $r_{ilt} = 0$ and $r'_{ilt} = 1$ for a specific l and t. Switching from the first to the second decision rule doesn't affect period t's variable profit, but it affects next period's cost and all future periods' productivities.

The difference between $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o'_z}|\boldsymbol{z}\right)$ and $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o_z}|\boldsymbol{z}\right)$ has the following components:

1. A change in period $t+1$'s cost:
$$\zeta^{t+1} r_{ilt+1}\left(\phi_s^r - \phi_f^r + \lambda_1 \max_{l'}\left\{c_{ll'} y_{il't+1}\right\}\right).$$

2. All future productivities will be increased by

$$\Delta\omega_{it+\tau} = \zeta^{t+\tau}\alpha^{\tau-1}\left[1 + X_{lt}\rho\right] \cdot \left[\beta_1 + \beta_2 y_{ilt}\right], \tau \geq 1.$$

This leads to a first-order increase in all future periods' profit that is equal to

$$\sum_{\tau=1}^{\infty}\zeta^{t+\tau} \cdot \frac{1}{\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta} \cdot \Phi_{jt+\tau} \cdot \left(e^{\beta_0} \cdot k_{it+\tau}^{\beta_k} \cdot w_{it+\tau}^{\beta_w} \cdot \left(p_{it+\tau}^{m}\right)^{\beta_m}\right)^{1-\eta}$$
$$*\alpha^{\tau-1}\left[1 + X_{lt}\rho\right] \cdot \left[\beta_1 + \beta_2 y_{ilt}\right] \cdot \exp\left(\left(\eta - 1\right) \cdot \omega_{it+\tau}\left(r_{ilt} = 0\right)\right).$$

Combining the two components, the first-order change from $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o_z}|\boldsymbol{z}\right)$ to $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o}'_{\boldsymbol{z}}|\boldsymbol{z}\right)$ is thus

$$\begin{aligned}\tilde{\Pi}^{\dagger}\left(\boldsymbol{o}'_{\boldsymbol{z}}|\boldsymbol{z}\right) - \tilde{\Pi}^{\dagger}\left(\boldsymbol{o_z}|\boldsymbol{z}\right) = {} & \zeta^{t+1} r_{ilt+1} \cdot \left(\phi_s^r - \phi_f^r + \lambda_1 \max_{l'}\left\{c_{ll'} y_{il't+1}\right\}\right) \\ & + \sum_{\tau=1}^{\infty}\zeta^{t+\tau} \cdot \frac{1}{\eta}\left(\frac{\eta}{\eta-1}\right)^{1-\eta} \cdot \Phi_{jt+\tau} \cdot \left(e^{\beta_0} \cdot k_{it+\tau}^{\beta_k} \cdot w_{it+\tau}^{\beta_w} \cdot \left(p_{it+\tau}^{m}\right)^{\beta_m}\right)^{1-\eta} \\ & * \alpha^{\tau-1}\left[1 + X_{lt}\rho\right] \cdot \left[\beta_1 + \beta_2 y_{ilt}\right] \cdot \exp\left(\left(\eta - 1\right) \cdot \omega_{it+\tau}\left(r_{ilt} = 0\right)\right).\end{aligned}$$

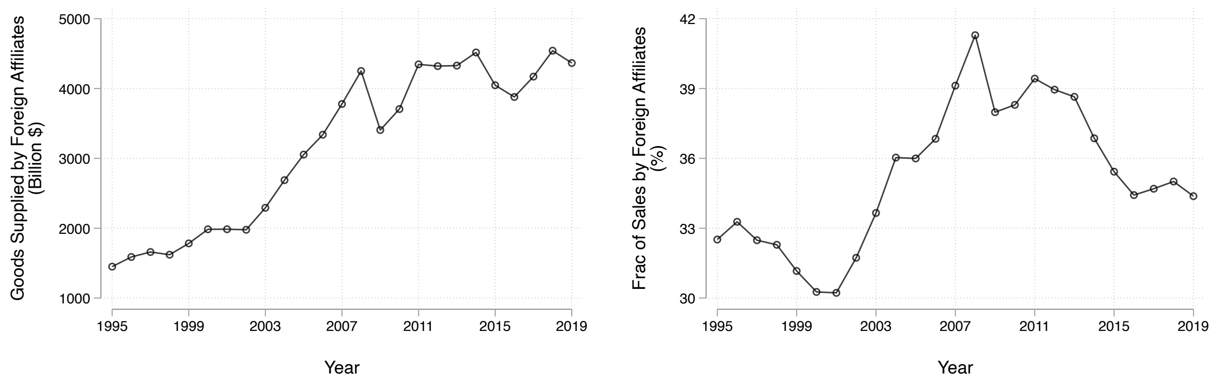
The first component is increasing in r_{ilt+1}, y_{ilt+1} and $y_{il't+1}$. The second component is increasing in y_{ilt} when $\left[1 + X_{lt}\rho\right] \cdot \left[\beta_1 + \beta_2 y_{ilt}\right] \geq 0$ and decreasing in $p_{it+\tau}^m$, implying that it is also increasing in $y_{ilt+\tau}$ and $y_{il't+\tau}$ for all $\tau \geq 1$. Therefore, $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o_z}|\boldsymbol{z}\right)$ has increasing differences along r_{ilt} for any l and t.

Combining the increasing differences along y_{ilit} and r_{ilt} for any l and t, I have showed that $\tilde{\Pi}^{\dagger}\left(\boldsymbol{o_z}|\boldsymbol{z}\right)$ has increasing differences in $\{0,1\}^{2\mathcal{L}\mathcal{T}}$. □

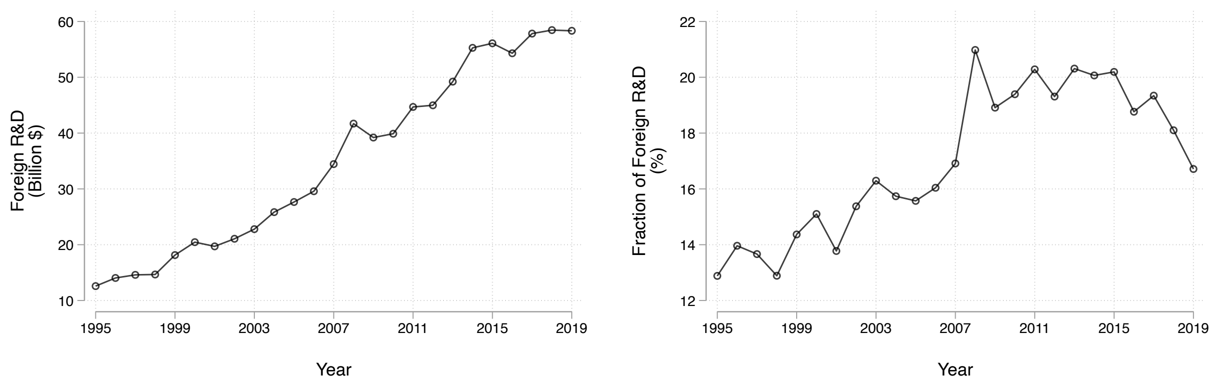
D Supplemental Figures and Tables

Figure A2: Trend of U.S. Offshoring, 1995-2020

Panel A. Production



Panel B. R&D



Notes: This figure plots the time trends of U.S. offshore production and R&D activities from 1995 to 2019. The data is sourced from the Bureau of Economic Analysis's Survey of U.S. Direct Investment Abroad (USDIA), which gathers information on the activities of U.S. multinational parent firms and their foreign affiliates. Panel (a) measures production offshoring, showing the dollar value of goods supplied by foreign affiliates of U.S. parent firms and the fraction of sales made by these foreign affiliates relative to the firm's total sales. Panel (b) measures innovation offshoring, showing the dollar value of foreign R&D expenditure by U.S. firms and the proportion of foreign R&D expenditure within the firm's total worldwide R&D expenditure.

Figure A3: BRDIS Survey Questionnaire

2-11 Of the amount reported in Question 2-10, column 2, how much R&D was performed in the following locations? For full list of countries in each region see Question by Question Guidance at https://www.census.gov/programs-surveys/brds/information/brdshelp.html#q2-11.

	$Bil.	Mil.	Thou.		$Bil.	Mil.	Thou.
Canada				Germany			
Puerto Rico				Hungary.			
Europe	$Bil.	Mil.	Thou.	Ireland.			
Austria.				Italy			
Belgium.				Luxembourg . . .			
Czech Rep				Netherlands. . . .			
Denmark				Norway			
Finland				Poland.			
France				Russia			

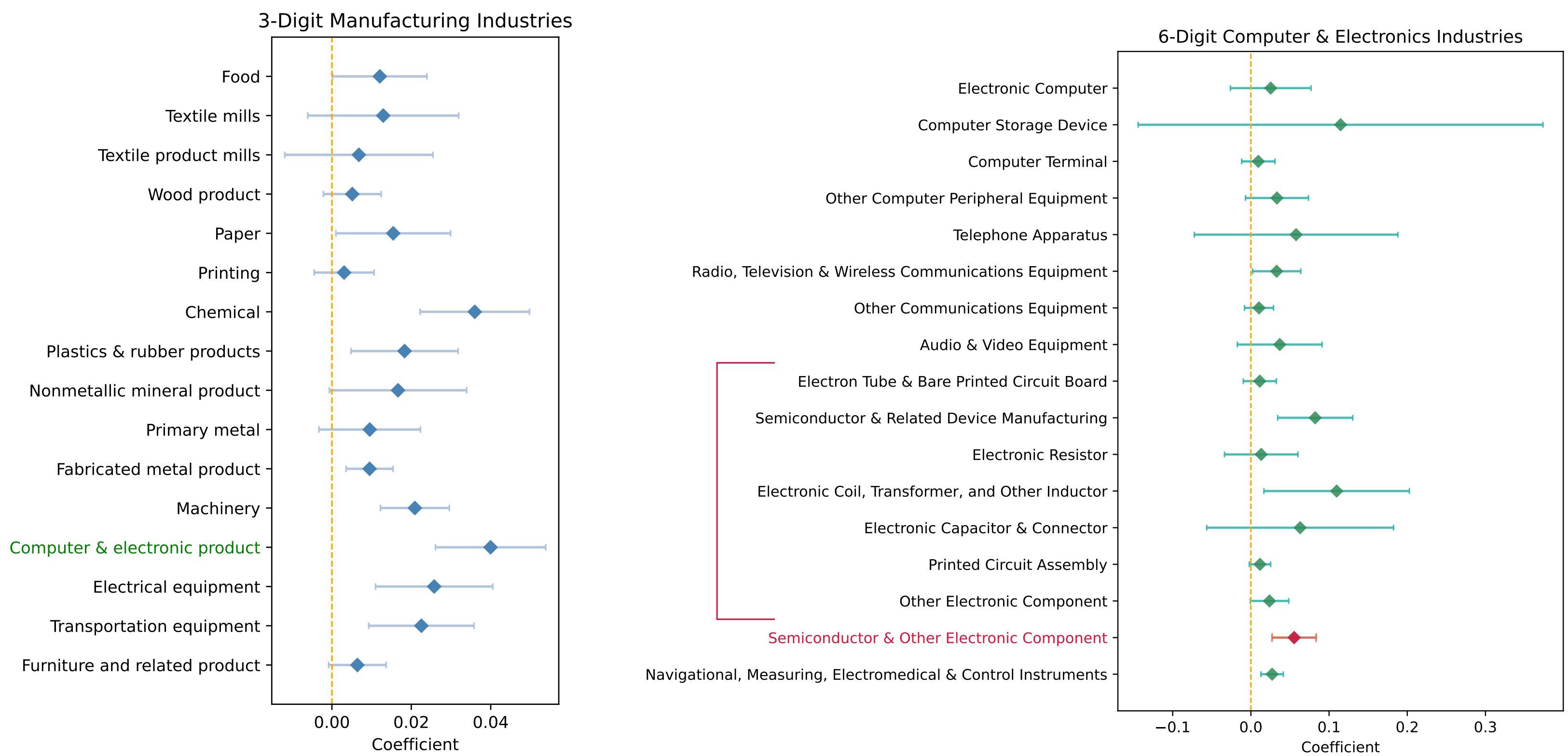
Question continues on next page

Notes: This figure presents a snapshot of Question 2-11 from "Section 2: R&D Paid For by Your Company" in the original Business R&D and Innovation Survey form. It lists 40 countries and regions, along with five residual categories: "Other Europe," "Other Latin America/OWH," "Other Asia/Pacific," "Other Middle East," and "Other Africa." These residual categories collectively account for less than 5% of U.S. offshore R&D expenditure.

Figure A4: OLS Coefficient Estimates for Two Facts—Industry Heterogeneity

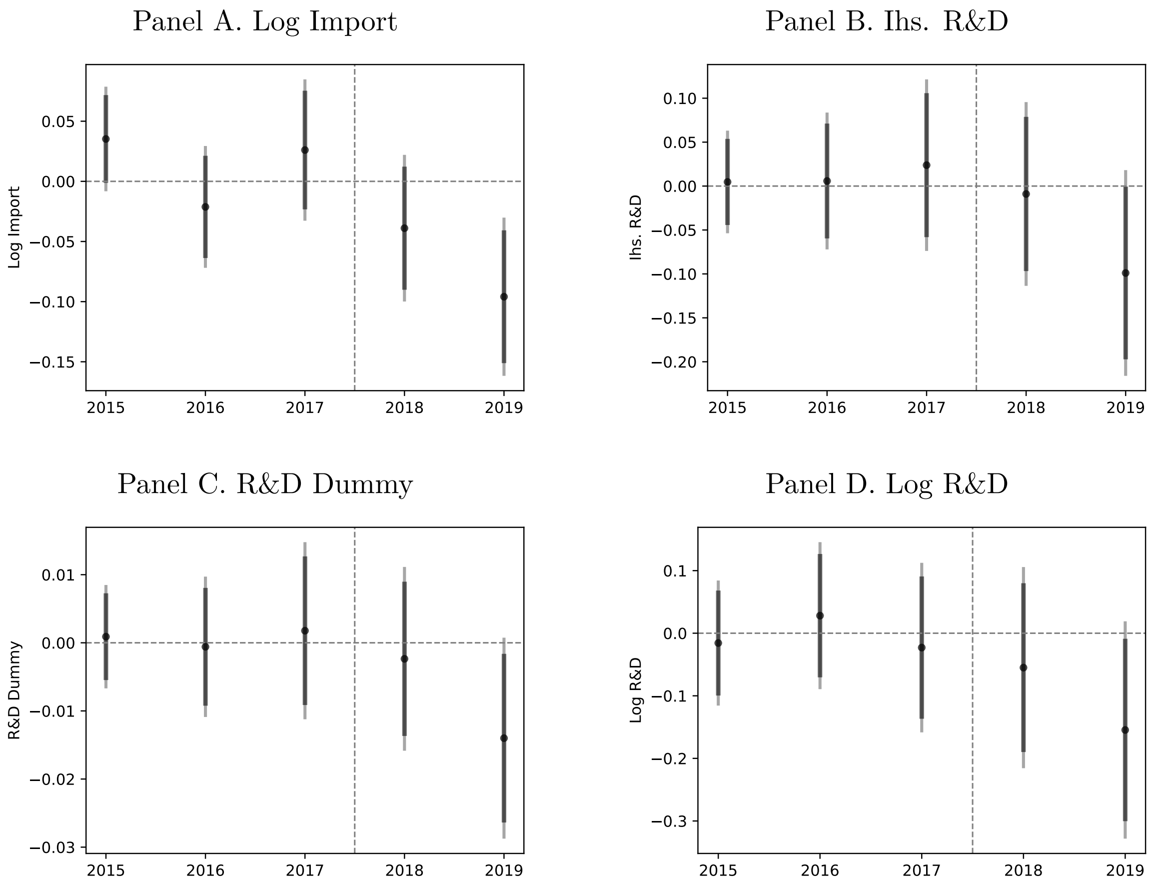
Panel A. Broad Manufacturing Industries

Panel B. Narrow Computer and Electronics Sub-Industries



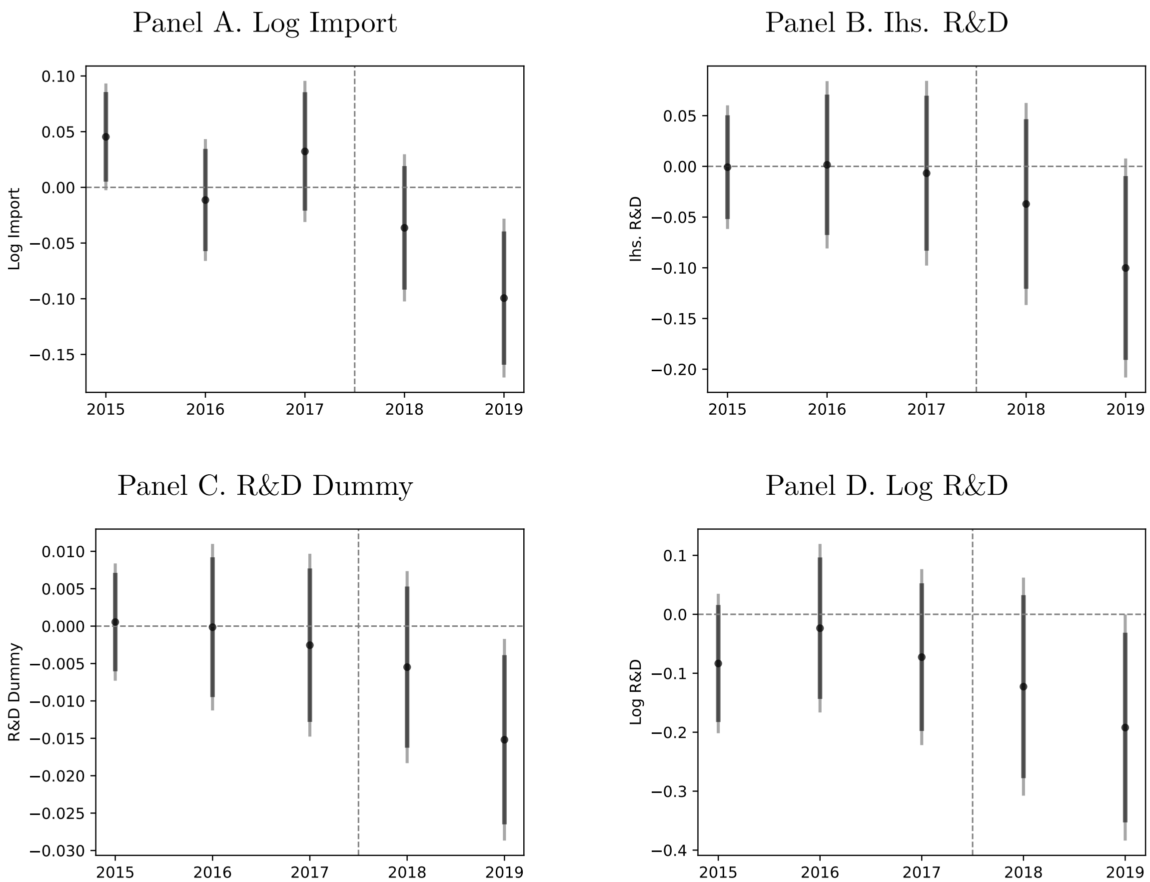
Notes: This figure presents coefficient estimates from equation (**??**), excluding the regional term x_{iRt}, using subsamples by industry. Observations are at the firm-country-year level. The outcome variable is the inverse hyperbolic sine (Ihs.) transformed R&D. The main regressor is the inverse hyperbolic sine (Ihs.) transformed imports. Firm-year and country-year fixed effects are included. Panel (a) examines broad manufacturing industries at the three-digit NAICS code level. Panel (b) examines narrow sub-industries within computer and electronics, based on six-digit NAICS codes. Standard errors are clustered at the firm level. 95% confidence intervals are plotted as error bars. Coefficient estimates are rounded to four effective digits in accordance with Census data disclosure requirements.

Figure A5: The Effect of Trump Tariffs on Offshoring—Excluding China



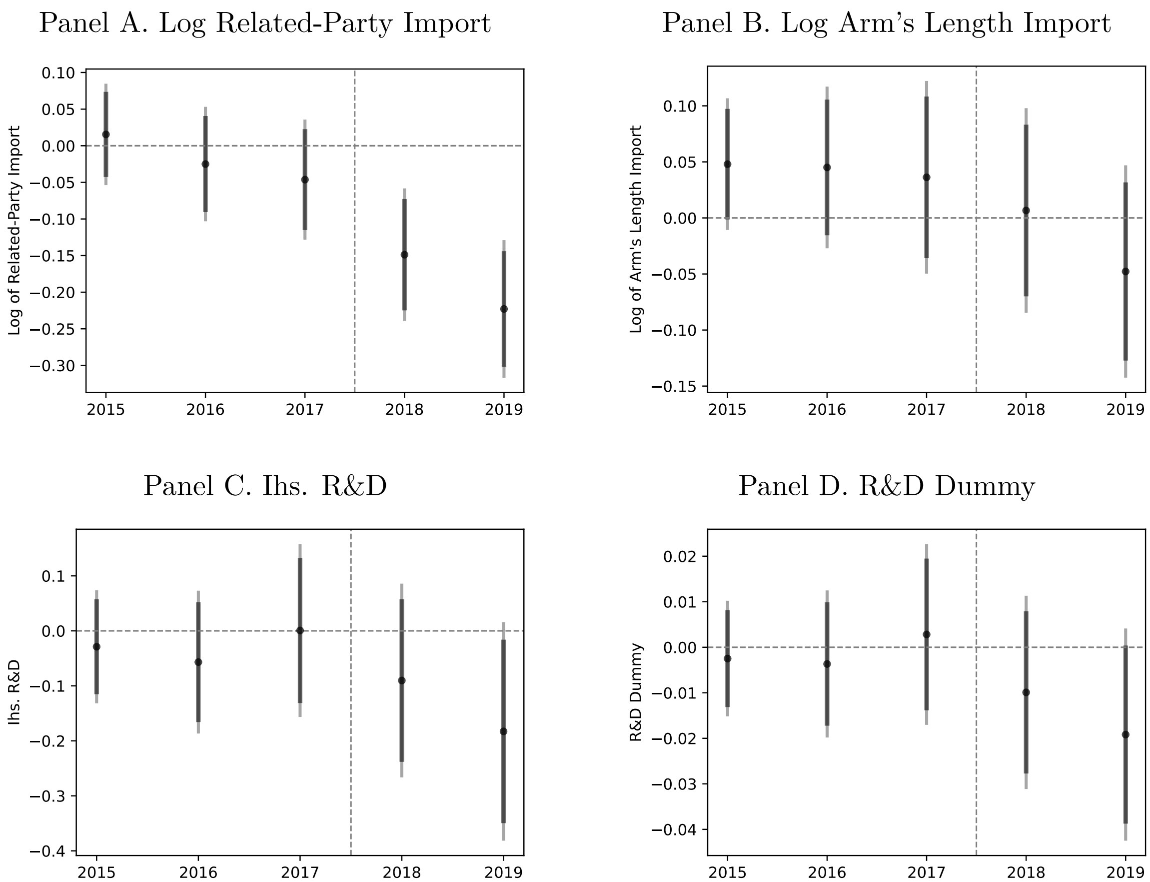
Notes: This figure presents coefficient estimates from equation (5), excluding China from the sample. This is a variant of Figure 5. Each panel corresponds to a different outcome variable. Dummy variables capture the extensive margin, log values capture the intensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. The regressions include firm-country fixed effects, country-year fixed effects, and firm sales and employment as control variables. Standard errors are clustered at the firm level. 90% and 95% confidence intervals are plotted as error bars. Coefficient estimates and statistics are rounded to four effective digits in accordance with Census data disclosure requirements.

Figure A6: The Effect of Trump Tariffs on Offshoring—Excluding Semiconductor Industry



Notes: This figure presents coefficient estimates from equation (5), excluding the semiconductor industry (broadly identified by NAICS code 3344) from the sample. This is a variant of Figure 5. Each panel corresponds to a different outcome variable. Dummy variables capture the extensive margin, log values capture the intensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. The regressions include firm-country fixed effects, country-year fixed effects, and firm sales and employment as control variables. Standard errors are clustered at the firm level. 90% and 95% confidence intervals are plotted as error bars. Coefficient estimates and statistics are rounded to four effective digits in accordance with Census data disclosure requirements.

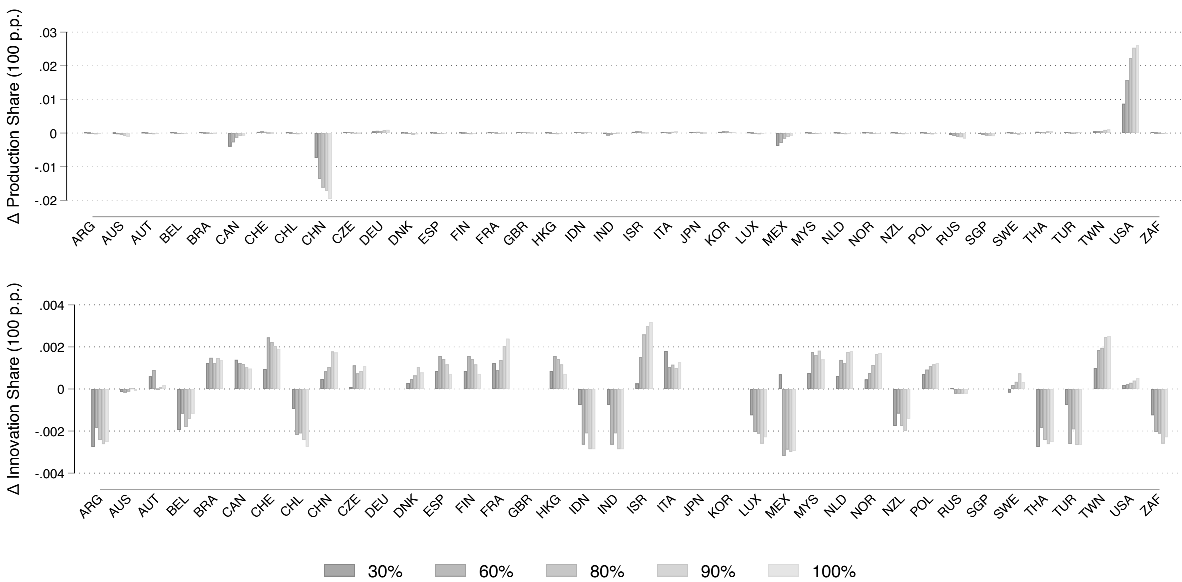
Figure A7: The Effect of Trump Tariffs on Offshoring—Treatment Based on Related Party Imports



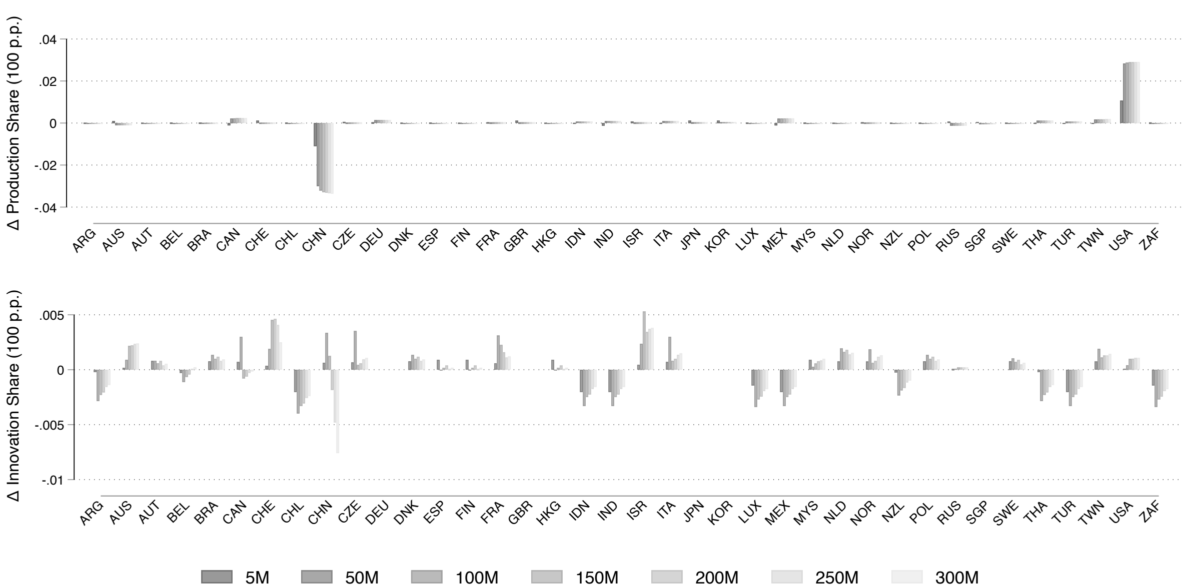
Notes: This figure presents coefficient estimates from equation (5), focusing exclusively on related-party imports. This is a variant of Figure 5. The "Treatment" dummy in this figure equals one for firm-country pairs whose *related-party* trade was affected by the Trump Tariffs. Each panel corresponds to a different outcome variable. Dummy variables capture the extensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. The regressions include firm-country fixed effects, country-year fixed effects, and firm sales and employment as control variables. Standard errors are clustered at the firm level. 90% and 95% confidence intervals are plotted as error bars. Coefficient estimates and statistics are rounded to four effective digits in accordance with Census data disclosure requirements.

Figure A8: Simulated Effects of Bilateral Policy Shocks, By Country

Panel A: Increasing Import Tariffs



Panel B: Increasing Increasing Production Costs



Notes: This figure presents the changes in production and innovation shares for each country under various counterfactual scenarios. The production share for l is computed as $\sum_i y_{il}/\sum_{il} y_{il}$, and the innovation share is computed similarly as $\sum_i r_{il}/\sum_{il} r_{il}$. Panel A shows how these shares adjust in response to increases in U.S. import tariffs on China, with tariff increases reflected as percentage decreases in China's offshoring potential (30%, 60%, 80%, 90%, and 100%). Panel B illustrates how these shares shift when the sunk and fixed costs of producing in China rise by different amounts, ranging from 5 to 300 million dollars. The sum of all countries, excluding China and the U.S., constitutes the ROW in Figure 8.

Table A2: Sample Structure and Survey Frequency

Survey Frequency	Number of Firms	Fraction of Firms	Fraction of Sales	Fraction of Value Added
	(1)	(2)	(3)	(4)
1-2	27500	76.39	3.05	3.50
3-5	5000	13.89	7.39	8.17
6-9	2500	6.94	22.42	16.24
10-12	1400	3.89	67.14	72.09
Total	36000	100	100	100

Notes: This table summarizes the frequencies at which firms in my sample are surveyed. The firm sample is constructed at the intersection of the BRDIS, LFTTD, and CMF/ASM datasets. The LFTTD and CMF cover the entire population of U.S. firms, while the BRDIS and ASM cover representative samples. Since the focus is on the period from 2008 to 2019, a firm can be sampled in at least one year and at most twelve years. Fractions are rounded to four effective digits, and firm counts are rounded to the nearest hundreds, in accordance with Census data disclosure requirements.

Table A3: Multiple Offshoring Locations for Production and Innovation

Panel A. R&D Locations

Number of Foreign R&D Locations (%)	Fraction of Observations (%)	Fraction of Sales (%)	Fraction of Worldwide R&D (%)	Fraction of Offshore R&D (%)
0	90.37	38.22	13.68	0
1	2.83	6.39	4.40	2.37
2-5	3.74	19.37	12.14	10.93
6-10	1.66	10.86	13.35	16.14
Above 10	1.40	25.16	56.44	70.56
Total	100	100	100	100

Panel B. Import Locations

Number of Import Origins	Fraction of Observations (%)	Fraction of Sales (%)	Fraction of Import Value (%)
0	16.60	0.52	0
1	13.18	0.88	0.09
2-10	48.26	14.18	4.97
11-20	14.39	29.10	19.55
Above 20	7.58	55.31	75.38
Total	100	100	100

Notes: This table summarizes the distributions of firms based on the number of foreign innovation and import locations, using data from 2008 to 2019. Observations are at the firm-year level. Panel A reports the fractions of observations, sales, worldwide R&D expenditure, and foreign R&D expenditure for firm groups categorized by the number of foreign countries in which they perform R&D. Panel B reports the fractions of observations, sales, and import value for firm groups categorized by the number of origin countries they import from. Fractions are rounded to four effective digits in accordance with Census data disclosure requirements.

Table A4: OLS Coefficient Estimates for Two Facts—Excluding Regional Terms

Panel A. Regress R&D on Import

	R&D Dummy (1)	R&D Dummy (2)	Log R&D (3)	Log R&D (4)	Ihs. R&D (5)
Import Dummy	0.0196***		0.322***		
	(0.000697)		(0.117)		
Log Import		0.0134***		0.211***	
		(0.000448)		(0.0167)	
Ihs. Import					0.0218***
					(0.000546)
N	499000	57000	4100	3400	499000
R-squared	0.392	0.478	0.569	0.595	0.419
Firm FE	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes

Panel B. Regress Import on R&D

	Import Dummy (1)	Import Dummy (2)	Log Import (3)	Log Import (4)	Ihs. Import (5)
R&D Dummy	0.210***		1.755***		
	(0.00675)		(0.0529)		
Log R&D		0.00711***		0.309***	
		(0.00261)		(0.0254)	
Ihs. R&D					0.578***
					(0.0118)
N	499000	4100	57000	3400	499000
R-squared	0.420	0.612	0.475	0.661	0.470
Firm FE	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates from equation (1) using data from 2017, as a variant of Table 4. The regional term x_{iR} is removed to test the robustness of Fact 1. Panel A regresses R&D measures on import measures, while Panel B does the opposite. Observations are at the firm-country level. Dummy variables capture the extensive margin, log values capture the intensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. Industries are classified by 3-digit NAICS codes. Standard errors are clustered at the firm level and reported in parentheses. Coefficient estimates and regression statistics are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: OLS Coefficient Estimates for Two Facts—Panel Version

Panel A. Regress R&D on Import

	R&D Dummy	R&D Dummy	Log R&D	Log R&D	Ihs. R&D
	(1)	(2)	(3)	(4)	(5)
Import Dummy	0.0180***		0.391***		
	(0.000844)		(0.0625)		
Region Import Dummy	0.00169***		-0.0482		
	(0.000261)		(0.0682)		
Log Import		0.0134***		0.208***	
		(0.000539)		(0.0134)	
Log Region Import		0.00100***		0.00734	
		(0.000376)		(0.0147)	
Ihs. Import					0.0213***
					(0.000862)
Ihs. Region Import					0.000927***
					(0.000200)
N	3387000	400000	39000	30000	3387000
R-squared	0.389	0.483	0.568	0.593	0.414
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Country-Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Panel B. Regress Import on R&D

	Import Dummy	Import Dummy	Log Import	Log Import	Ihs. Import
	(1)	(2)	(3)	(4)	(5)
R&D Dummy	0.171***		1.639***		
	(0.00652)		(0.0371)		
Region R&D Dummy	0.0442***		0.171***		
	(0.00367)		(0.0298)		
Log R&D		0.00838***		0.296***	
		(0.00172)		(0.0190)	
Log Region R&D		0.00228		0.0431*	
		(0.00166)		(0.0229)	
Ihs. R&D					0.502***
					(0.0121)
Ihs. Region R&D					0.0968***
					(0.00655)
N	3387000	25500	536000	22000	3387000
R-squared	0.449	0.637	0.467	0.689	0.501
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Country-Industry-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates from the panel version of equation (1):

$$y_{ilt} = \beta_1 \cdot x_{ilt} + \beta_2 \cdot x_{iRt} + \gamma_{it} + \gamma_{jlt} + \varepsilon_{ilt} \tag{2}$$

using data from 2008 to 2019, as a variant of Table 4. Panel A regresses R&D measures on import measures, while Panel B does the opposite. Observations are at the firm-country-year level. "Region Import" and "Region R&D" refer to the firm's total import value and R&D expenditure in all countries of the host region, excluding the focal host country itself. Standard errors are clustered at the firm level and reported in parentheses. Coefficient estimates and regression statistics are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: OLS Coefficient Estimates for Two Facts—Distinguishing Between Related Party and Arm's Length Imports, Panel Version

	R&D Dummy (1)	R&D Dummy (2)	Log R&D (3)	Log R&D (4)	Ihs. R&D (5)	Ihs. R&D (6)
Arm's Length						
Import Dummy	0.00401***		0.116**		0.0206***	
	(0.000510)		(0.0492)		(0.00427)	
Region Import Dummy	0.000158		-0.0650		0.00114	
	(0.000245)		(0.0618)		(0.00189)	
Related Party						
Import Dummy	0.0692***		0.661***		0.555***	
	(0.00248)		(0.0483)		(0.0206)	
Region Import Dummy	0.00113**		0.0572		0.0138***	
	(0.000523)		(0.0514)		(0.00408)	
Arm's Length						
Log Import		0.00254***		0.0284**		0.0256***
		(0.000857)		(0.0139)		(0.00710)
Log Region Import		0.0000565		-0.0282		-0.000212
		(0.00117)		(0.0174)		(0.0101)
Related Party						
Log Import		0.0212***		0.214***		0.203***
		(0.00105)		(0.0151)		(0.0103)
Log Region Import		0.000702		0.00731		0.0109
		(0.000826)		(0.0147)		(0.00794)
N	3387000	128000	39500	21000	3387000	128000
R-squared	0.402	0.567	0.573	0.611	0.422	0.584
Firm-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates from the panel version of equation (1) and distinguishes between related-party and arm's length imports:

$$\text{R\&D}_{ilt} = \beta_1^R \cdot \text{Imp}_{ilt}^R + \beta_1^A \cdot \text{Imp}_{ilt}^A + \beta_2^R \cdot \text{Imp}_{iRt}^R + \beta_2^A \cdot \text{Imp}_{iRt}^A + \gamma_{it} + \gamma_{jlt} + \varepsilon_{ilt},$$

using data from 2008 to 2019, as a variant of Panel A of Table 4. The superscript "R" refers to related-party imports, and "A" refers to arm's length imports. "Region Import" refers to the firm's total import value and R&D expenditure in all countries of the host region, excluding the focal host country itself. Standard errors are clustered at the firm level and reported in parentheses. Coefficient estimates and regression statistics are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Testing Parallel Trend Assumption

	R&D Growth Rate	T-test
	(1)	(2)
Control	0.0528***	Null: Control - Treat =0
	(8.04)	
Treat	0.0558***	F-statistic: 0.08
	(7.01)	
N	12500	Prob>F: 0.7744

Notes: This table tests the parallel trend assumption for the Trump Tariffs quasi-experiment. Column (1) presents coefficient estimates from regressing the growth rate of R&D on dummies for the control and treated groups prior to and including the year 2017. Observations are at the firm-country-year level, with t-statistics reported in parentheses. Column (2) shows the results of the T-test, where the null hypothesis states that there is no difference in the growth rate of R&D between the two groups.

Table A8: Instrumental Strategy Coefficient Estimates—Using Related Party Imports

	Ihs. Related Party Import	Ihs. R&D	Ihs. R&D	R&D Dummy	R&D Dummy
	(1)	(2)	(3)	(4)	(5)
Ihs. Related-Party Import		0.0632***	0.0907***	0.00753***	0.0109**
		(0.00249)	(0.0349)	(0.000284)	(0.00439)
T^R_{ilt}	-2.230***				
	(0.267)				
Method	OLS	OLS	IV	OLS	IV
1st-stage F	69.82				
N	954000	954000	954000	954000	954000
Firm-Year FE	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates for the 2SLS specification in equation (4), focusing exclusively on related-party imports. The updated tariff rate T^R_{ilt} is constructed using the firm's initial import product bundle from related parties and serves the instrument. Observations are at the firm-country-year level. Dummy variables capture the extensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both the extensive and intensive margins. Standard errors are clustered at the firm level and reported in parentheses. Coefficient estimates and regression statistics are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Difference-in-Differences Coefficient Estimates—Adding Regional Treatment

	Log Import	Ihs. R&D	R&D Dummy	Log R&D
	(1)	(2)	(3)	(4)
Treat × Post	-0.0976***	-0.0852**	-0.0113**	-0.127*
	(0.0254)	(0.0428)	(0.00557)	(0.0652)
TreatNeighbor × Post	-0.0293	-0.0340	-0.00657	-0.0833
	(0.0263)	(0.0408)	(0.00536)	(0.0613)
N	185000	185000	185000	16500
R-squared	0.890	0.877	0.838	0.894
Firm-Country FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes

Notes: This table presents coefficient estimates from equation (6) with an additional regressor, "TreatNeighbor" interacted with "Post," as a variant of the first row in Table 6:

$$y_{ilt} = \beta \cdot \text{Treat}_{il} \times \text{Post}_t + \text{TreatNeighbor}_{il} \cdot \text{Post}_t + \gamma_{il} + \gamma_{lt} + z_{it} + \varepsilon_{ilt}.$$

The dummy variable "Treat" equals one for firm-country pairs affected by the Trump Tariffs. The "TreatNeighbor" dummy equals one if the firm's tariff rate in neighboring countries within the host region (excluding the focal host country itself) was affected by the Trump Tariffs. The "Post" dummy equals one for the year 2019 and zero for the years 2014-2017. Dummy variables capture the extensive margin, log values capture the intensive margin, and the inverse hyperbolic sine (Ihs.) transformed values capture the combination of both margins. Standard errors are clustered at the firm level and reported in parentheses. Coefficient estimates and regression statistics are rounded to four effective digits, and the number of observations is rounded to the nearest thousand, in accordance with Census data disclosure requirements. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The coefficient estimates suggest that the direct treatment effect (Treat_{il}) is still significantly negative as in Table 6; the indirect treatment effect ($\text{TreatNeighbor}_{il}$) is negative and of nontrivial magnitude despite its statistical insignificance.

Table A10: Transition of Offshoring Status Across Years

Panel A. Transition of Import Status

	$100 \times \Pr(\text{Import}_{ilt+1} = 0)$	$100 \times \Pr(\text{Import}_{ilt+1} = 1)$
$\text{Import}_{ilt} = 0$	93.98	6.02
$\text{Import}_{ilt} = 1$	17.69	82.31

Panel B. Transition of R&D Status

	$100 \times \Pr(\text{R\&D}_{ilt+1} = 0)$	$100 \times \Pr(\text{R\&D}_{ilt+1} = 1)$
$\text{R\&D}_{ilt} = 0$	99.55	0.45
$\text{R\&D}_{ilt} = 1$	12.92	87.08

Notes: This table presents the transition probabilities of firms' R&D and import statuses. Calculations are based on panel data with firm-country-year level observations. Rows represent the status in the current year, while columns represent the status in the next year. Data on import is from the LFTTD, and data on R&D is from the BRDIS. Probabilities are rounded to four effective digits in accordance with the Census data disclosure requirements.

Table A11: Validation of Estimates of Production Offshoring Potentials

	Log Number of Importing Firms		
	(1)	(2)	(3)
Log Production Offshoring Potential Estimate, $\ln \hat{\theta}_{lt}$	0.776***	0.764***	0.362***
	(0.0233)	(0.0216)	(0.0751)
N	450	450	450
FE	No FEs	Year FEs	Country FEs

Notes: This table presents coefficient estimates from regressing the log number of importing firms on the country's log estimated production offshoring potential, $\ln \hat{\theta}_{lt}$. Observations are at the country-year level. The regressor, $\ln \hat{\theta}_{lt}$, is obtained from estimating equation (9) using OLS. Coefficient estimates are rounded to four effective digits, and the number of observations is rounded to the nearest hundred, in accordance with Census data disclosure requirements. Standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.