Trade Wars with FDI Diversion*

Sifan Xue†

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Abstract

I develop a model of multinational production with heterogeneous FDI diversion elasticities that capture flexible substitution patterns among production locations. These elasticities are larger for locations that are more suitable for "China-alike" production ideas in the context of the 2018–2019 China–U.S. trade war. The estimates indicate that, over 2017–2023, a 1% increase in a destination economy's market access due to the Trump tariffs raises FDI from a given source by 14.9% on average, with substantially larger responses for more "China-alike" destinations. Quantitatively, FDI diversion amplifies China's welfare loss by 38% while mitigating that of the U.S. by 34%. In a counterfactual that raises the suitability of the U.S. for "China-alike" production, FDI diversion to the U.S. nearly doubles, while diversion to other economies falls to near zero, further amplifying uneven welfare effects across countries.

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†China Center for Economic Research, National School of Development, Peking University. Email: sifanx@nsd.pku.edu.cn.

The China–U.S. trade war that began in 2018 has renewed interest in the effects of trade policies on global trade patterns and welfare. Much of the recent literature has focused on trade diversion, but the trade war also highlighted an equally important channel: the reallocation of productive capital, particularly through foreign direct investment (FDI) and multinational production.[1]

Yet the quantitative importance and patterns of FDI diversion remain imperfectly understood, even though they play an important role in shaping the welfare and policy implications of major trade shocks worldwide. The possibility that manufacturers relocate production back to the United States, or "reshoring," has been a central motivation for U.S. policy. At the same time, several studies document sizable firm relocation to alternative destinations such as Vietnam and Mexico (e.g., Alfaro and Chor 2023; Freund et al. 2024), consistent with the rhetoric of "friendshoring" and "nearshoring." To what extent the U.S. can achieve its goal, and how different third-party countries are affected in the wake of the China–U.S. trade war, are among the many important questions related to FDI diversion.

In this paper, I develop a quantitative general equilibrium model of trade and multinational production featuring heterogeneous FDI diversion elasticities. I estimate the magnitude and heterogeneity of FDI diversion elasticities with respect to trade policy changes and link them to model primitives. I show that accounting for the existence and systematic patterns of FDI diversion significantly alters the implications of the Trump tariffs.

On the theoretical side, I develop a general equilibrium model of trade and multinational production (or FDI) with latent production technology types. Tariff shocks that trigger trade diversion change market access and, in turn, the value of operating across production locations. Consequently, producers adjust their optimal production locations, giving rise to FDI diversion.

I decompose a country's aggregate welfare change into different channels, underscoring the importance of a "relocation" mechanism driven by FDI diversion. In trade-only models, tariffs mechanically raise prices in the tariff-imposing economy. Once firms can relocate production internationally, however, tariff shocks trigger production relocation that can offset these price increases, implying that the welfare effects of the Trump tariffs can differ sharply from those in standard trade-only analyses, such as Fajgelbaum et al. (2020).

I offer a tractable method for generating heterogeneous FDI diversion elasticities in a general equilibrium model that can be taken to the data. To do so, I specify two types of production technologies — "China-alike" and "location-specific" — in the context of the 2018–2019 China–U.S. trade war. For a given change in market access, the FDI diversion *elasticities* are larger — not merely FDI diversion *levels* — for economies that are better

[1] I do not distinguish between the two and will refer to both simply as FDI throughout the paper.

locations for "China-alike" production ideas. For example, Vietnam and other Southeast Asian economies arguably have endowments and production environments similar to those of China. This makes them natural alternatives for firms relocating out of China and leads to larger FDI diversion elasticities. Similarly, investing economies that are more productive in "China-alike" production ideas exhibit larger outward FDI diversion elasticities, on average across destinations, in response to the Trump tariffs. The microfoundations for this interpretation build on the recently developed approach to studying trade elasticity heterogeneity (Lind and Ramondo 2023*a*) and adapt it to the FDI diversion setting.

Based on the FDI gravity equation derived from the model, I present evidence of significant FDI diversion during the 2018–2019 China–U.S. trade war. Instead of relying on micro firm-level data for one or a few countries, often dictated by availability, the analysis uses exclusively official, publicly available, country-level aggregate FDI data covering a broad set of countries and years. The FDI gravity equation links bilateral FDI responses to changes in the value of operating in a destination economy through market access, which in turn determines observable changes in the destination's total exports.

However, using a country's export changes as the independent variable to quantify FDI diversion is problematic because export changes are endogenous and affected by many other shocks. To obtain exogenous variation in the value of operating and in total exports, I construct a theory-consistent index of each economy's exposure to trade diversion from the Trump tariffs, based on U.S. tariff changes and pre-shock global trade data. Economies with higher exposure are those with greater potential to substitute for China's exports to the U.S. and for which such export opportunities are economically important. For example, Vietnam's index places it at approximately the 95th percentile of the sample. This measure captures the market-access component of changes in the value of operating across destinations in the model. I use this index as an instrumental variable that shifts the destination economy's total exports and thereby affects the outcome of interest, FDI.

This IV strategy ensures that the estimated coefficients are interpretable: they measure an average of deep parameters governing FDI diversion rather than merely documenting its existence. The estimates imply that, on average, when a destination becomes 1% more attractive as a production location, the investing economy increases its FDI there by 6.8% over two years (2017–2019) and 14.9% over 6 years (2017–2023).

I next present evidence of systematic heterogeneity in FDI diversion elasticities. In the model, the heterogeneity is determined by a bilateral variable: the share of production using China-alike technologies among all FDI investments within a given economy pair. However, this characteristic is inherently latent and therefore unobservable. I therefore construct proxies motivated by the China-alike interpretation.

I use two measures to proxy for how suitable a destination economy is for China-alike technologies. The first is the correlation between the export shares of economy i and China across NAICS 2007 three-digit industries (COR) in 2017. The second is the Grubel-Lloyd index (GLI), a popular measure of supply chain linkages between economy i and China. The first captures the idea that economy i has endowments and a production environment similar to those of China, while the second captures how cost-efficient it is to move goods between economy i and China. To proxy for the relative productivity of "China-alike" technologies operated by investing economies, I again use the COR index. I then use the product of the destination- and investing-economy measures as bilateral proxies (COR $\times$ COR and GLI $\times$ COR). I interact these bilateral proxies with changes in total exports and estimate the coefficient on the interaction term using the same IV strategy.

A major debate and central policy concern during the China–U.S. trade war has been the role of connecting countries such as Vietnam, as well as whether the U.S. itself can attract production relocation.[2] My analysis provides a theoretical framework and a systematic empirical examination of these discussions. According to my measures, Vietnam scores highly on both proxies, helping to explain its prominent role in global relocation during the China–U.S. trade war. On the other hand, the U.S. lies in the lower range of these proxies.

The empirical results indicate substantial heterogeneity in FDI diversion elasticities. Moving from the economy pair with the smallest to that with the highest China-alike bilateral proxies increases FDI diversion, in response to a 1% rise in the value of operating, by more than 8.4% over two years and more than 21.1% over six years. The estimated coefficients suggest that this heterogeneity is large relative to the average bilateral FDI diversion elasticity.

These findings do not align with the predictions of standard multinational production models that assume homogeneous FDI diversion elasticities (e.g., Arkolakis et al. 2018). Explicitly modeling heterogeneous FDI diversion differs fundamentally from a trade-only framework, even when the latter allows for richer correlation structures across locations (e.g., Lind and Ramondo 2023*b*; Fajgelbaum et al. 2024). Consider a model with homogeneous FDI diversion elasticities but heterogeneous trade elasticities: tariff shocks may

[2] For example, Flaaen and Pierce (2025) argue that, despite being intended to boost domestic manufacturing, U.S. industries more exposed to tariff hikes experienced relative declines in employment, as a small positive effect from import protection is offset by larger negative effects from rising input costs and retaliatory tariffs. Similarly, Iyoha et al. (2024) show that import tariffs on foreign goods neither raised nor lowered U.S. employment in newly protected sectors. In terms of connecting countries, many studies on Vietnam attempt to distinguish between tariff-jumping transshipment and genuine relocation, e.g., Iyoha et al. (2024). Schulze and Xin (2025) argue that Vietnam benefited from genuine reallocation, with greater domestic content in its exports to the U.S. in strategic sectors, rather than simply facilitating transshipment of Chinese goods.

generate heterogeneous substitutability of export opportunities across destinations, but conditional on changes in export opportunities or in the value of operating, the elasticity of FDI diversion is identical across locations. My method also highlights mechanisms based on technological linkages across country pairs,[3] distinct from alternative mechanisms that can generate heterogeneous FDI diversion elasticities, such as the role of headquarter inputs in Ramondo and Rodriguez-Clare (2013) and the role of market proximity and plant fixed costs in Tintelnot (2017).

Finally, I use this framework and the estimated model parameters to assess the quantitative importance of FDI diversion in shaping the effects of the Trump tariffs. I calibrate the model to a world economy consisting of fourteen economies and multiple sectors, taking the year prior to the China–U.S. trade war as the initial equilibrium. I then subject this calibrated economy to the Trump tariffs in a series of quantitative exercises.

I show that ignoring FDI diversion leads to substantial differences in predicted welfare changes. This is illustrated by comparing the predictions from the baseline model with those from a counterfactual exercise that holds FDI fixed across locations. The results indicate that FDI diversion significantly amplifies China's welfare losses from the tariffs by about 38% while mitigating those faced by the U.S. by about 34%.

I decompose countries' aggregate welfare changes into different channels. The relocation effect emerges as a significant driver of aggregate welfare changes, outweighing the traditional terms-of-trade effect. The U.S. benefits primarily from the relocation effect, as more goods are produced domestically, lowering the price index.

I emphasize the central role of heterogeneous FDI diversion elasticities in shaping relocation patterns. These elasticities help explain why economies such as Vietnam have become salient destinations for production relocated from China, while relocation to other economies, such as the U.S., has been less responsive. According to my proxy measures, the U.S. lies at the lower end of FDI diversion elasticities. I conduct counterfactuals that vary the suitability of the U.S. for "China-alike" production. If the U.S. were a top location for "China-alike" production, I show that both Chinese and global FDI diversion to the U.S. would almost double, further alleviating welfare losses for the U.S. by about 30% and amplifying welfare losses for China by about 22%. On the other hand, FDI diversion to other prominent economies in the baseline, such as Vietnam, Malaysia, Japan, and Korea, would decrease by more than half from China and become negligible when aggregated across all investing economies.

[3]The specific meaning of technological linkages is flexible in my framework and can be adapted for different contexts. For example, the *COR*-based proxy relates more to country endowments, while the *GLI*-based proxy relates more to supply chain relationships between countries.

Related Literature. My treatment of FDI diversion is closely related to the literature on multinational production (e.g., Ramondo and Rodriguez-Clare 2013; Irarrazabal, Moxnes and Opromolla 2013; Tintelnot 2017; Arkolakis et al. 2018), as surveyed by Antràs and Yeaple (2014) and Bernard et al. (2018).[4] Building on this literature, I apply the generalized extreme value distribution method from Lind and Ramondo (2023*a*,*b*, 2024) to model patterns of FDI diversion. This provides a tractable framework for generating heterogeneous FDI elasticities that are directly disciplined by the data.[5] My model's mechanism and empirical sources of heterogeneous elasticities differ from other mechanisms emphasized in the literature, such as proximity to key markets (e.g., Tintelnot 2017; Utar, Cebreros and Torres 2025) and geopolitical alignment (e.g., Aiyar, Malacrino and Presbitero 2024; Gopinath et al. 2025*a*,*b*).

This paper emphasizes the importance of large FDI movements during the China–U.S. trade war,[6] a development often highlighted in media reports and of considerable policy concern (e.g., IMF 2023; Alfaro and Chor 2023). A growing body of work documents the restructuring of global linkages in more descriptive terms (Flaaen, Hortaçsu and Tintelnot 2020) and examines systematic forces such as geopolitics (Gopinath et al. 2025*a*,*b*; Aiyar, Malacrino and Presbitero 2024), supply chain networks (Freund et al. 2024; Garred and Yuan 2025), and other structural factors (Graziano et al. 2024). Vietnam and Mexico have frequently been spotlighted as "winners" in both policy discussions and the academic literature cited above.[7]

In contrast, my paper develops a model that explicitly links FDI to trade and production fundamentals in a general equilibrium multiple-country setting. Using this framework and relying solely on publicly available aggregate data, I conduct quantitative FDI diversion analysis at the global level, whereas most existing studies focus on individual countries

[4] Recent work has employed both aggregate and micro-level data to document and model richer patterns of multinational behavior — including production, location, sourcing, and export decisions (e.g., Gumpert et al. 2020; Li, Nie and Wang 2020; Li 2026). Li, Li and Lu (2025) study optimal unilateral policies with both multinational production (MP) and trade.

[5] Recent studies have developed related methods to study heterogeneous trade elasticities through flexible demand systems (e.g., Adão, Costinot and Donaldson 2017; Fajgelbaum et al. 2024) and flexible technologies (e.g., Farrokhi and Pellegrina 2023).

[6] Most papers on the China–U.S. trade war analyze trade-only models, e.g., Amiti, Redding and Weinstein (2020); Fajgelbaum et al. (2020, 2024); Cavallo et al. (2021); Ma et al. (2024); He et al. (2025). Other work incorporates additional margins of adjustment and channels, such as labor and firm reallocations within countries (Caliendo and Parro, 2019), firm-to-firm supply relationships (Grossman, Helpman and Redding, 2023), and interactions with industrial policies (Ju et al., 2024). Trade diversion arises naturally from changes in relative prices induced by tariffs and other trade policies (Fajgelbaum et al., 2024; Dang, Krishna and Zhao, 2023). More recent papers explore a range of further consequences of the trade war, including employment and consumption (Waugh, 2019), electoral outcomes (Autor, Beck and Dorn, 2024), environmental impacts (Du and Li, 2025), and technological interdependence (Chen, Fan and Luo, 2025).

[7] Some papers study whether increases in Vietnam's exports and investment reflect genuine relocation or phantom activity, e.g., Iyoha et al. (2024).

(e.g., McCaig, Pavcnik and Wong 2022) given the difficulty of compiling micro-level data across many economies. The general equilibrium framework also clarifies the central role of relocation effects as a countervailing force on price levels in the tariff-imposing country, relative to the tariff effects and their underlying mechanisms in trade-only models (e.g., (Venables, 1987; Ossa, 2011, 2014; Bagwell and Staiger, 2012)).

1 Model: Heterogeneous FDI Diversion Elasticities

I study a world economy consisting of N countries and S sectors. To simplify notation, I suppress the sector superscript when it is not essential. The model is static. Each country j is endowed with an exogenous, inelastically supplied stock of efficiency units of labor L_j and an aggregate firm productivity level z_j. For each country–sector pair, there is a fixed unit mass of producers indexed by ω. Each producer has a technology to produce a differentiated variety. Every producer ω is constrained to operate in one production country i and sells its variety to all potential importing countries h.[8] I will generally index the source country (where producers originate) by j, the production country by i, and the importing country by h.

Two simplifying assumptions are not innocuous. The first is that producers are restricted to a single production location. In Appendix A.4, I show that the model's results are essentially unchanged under the opposite extreme assumption — that producers can operate in all locations without incurring fixed costs of establishing production sites, as in Arkolakis et al. (2018). Empirically, because the analysis relies only on aggregate data and focuses on aggregate outcomes, these two assumptions are effectively equivalent for aggregate implications. The intermediate case, as in Tintelnot (2017), is more complex. I discuss how it relates to the mechanisms in this model and argue that the "proximity to key markets" channel emphasized by Tintelnot (2017) is not a substitute for the channels considered here.

The second assumption is that there is no heterogeneity in trade elasticities, unlike in the case of FDI. A growing literature, including Adão, Costinot and Donaldson (2017); Lind and Ramondo (2023*b*); Fajgelbaum et al. (2024), has highlighted the importance of heterogeneous bilateral trade elasticities in the China–U.S. trade war and in other contexts. While it is possible to incorporate such methods to introduce heterogeneous trade elasticities, I abstract from them to maintain focus on heterogeneity in FDI elasticities, which is conceptually distinct. If a country is more substitutable for Chinese exports, as in Fajgelbaum et al. (2024), this would manifest as a larger increase in its value of operating. By contrast,

[8] For example, one can assume that there is a sufficiently large span-of-control cost such that no producers operate in multiple locations.

heterogeneity in FDI diversion elasticities is defined conditional on changes in the value of operating, not on the shock itself. Moreover, because the empirical analysis is conducted using measures of the value of operating, it arguably already captures the consequences of potential heterogeneity in trade diversion elasticities, should they exist.

1.1 Household Demand

For each importing country h and sector s, there is a competitive producer of the sectoral composite good Q_h^s who supplies it by purchasing and combining all tradable varieties. Let M_{ij}^s denote the set of varieties in sector s owned by producers from country j and produced in country i. These tradable varieties face two types of frictions between the production (or exporting) country i and the importing country h: (i) iceberg trade costs τ_{hi}^s, and (ii) a gross ad valorem tariff t_{hi}^s.[9] Specifically,

$$Q_h^s = \left(\sum_{j=1}^{N} \sum_{i=1}^{N} \int_{M_{ij}^s} q_{hij}^s(\omega)^{\frac{\epsilon^s - 1}{\epsilon^s}} \, \mathrm{d}\omega \right)^{\frac{\epsilon^s}{\epsilon^s - 1}},$$

where $q_{hij}^s(\omega)$ denotes the quantity of variety ω in sector s imported by h, produced in i, and owned by a producer from j, and ϵ^s is the sector-specific elasticity of substitution across varieties. The corresponding price of variety ω is $p_{hij}^s(\omega)$.

The sectoral composites are purchased at their associated price indices P_h^s and aggregated into a final good for household consumption: $Q_h = \prod_{s=1}^{S} (Q_h^s)^{\phi_h^s}$, where $\sum_s \phi_h^s = 1$ and ϕ_h^s denotes the exogenous expenditure share on each sectoral composite. The corresponding final-good price index is P_h.

The representative household consumes the final good, and its expenditure $X_h = P_h C_h$ equals total income. Income consists of labor income, $w_h L_h$, and other sources taken as given: (i) aggregate domestic producers' profits D_h, since all firms are ultimately owned by the household; (ii) government tariff revenue T_h; and (iii) an exogenous country-level transfer Γ_h. The transfer can be interpreted as reserves or other mechanisms that affect the country's balance of payments but are not modeled endogenously.

[9] I abstract from fixed costs of exporting, since firm heterogeneity does not play a key role in the model and the empirical analysis does not focus on heterogeneity across firms within a given country–sector.

1.2 Production Technology

There are K technology classes, each corresponding to a "system" for producing goods.[10] For each technology class k, producers receives a productivity draw for every potential production location i. The efficiencies of class k for firms from country j producing variety ω across all locations i are distributed as:

$$\Pr\left[a_{1j}^k(\omega) \leq a_1^k, \ldots, a_{Nj}^k(\omega) \leq a_N^k\right] = \exp\left[-z_j\left(\sum_{i=1}^N \left(\eta_{ij}^k\left(a_{ij}^k\right)^{-\theta}\right)^{\frac{1}{1-\rho^k}}\right)^{1-\rho^k}\right],$$

where θ captures the dispersion of productivity across varieties, $0 \leq \rho^k \leq 1$ measures the correlation of productivity for the same variety across production locations, and η_{ij}^k measures the productivity level of firms from j operating technology class k in country i.

Productivity in each location is then determined by the best available technology class:

$$a_{ij}(\omega) = \max_k a_{ij}^k(\omega).$$

In the context of the Trump tariffs and FDI diversion, with a focus on understanding firms relocating from China to other locations, I set $K = 2$ and interpret the first technology class as *"location-specific"* (LS) technology with no correlation, and the second as *"China-alike"* (CA) technology with positive correlation across production locations, captured by a parameter $0 \leq \rho \leq 1$. The idea is that CA technologies correspond to production ideas most suitable for the Chinese production environment, but firms from all countries can generate ideas in this class with varying levels of efficiency and apply them to production in other locations. Since applications in different locations are based on the same CA idea, their productivities are correlated. On the other hand, the LS technologies are only suitable for each specific location, and therefore exhibit no correlation across production locations. A more detailed microfoundation, adapted from Lind and Ramondo (2023*a*,*b*, 2024), for the following reduced-form productivity draw distribution is laid out in Appendix A.3.1.

Specifically, the joint productivity a firm effectively faces across production locations follows a max-stable Fréchet distribution:

$$\mathbb{F}_j(\{a_i\}) = \exp\left(-z_j G\left(a_1^{-\theta}, \ldots, a_N^{-\theta}\right)\right) \tag{1}$$

[10] For example, technology classes could represent production networks tied to location-specific supply chains or other country-centered global supply chains. They could capture production procedures that are more centralized and disciplined versus those that are more decentralized and creativity-enhancing. Alternatively, they could reflect production methods that rely heavily on numerous inputs and thus require good infrastructure, as opposed to methods that are more self-sufficient. Different interpretations may be more suitable in different contexts.

where $G(\cdot)$ is a cross-nested CES (CNCES) correlation function:

$$G\left(a_1^{-\theta}, a_2^{-\theta}, \ldots, a_N^{-\theta}\right) = \sum_{i=1}^{N} a_i^{-\theta} + \left(\sum_{i=1}^{N} \left(\eta_{ij} a_i^{-\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho},$$

where the scale parameters for the location-specific technology are normalized to 1 for all locations, while those for the China-alike technology are denoted by $\eta_{ij} > 0$, for $i, j = 1, \ldots, N$. The correlation function $G(\cdot)$ provides a flexible structure for the dependence of productivity draws across production locations i for producers from source country j. This flexibility is crucial for generating heterogeneous FDI diversion elasticities across country pairs, as highlighted later.

A higher η_{ij} implies that firms from j are relatively better at using CA than LS technologies or that location i is relatively better suited for applying CA than LS technologies. When firms make relocation decisions out of China in response to the Trump tariffs in this context, all else equal, they are more likely to move to locations that are better at applying CA ideas, and firms from countries that are more proficient in CA technologies relocate with larger elasticities. Although η_{ij} across country pairs is an inherently latent fundamental and thus unobservable, I use measurable proxies in the empirical analysis to capture the idea that some country pairs are better at applying CA production technologies.

Other mechanisms that could explain why relocation elasticities toward some countries were greater than toward others during the China–U.S. trade war are certainly relevant but are not the focus here. One such mechanism is closely related to the microfoundation above but digs deeper into why certain locations are better at applying China-related ideas. In Appendix A.3.2, I adapt the model setup to include intermediate goods and supplier sourcing decisions. I assume that productivity is a combination of idea quality and matching-specific price-adjusted quality of the intermediate input. Locations that are cheaper for sourcing from China can thus better apply China-related ideas. One useful feature of this microfoundation is that it can be mapped into the same reduced-form productivity draw distribution (1). Empirically, Freund et al. (2024) show that countries replacing China tend to experience faster import growth from China, while Garred and Yuan (2025) document that Chinese investment and intermediate inputs increasingly flow to third-country "winners" who simultaneously expand their U.S. market share.[11] A second mechanism is proximity to key markets, with Mexico as the prime example. Tintelnot (2017) provides a framework in which, with many potential but costly-to-set-up production locations, tariff shocks make Mexico particularly attractive, leading to high FDI diversion elasticities toward it. Utar,

[11] Exploring this mechanism requires more detailed information on multinational firms' sourcing decisions, which is beyond the scope of this paper.

Cebreros and Torres (2025) provide firm-level evidence of nearshoring to Mexico triggered by the China–U.S. trade war. Finally, another mechanism that has received substantial attention is geopolitical alignment; see, for example, Aiyar, Malacrino and Presbitero (2024); Gopinath et al. (2025*a*,*b*).

1.3 Producers' Pricing and Location Decisions

Conditional on productivity in a given location i, the producer uses a constant-returns-to-scale technology with a single factor of production, labor, to produce output:

$$q_{ij}(a) = \frac{a^{\frac{1}{\epsilon-1}}}{\kappa_{ij}} l_{ij}(a),$$

where $q_{ij}(a)$ is the quantity of output, $l_{ij}(a)$ is the amount of labor hired in country i, and κ_{ij} is the bilateral foreign operation friction (or MP cost), normalized to one when the producer operates in its home country (i.e., $i = j$).

I solve the producer's problem in two steps. First, I solve for the producer's optimal pricing and production decisions, given the choice of production location. This yields the value of operating in each location. Second, producers choose their production location by comparing these values across locations and taking into account random productivity draws.

Conditional on operating in location i, and given the production technology and CES demand, each producer chooses the price at which it sells its variety to importing country h and the quantity of labor to hire, subject to the constraint that total output equals total sales adjusted for trade costs: $\sum_{h=1}^{N} \tau_{hi} q_{hij}(a) = q_{ij}(a)$. The optimal price $p_{hij}(a)$ is set as a markup over marginal cost. The markup equals $\frac{\epsilon}{\epsilon-1}$ and depends on the elasticity of substitution. Marginal cost depends on trade costs, tariffs, bilateral operation frictions, the wage rate in the production location, and the producer's productivity. The optimal price is $p_{hij}(a) = \frac{\epsilon}{\epsilon-1} \frac{t_{hi}\tau_{hi}w_i}{a^{\frac{1}{\epsilon-1}}/\kappa_{ij}}$. The profit from selling to all destinations h is $d_{ij}(a) = a v_{ij}$, where

$$v_{ij} \equiv \frac{1}{\epsilon - 1} A_i \left(w_i \kappa_{ij}\right)^{1-\epsilon}$$

is referred to as the value of operating in i for producers from j (profit earned by a producer from j operating in i with normalized productivity $a = 1$), and $A_i = \sum_h \left(\tau_{hi}\right)^{-\epsilon} \left(t_{hi}\right)^{1-\epsilon} \left(\frac{\epsilon}{\epsilon-1}\right)^{-\epsilon} P_h^{\epsilon} Q_h$ is the market access of country i as a production location for a given sector.

In Appendix A.1, I derive that the probability that location i is the best choice for a producer from j — and hence the mass of j firms choosing i — is given by:

$$\mathbb{P}\left(v_{ij}a_{ij} = \max_{i'} v_{i'j}a_{i'j}\right) = \frac{v_{ij}^{\theta} G_i(v_{1j}^{\theta}, \ldots, v_{Nj}^{\theta})}{G(v_{1j}^{\theta}, \ldots, v_{Nj}^{\theta})} \equiv M_{ij},$$

where $G_i \equiv \frac{\partial G(x_1,\ldots,x_N)}{\partial x_i}$. The numerator measures how attractive location i is as a production location. The denominator is the sum of this measure across all locations, i.e., $G(v_{1j}^{\theta}, \ldots, v_{Nj}^{\theta}) = \sum_i v_{ij}^{\theta} G_i(v_{1j}^{\theta}, \ldots, v_{Nj}^{\theta})$.[12]

1.4 Aggregation and Equilibrium

For each sector s, the price index is

$$P_h^s = \left(\sum_{j=1}^{N}\sum_{i=1}^{N} \tilde{M}_{ij}^s \tilde{z}_j \left(P_{hij}^s\right)^{1-\epsilon^s}\right)^{\frac{1}{1-\epsilon^s}},$$

where $\tilde{M}_{ij}^s \equiv \left(M_{ij}^s\right)^{\frac{\theta-1}{\theta}} G_i\left(v_{1j}^s, \ldots, v_{Nj}^s\right)^{\frac{1}{\theta}}$ captures the productivity-adjusted mass of producers from j producing in i; $\tilde{z}_j^s \equiv \Gamma(1-1/\theta)\left(z_j^s\right)^{1/\theta}$ is the average productivity of producers from j; and $P_{hij}^s \equiv \frac{\epsilon^s}{\epsilon^s-1} t_{hi}^s \tau_{hi}^s \kappa_{ij}^s w_i$ captures the markup and marginal cost faced by these producers. Similarly, the aggregate profit earned by producers from j producing in i is given by $D_{ij}^s = \tilde{M}_{ij}^s v_{ij}^s \tilde{z}_j^s$. Denote $D_j \equiv \sum_i \sum_s D_{ij}^s$ and $D_j^{out} \equiv \sum_i \sum_s D_{ji}^s$ to be country j's total inward and outward profits, respectively.

The import share of goods shipped from i to importing country h in sector s, denoted by π_{hi}^s, is

$$\pi_{hi}^s = \frac{\sum_j \tilde{M}_{ij}^s \tilde{z}_j^s \left(P_{hij}^s\right)^{1-\epsilon^s}}{\left(P_h^s\right)^{1-\epsilon^s}}. \tag{2}$$

The goods market clearing condition is

$$Y_i = \sum_h \sum_s \frac{\pi_{hi}^s}{t_{hi}^s} X_h^s,$$

where $Y_i \equiv w_i L_i + D_i^{out}$ denotes total output in country i, and $X_h^s \equiv P_h^s Q_h^s$ denotes total expenditure in country h on sector s.

[12] For example, when the correlation function is additive and thus productivity draws are independent across locations, as in Eaton and Kortum (2002), the location choice probability simplifies to $\mathbb{P}\left(v_{ij}a_{ij} = \max_{i'} v_{i'j}a_{i'j}\right) = \frac{v_{ij}^{\theta}}{\sum_{i'} v_{i'j}^{\theta}}$. Here, the choice probability depends solely on the relative value of v_{ij} and the parameter θ, which governs the dispersion of productivity across varieties.

Net exports for country j are defined as Net $\text{Exports}_j \equiv Y_j - X_j$, and net income is defined as Net $\text{Income}_j \equiv D_j - D_j^{out}$. Each country's budget constraint must hold:

$$\text{Net Export}_j + \text{Net Income}_j + T_j - \Gamma_j = 0,$$

where tariff revenue is $T_j = \sum_s \sum_i \frac{t_{ji}-1}{t_{ji}} \pi_{ji}^s X_j^s$.

An equilibrium is a set of prices (goods prices and wages) and allocations (consumption and producer distributions), given fundamentals (productivities, labor endowments, trade costs, tariffs, foreign operation frictions, and distributions of idiosyncratic productivity draws), such that households and producers optimize, producer distributions are consistent with these decisions, goods markets clear, and country budget constraints are satisfied.

1.5 Welfare Decomposition: New Mechanism from FDI Diversion

Using the country budget constraint and the aggregate price index, welfare changes in response to trade shocks can be decomposed as follows:

$$\mathrm{d}\ln C_j \approx TOT_j + Profit_j + Relocation_j + Volumn_j + Transfer_j, \tag{3}$$

where the detailed equation is given in Appendix A.2.

The first term TOT_j on the right-hand side is the terms-of-trade effect from tariff changes, capturing differential changes in the world prices of country j's production and consumption bundles.[13] The second term $Profit_j$ represents the profit-shifting effect, capturing changes in country j's real income arising from changes in aggregate industry profits.[14] [15]

The third term $Relocation_j$ represents the production relocation effect, and is the new

[13]Following the existing literature, I define the terms of trade as the ratio of the ex-factory price of a foreign variety to that of a domestic variety. Since labor is the only production factor and producers charge a constant markup, wage changes are proportional to changes in ex-factory prices. Relative to a model without FDI, world price changes in country j's production bundle include not only domestically produced goods but also goods produced abroad, weighted by j's income shares from domestic production and foreign production in country i. The consumption bundle price change is a weighted average of wage changes across all countries, with weights given by factual import value shares.

[14]The profit-deviation term incorporates changes in the mass of producers, whereas the wage-deviation term, which reflects production costs, does not. Thus, this term reflects the profit-shifting effect averaged over the new mass of producers.

[15]The first two terms arise even in the absence of multinational production or FDI diversion. As discussed in Ossa (2014), in models with only domestic production, tariffs affect output at the intensive margin without free entry and at the extensive margin with free entry. The former generates a profit-shifting effect, while the latter generates a dislocation effect. My model assumes a fixed mass of producers, yet a distinct relocation effect emerges because firms can shift across production locations.

mechanism directly coming from FDI diversion. It equals

$$Relocation_j \equiv \sum_i \sum_s \frac{1}{\epsilon^s - 1} \frac{t^s_{ji} \mathcal{T}^s_{ji}}{X_j} \sum_{j'} \omega^s_{ij'} \, \mathrm{d} \ln \tilde{M}^s_{ij'} \, ,$$

where $\mathcal{T}^s_{ji} \equiv \left(\pi^s_{ji}/t^s_{ji}\right) X^s_j$ denotes the factual trade value exported from i to j in sector s, and $\omega^s_{ij'} \equiv D^s_{ij'} / \left(\sum_j D^s_{ij}\right)$ is the share of FDI stocks in i and sector s by producers from j'.

Household j consumes varieties exported from all countries i, while production in each country i can originate from multiple source countries j'. When tariff changes induce producers to relocate to locations that serve consumers in j at lower cost, the aggregate price index faced by consumers in j falls, improving their welfare.

As I will show later in the quantitative analysis, the relocation effect outweighs the traditional terms-of-trade effect emphasized in the existing literature and the profit-shifting effect. In trade-only models, tariffs lead to higher prices in the imposing economy because of direct tariff and wage (terms-of-trade) effects. The relocation effect, reflects changes in price indices due to shifts in producer locations, excluding direct tariff and wage effects (absorbed in the TOT_j and $Volumn_j$ terms), and thus points to a countervailing force affecting price levels in the economy that imposes tariffs on others. Since this effect exists only when there is FDI diversion, this decomposition highlights that the price implications of the Trump tariffs can be very different from those in trade-only models with FDI diversion, such as Fajgelbaum et al. (2020).

The fourth term represents the trade-volume effect, arising from changes in import volumes, and the final term captures changes in the value of the exogenous transfer.

1.6 Heterogeneous FDI Diversion Elasticities

I now derive the model's FDI gravity equation and the implied FDI diversion elasticities. Since all producers charge the same markup, the ratio $D_{ij}/D_{i'j}$ also measures relative FDI by producers from j between countries i and i' in this static model. Define the probability of choosing location i under the China-alike technology as $Z_{ij} \equiv \left(\eta_{ij} v^{\theta}_{ij}\right)^{\frac{1}{1-\rho}} / \left(\sum_{i'} \left(\eta_{i'j} v^{\theta}_{i'j}\right)^{\frac{1}{1-\rho}}\right)$, and the share of FDI in location i operating under the China-alike technology as $C_{ij} \equiv \frac{\eta_{ij} Z^{\rho}_{ij}}{1+\eta_{ij} Z^{\rho}_{ij}}$ (shown in Appendix A.1). Plugging in the correlation function, this elasticity is

$$\frac{\partial \ln \frac{D_{ij}}{D_{i'j}}}{\partial \ln v_{ij}} = \theta + \frac{\rho}{1-\rho} \theta \left(C_{ij} \left(1 - Z_{ij}\right) + C_{i'j} Z_{ij}\right) .$$

Note that Z_{ij} is small for most locations other than the domestic country j, and that for each i I can always choose i' as the location with the smallest proxy measure of $\eta_{i'j}$; I therefore make the following approximations:

$$1 - Z_{ij} \approx 1, \quad C_{i'j} \approx 0.$$

With these approximations, the FDI diversion response equation can be rewritten as

$$\frac{\partial \ln \frac{D_{ij}}{D_{i'j}}}{\partial \ln v_{ij}} \approx \theta + \frac{\rho}{1-\rho} \theta \, C_{ij}. \tag{4}$$

Equation (4) provides the basis for empirical tests of FDI diversion during the China–U.S. trade war, capturing systematic diversion patterns in a theory-consistent manner. When $\rho = 0$, so that the productivity distribution effectively collapses to a single technology class, all FDI diversion elasticities are homogeneous and determined solely by the Fréchet shape parameter θ. When the productivity distribution consists only of the correlated technology class, elasticities are again homogeneous and are determined by $\theta/(1-\rho)$. This corresponds to the case considered in multinational production models such as Ramondo and Rodriguez-Clare (2013); Arkolakis et al. (2018).

With two technology classes, as in this paper, FDI diversion elasticities are heterogeneous. Equation (4) clarifies under what conditions the elasticity of FDI diversion toward destination i is higher for firms from a given investing country j. First, when the value of operating in location i increases, producers from j raise the probability of choosing i (relative to i') more strongly when the dispersion parameter θ and the correlation parameter ρ are larger. Second, when production by firms from j in location i relies more heavily on China-alike technologies — that is, when C_{ij} is higher — the FDI diversion elasticity is higher. This can occur both because firms from j are relatively good at China-alike technologies and because location i is particularly well suited to applying China-alike technologies.

2 The Evidence and Patterns of FDI Diversion

This section presents two empirical exercises on global FDI movements. The first provides evidence that trade policy shocks — in this case, the Trump tariffs — generate systematic FDI responses, a phenomenon I refer to as FDI diversion.[16][17] The Trump tariffs affected many countries simultaneously, allowing for comparable quantitative measurement. These shocks serve as instruments for the model's value of operating, which drives FDI location choices. The second exercise examines why, during the China–U.S. trade war, certain economies — such as Vietnam — emerged as especially attractive and responsive destinations for production relocation, while others — such as the U.S. — were less successful in attracting FDI diversion. I focus on systematic heterogeneity in FDI diversion elasticities in the context of the Trump tariffs.[18]

While neither idea is entirely novel, this paper provides a theory of heterogeneous FDI diversion elasticities and connects these elasticities to model primitives. The empirical results reveal systematic deviations from the predictions of standard FDI gravity models and highlight the importance of moving beyond these benchmarks to account for observed FDI movement patterns and to understand the welfare implications of the Trump tariffs. Moreover, I rely exclusively on aggregate data, which are more systematically collected and broadly available.

2.1 FDI Data

I use FDI data collected and published by national governments and international agencies. I start with the OECD International Direct Investment Database, which reports both country-level FDI aggregates and FDI by partner country or by industry.

The OECD database is limited in terms of country coverage. To expand coverage, I also use the Coordinated Direct Investment Survey (CDIS) compiled by the International Monetary Fund (IMF), which provides bilateral FDI positions for a larger set of countries than the OECD database.

[16] FDI diversion in response to trade and other external shocks is not new. For example, European integration led to significant capital formation and reallocation across member economies — such as Spain, Portugal, and Estonia — following their accession to EU membership (see Baldwin and Wyplosz 2022). Similarly, concerns have long been raised that China's integration into the world economy diverted investment away from other developing economies.

[17] Most prior research uses shocks such as bilateral trade or investment agreements to study FDI responses. For example, McCaig, Pavcnik and Wong (2022) show that the U.S.-Vietnam Bilateral Trade Agreement, which reduced U.S. tariffs on Vietnamese exports, led to a significant increase in foreign firms entering Vietnam. However, because that study focuses on a single FDI-recipient country, it is difficult to compare the magnitude of FDI responses to other shocks, such as additional tariff reductions. Even in multi-country contexts, comparing the size of shocks across investment agreements is challenging.

[18] Since 2018, policy reports, media coverage, and academic work have increasingly debated where firms are relocating and why. Existing studies often examine macro-level patterns (e.g., Alfaro and Chor 2023; Gopinath et al. 2025*a*) or rely on micro-level data with stronger identification but limited geographic scope. For instance, Graziano et al. (2024) focus on Chinese multinationals, while Garred and Yuan (2025) study Chinese listed firms.

For some economies required for the quantitative exercises but not fully covered in these databases, I manually collected data from national statistical offices.

In sum, this combined dataset from multiple official sources provides bilateral FDI positions for major investing and recipient countries over the period 2013–2023. Appendix B.1 provides a more detailed explanation of the FDI data sources and cleaning procedures.

2.2 The Trump Tariffs Trade Diversion Index

In 2018 and 2019, the United States increased tariffs on Chinese goods covering about $350 billion in trade flows. Following studies of trade diversion (e.g., Fajgelbaum et al. 2024), I treat product-level variation in U.S. tariff increases on Chinese exports as uncorrelated with other countries' specialization patterns and construct an index that serves as an instrument for firms' perceived value of operating in each location. Because bilateral FDI data are not available at the product level (or even at the sector level), I construct the index at the country level by combining variation in the Trump tariffs across goods with countries' trade shares.

The index is designed to capture the relative potential of each country to substitute for Chinese exports in meeting U.S. demand.[19] I take HS 6-digit-level tariff increases imposed by the U.S. on China from Fajgelbaum et al. (2020).[20]

To construct the weights, I use BACI trade flow data for 2017.[21] For each product ν, I calculate country i's export revenue share, $r_i(\nu)$; country i's export revenue share to the U.S., $r_{\text{US},i}(\nu)$; and the U.S. import share from China, $\pi_{\text{US,CN}}(\nu)$.[22] Denoting the U.S. tariff

[19]The index follows a shift-share design, where tariff variation across products provides the shift and trade shares provide the share. To identify the effect of this index on inward FDI stocks, the shifters must be mean-independent of the shares, the potential outcomes (inward FDI stock growth absent the tariffs), and the treatment effects per unit of the shifter on each country (see Proposition 1 in Adão, Kolesár and Morales 2019).

[20]The tariff changes are rescaled in proportion to their duration within a 24-month interval; see Fajgelbaum et al. (2020) for details. The Trump tariffs consist of a sequence of tariff increases over 2018 and 2019, which I treat as a single event occurring in 2018. I use the simple average of the scaled 2018 and 2019 tariffs for each variety. Using alternative measures, such as the maximum tariff increase, does not qualitatively affect the results.

[21]BACI provides bilateral trade flows for about 200 countries at the product level (roughly 5,000 products, defined at the HS 6-digit level). See `http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37`.

[22]Let $\text{EX}_{hit}(\nu)$ be the export value from country i to h for a product ν in year t, then the three weights are calculated as

$$r_i(\nu) = \frac{\sum_h \text{EX}_{h,i}(\nu)}{\sum_\nu \sum_h \text{EX}_{h,i}(\nu)}, \quad r_{\text{US},i}(\nu) = \frac{\text{EX}_{\text{US},i}(\nu)}{\sum_h \text{EX}_{h,i}(\nu)}, \quad \pi_{\text{US,CN}}(\nu) = \frac{\text{EX}_{\text{US,CN}}(\nu)}{\sum_i \text{EX}_{\text{US},i}(\nu)}.$$

increase by $\Delta t_{\mathrm{US,CN}}(\nu)$, the trade diversion index for country i is

$$\mathrm{DI}_i = \sum_{\nu} r_i(\nu)\, r_{\mathrm{US},i}(\nu)\, \pi_{\mathrm{US,CN}}(\nu)\, \Delta t_{\mathrm{US,CN}}(\nu). \tag{5}$$

As shown in Appendix A.5, this construction corresponds precisely to the model's relevant variation in $\mathrm{d}\ln A_i$, the change in country i's market access. Intuitively, countries specializing in goods subject to larger U.S. tariff increases on Chinese exports are more likely to experience increases in diverted export demand. This effect is stronger when the U.S. is a relatively important market for both the good and the exporting country, and when China was a prominent supplier of the good to the U.S.

2.3 Proxies for China-alike Suitability

I use two measurable proxies for the share of FDI in location i that operates under the China-alike technology, C_{ij}, which is a latent and unobservable bilateral characteristic.

First, I calculate the correlation between country i's and China's export shares across industries at the NAICS 2007 three-digit level in 2017, the year before the tariffs, denoted by COR_i. The idea is that a country's export portfolio across industries reflects its production portfolio, which in turn captures fundamental abilities or endowments relevant for those industries.

Second, I calculate the Grubel-Lloyd index (GLI) between country i and China, denoted by GLI_i. It is defined as $1-\frac{|EX-IM|}{EX+IM}$ at the HS four-digit level and averaged across products with $(EX+IM)$ as weights, where EX and IM denote bilateral exports and imports between country i and China in 2017. The Grubel-Lloyd Index is a common measure of supply chain linkages.[23] A country with strong supply chain connections to China is likely to be well suited to producing goods using China-alike ideas.

I normalize both COR_i and GLI_i so that their minimum equals zero and their maximum equals one. Table 1 reports these two variables for a set of selected economies used in later quantitative analysis, along with summary statistics across all available economies. Notably, Vietnam — a prime example of a "connector" or "winner" economy — has very high values of both proxies, while the U.S. has relatively low values.

Using these measures, I construct two variables to proxy for C_{ij}:

$$C_{ij}^{COR} = COR_i\, COR_j, \quad C_{ij}^{GLI} = GLI_i\, COR_j. \tag{6}$$

A higher COR_j captures the idea that the investing economy is more likely to use China-alike

[23]See Freund et al. (2024) for a discussion of its advantages over other measures.

Table 1: China-alike Measures for Selected Economies

Economy	COR	GLI
Argentina	0.091	0.028
Australia	0.076	0.082
Brazil	0.074	0.082
Canada	0.229	0.206
Chile	0.058	0.022
Germany	0.571	0.592
France	0.456	0.325
UK	0.502	0.262
India	0.295	0.195
Japan	0.655	0.716
Korea	0.901	0.652
Mexico	0.729	0.215
Malaysia	0.953	0.613
Taiwan, China	1.000	0.668
The U.S.	0.702	0.307
Vietnam	0.970	0.692
Mean	0.263	0.119
Median	0.169	0.050
SD	0.241	0.174
Obs	225	210

Notes: Summary statistics for all countries in the sample are reported in the last three rows. The sample contains 225 economies for COR and 210 for GLI.

technologies for a given destination economy. To capture destination economy characteristics, both COR_i and GLI_i capture how suitable a location is for China-alike technologies relative to others, the location-specific technologies in the model. Figure A1 in Appendix B.2 plots the histograms of the two proxies. Although I argue that these two proxies are positively correlated with C_{ij}, there is no exact quantitative mapping between them. Thus, regression coefficients based on these proxies should not be interpreted as the structural parameters θ and ρ, which are disciplined more formally in the calibration section. Nevertheless, the regression coefficients are still economically interpretable.

2.4 Regression Specifications

I now specify the regression equations. For the dependent variable, I use bilateral FDI data to measure over-time changes in the model variable $\ln \frac{D_{ij}}{D_{i'j}}$, where i' is chosen to be the location with the smallest proxy measure of $CA_{i'j}$ for each j. Let FDK_{ijt} denote the inward FDI stock in country i held by firms from j at time t.[24] For $s = 2019, \ldots, 2023$,

[24]I use FDI stocks (FDK) rather than flows because stocks are the primary statistics reported by countries, and flows are often negative, which generates many missing values.

define $\Delta_s F_{ij} = \frac{\text{FDK}_{ijs}}{\text{FDK}_{i'js}} / \frac{\text{FDK}_{ij,2017}}{\text{FDK}_{i'j,2017}} - 1$. The year 2017 serves as the pre-shock period, and the analysis covers outcomes from 2019 — since the tariffs were imposed during 2018–2019 — through the latest available year, 2023.

For the independent variable, I use total export growth from 2017 to 2019 for country i, denoted by ΔEX_i to measure over-time changes in the model variable $\ln v_{ij}$. I focus on the change from 2017 to 2019 because trade adjusts relatively quickly, so changes observed by 2019 are likely to reflect the impact of the Trump tariffs on the value of operating for a production location while being less influenced by other shocks such as COVID-19. Note that v_{ij} is the value of operating for firms from j in location i, which is a bilateral variable. However, I implicitly assume that the changes of this bilateral variable induced by the Trump tariffs is the same across firms from all investing countries j — because it only affects A_i but not bilateral primitives such as κ_{ij} — and thus that changes in total export by production country i apply to all bilateral relationships.[25]

With these measures, I run the following two regressions using instrumental variables, for $s = 2019, \ldots, 2023$ and for both proxies $P \in \{COR, GLI\}$:

$$\Delta_s F_{ij} = \bar{\beta}\, \Delta\text{EX}_i + \alpha_j + \bar{u}_{ij}, \tag{7}$$

$$\Delta_s F_{ij} = \beta\, \Delta\text{EX}_i + \gamma\, \Delta\text{EX}_i \times C^P_{ij} + \alpha_j + u_{ij}. \tag{8}$$

The obvious identification problem is that ΔEX_i is endogenous, and this is precisely where variation in the Trump tariffs and my trade diversion index play an important role. The trade diversion index isolates exogenous variation stemming from the tariffs that drives ΔEX_i; accordingly, I use DI_i to instrument ΔEX_i and $\text{DI}_i \times C^P_{ij}$ to instrument $\Delta\text{EX}_i \times C^P_{ij}$.[26]

The objective here is not to estimate the structural parameters θ and ρ,[27] but rather to test for the existence and gauge the magnitude of systematic heterogeneity of FDI diversion elasticities. More specifically, regression (7) provides the simplest evidence for the existence of FDI diversion due to the Trump tariffs at the bilateral country level. The coefficient $\bar{\beta}$ captures the baseline average causal effect of the value of operating in a destination country on relative FDI stock growth for a given investing country. Regression (8) corresponds

[25]The ideal independent variable would be total profits earned by firms from j in i, which are not available for a large number of country pairs. However, the following model features and empirical observations alleviate this imperfect-measure problem: (1) sales and profits are proportional under the CES assumption, (2) the operation frictions κ_{ij} are assumed to be fixed over time, (3) many relocating firms in the context of the Trump tariffs are export-oriented rather than primarily serving the destination market.

[26]The identification assumption for the IV regression (8) are as follows: (1) Relevance (first stage): DI_i (and its interactions) shift ΔEX_i and $\Delta\text{EX}_i C^P_{ij}$ conditional on investing-country fixed effects; (2) Exclusion (orthogonality): $\mathbb{E}\left[u_{ij} \mid \text{DI}_i, \text{DI}_i \times C^P_{ij}, j\right] = 0$.

[27]In the quantitative analysis, I further rescale C^P_{ij} to estimate θ and ρ.

directly to the model's FDI diversion equation (4) and tests for heterogeneity in FDI diversion elasticities. Conditional on the measures C_{ij}^{P}, I impose a linear relationship between the proxies and the dependent variable; accordingly, γ can be interpreted as the increase in the causal effect when moving from the country pair with the lowest to that with the highest China-alike technology production share in the sample.

2.5 Regression Results

I first present empirical evidence of FDI diversion in response to the Trump tariffs.

Table 2: IV Estimates of $\bar{\beta}$ by Year

	2019	2020	2021	2022	2023
ΔEX_i	6.817***	4.002*	7.624**	9.984**	14.888***
	(2.311)	(2.048)	(3.070)	(3.859)	(5.207)
Kleibergen–Paap F			11.12		
# Obs.			3435		

Notes: All regressions include investing economy fixed effects. The sample is restricted to economies with the largest inward FDI stocks in 2017, excluding those typically classified as tax havens. The regressions cover 74 investing economies and 138 destination economies. Standard errors are clustered at the investing economy level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 reports the estimates of $\bar{\beta}$. The coefficients are consistently positive and statistically significant from 2019 through 2023. They also increase over time — except in 2020, when COVID-19 likely disrupted FDI patterns — suggesting gradual and continuing FDI diversion. Quantitatively, the estimates imply that, on average, when a destination economy becomes 1% more attractive as a production location, firms from the investing economy increase FDI there — relative to the least responsive destination — by 6.8% within two years and by 14.9% within six years.[28]

For robustness, I run the same regressions for the pre-shock years, i.e., for $\Delta_s F_{ij}$ with $s = 2013, \dots, 2016$. Table A1 in Appendix B.3.1 shows that none of the coefficients for the year 2013 to 2016 are statistically significant.

[28] My estimates of the average effects are in the same range as a related estimate in the literature by Arkolakis et al. (2018). Their estimates of the coefficient $\hat{\beta}^r$ in their equation (30), which has the structural interpretation $\theta/(1-\rho)$ (their homogeneous multinational production trade elasticity), range between 8.4 to 11.6 across specifications.

Systematic Heterogeneous FDI Diversion Elasticities Next, I present evidence that locations better suited to China-alike technologies exhibit stronger inward FDI diversion responses to the same shock.

Table 3: IV Estimates of β, γ by Year

Panel A. Proxy C_{ij}^{COR}					
	2019	2020	2021	2022	2023
ΔEX_i	1.133*	0.207	0.260	0.519	0.791
	(0.630)	(0.756)	(0.858)	(0.960)	(1.231)
$\Delta\text{EX}_i \times C_{ij}^{COR}$	8.406***	5.418**	10.785***	13.966***	21.131***
	(2.096)	(2.405)	(2.711)	(3.237)	(3.483)
Kleibergen–Paap F			20.82		
# Obs.			3369		
Panel B. Proxy C_{ij}^{GLI}					
	2019	2020	2021	2022	2023
ΔEX_i	1.742***	0.349	1.116	2.021*	3.009**
	(0.654)	(0.648)	(0.877)	(1.037)	(1.339)
$\Delta\text{EX}_i \times C_{ij}^{GLI}$	13.949***	9.701***	17.684***	21.782***	33.114***
	(3.210)	(3.311)	(4.592)	(5.795)	(6.832)
Kleibergen–Paap F			30.87		
# Obs.			3369		

Notes: All regressions include investing economy fixed effects. The sample is restricted to economies with the largest inward FDI stocks in 2017, excluding those typically classified as tax havens. The regressions cover 74 investing economies and 138 destination economies. Standard errors are clustered at the investing economy level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3 shows that the coefficients on $\Delta\text{EX}_i \times C_{ij}^P$ are consistently positive and statistically significant from 2019–2023, across both proxies capturing different sources of systematic heterogeneity. Similar to the estimates of $\bar{\beta}$, these coefficients also increase over time (except in 2020), suggesting that heterogeneity in diversion elasticities has grown gradually over the period. The magnitudes are economically meaningful. When the destination economy is at the maximum rather than the minimum value of C_{ij}^{COR} (C_{ij}^{GLI}), the increase in FDI is 8.4% (13.9%) larger after two years and 21.1% (33.1%) larger after six years, following a 1% rise in the destination's value of operating.

As a robustness check, I run the same interaction regressions for the pre-shock years.

Table A2 in Appendix B.3.1 again shows that neither the causal effects of the Trump tariffs nor its heterogeneity captured by C_{ij} proxies exist are statistically significant in the pre-shock period.

The two measures used to construct the proxies, COR_i and GLI_i, capture — from different perspectives — why some countries more easily attract FDI diversion during the China–U.S. trade war. They are neither perfect nor the only possible proxies, as the latent country characteristics η_{ij} and C_{ij} are inherently difficult to measure. Some empirical work has tried to examine such patterns. For instance, Freund et al. (2024) examine which countries absorbed U.S. imports diverted from China, finding that large and developing economies disproportionately replaced China. In Appendix B.3.2, I show that the main results remain robust when further controlling for destination-economy size (log employment) and GDP per capita in both the diversion and heterogeneity regressions.

Finally, because the empirical exercises are conducted at the country level due to data limitations, part of the observed heterogeneity may reflect industry-specific θs. The proxies may also partly capture differences in industrial composition across economies. As shown in Appendix B.3.3, economies with higher value-added share in certain industries (e.g., Computer, electronic & optical) respond more strongly to the Trump tariffs and thus display higher FDI diversion elasticities. Nonetheless, the two proxies capture systematic heterogeneity beyond these industry effects, and are significantly positive after controlling for industry shares. Further research using more detailed sectoral or micro-level data could refine the measurement of FDI diversion elasticities, complementing the general theoretical framework and empirical strategy developed in this paper.

3 Calibration & Estimation

I now take the model to the data by calibrating it to the world economy in 2017, which is treated as the initial equilibrium. The calibration includes thirteen economies plus a combined rest of the world economy (labeled WorldRest),[29] and three sectors: (1) agriculture and mining, (2) manufacturing, and (3) services.

To calibrate the initial equilibrium, I group the model parameters into three categories. The first category consists of parameters externally calibrated directly from data, including L_i, ϕ_h^s, and t_{hi}^s. The second category consists of fundamentals recovered by solving the model to match country-specific and bilateral observables, including τ_{hi}^s, κ_{ij}^s, and z_j. The

[29]The calibrated economies are Australia, Canada, China, Germany and France (combined and labeled as DeFr), the United Kingdom, India, Japan and Korea (combined and labeled as JpKr), Mexico, Malaysia, South America, Taiwan, China, the United States, and Vietnam. Countries are combined due to the lack of consistently measured bilateral FDI data when expanding the number of economies in the calibration.

third category consists of elasticity parameters governing trade and FDI. Trade elasticities, ϵ^s, are calibrated using a standard trade gravity regression with fixed effects. The FDI elasticities, θ and ρ, are calibrated to match an adjusted version of the regression moments associated with heterogeneous FDI diversion elasticities (8), as detailed below. The related "China-alike" parameters η_{ij} are then calibrated to match C_{ij} proxies, given the calibrated values of θ and ρ.

3.1 External Calibration and Original Steady State Fundamentals

External Calibration. I measure efficiency units of labor, L_i, as the product of employment (*emp*, measured as the number of persons engaged, in millions) and human capital (*hc*, an index of human capital index based on years of schooling and returns to education), both taken from the Penn World Table (PWT, version 10.01). Sectoral expenditure shares, ϕ_h^s, are measured using the 2017 Inter-Country Input-Output (ICIO) Tables (OECD, 2021 edition). I obtain PPP-adjusted total expenditures for each economy from PWT. Together with nominal expenditures from ICIO, these data allow me to infer the price index, P_i, for each economy. I use most-favored-nation (MFN) tariffs from the Global Tariff Database (GTD) to construct sector-level tariffs.[30] I aggregate GTD sector-level bilateral tariffs to the three sectors using 2017 BACI trade flows as weights, yielding trade-weighted average tariffs for each economy pair and sector.

Recovery of Original Steady-State Fundamentals. Table 4 summarizes the calibrated parameters and the targeted moments in the data.

Conditional on the elasticities to be estimated later, I recover $\{z_j\}_{j=1}^N$, $\{\tau_{hi}^s\}_{h=1,i=1,h\neq i,s}^{N,N,S}$, and $\left\{\kappa_{ij}^s\right\}_{i=1,j=1,j\neq i,s}^{N,N,S}$ to exactly match $\{X_j\}_{j=1}^N$, $\{\pi_{hi}^s\}_{h=1,i=1,h\neq i,s}^{N,N,S}$, and $\left\{M_{ij}^s\right\}_{i=1,j=1,j\neq i,s}^{N,N,S}$ for the 14 economies and three sectors in 2017.

Bilateral FDI stocks are only available at the country level. To obtain bilateral FDI stocks at the sector level, I use fDi Markets to calculate sectoral investment shares for each country pair in 2017.[31] Specifically, let N_{ij}^s denote the cumulative number of projects invested

[30]Feodora Teti's Global Tariff Database is available at `https://feodorateti.github.io/data.html`.

[31]fDi Markets is a project-level database maintained by the *Financial Times* that tracks cross-border greenfield investments globally since 2003. The database records the industry classification of each project, which I use to construct FDI measures at a granular industry level and then aggregate to the three-sector level. Coverage is based on reports from news and business agencies, so quality and completeness may vary across countries. In addition, investments through mergers and acquisitions are not included. For my analysis, I extract all available FDI projects for the selected countries (as source or host), map them to sectors, and aggregate to the source−destination−sector−year level to construct bilateral FDI investment shares.

Table 4: Calibrated Model Parameters and Data Targets

Parameters			**Moments**
Notation	Value	Description	Description
$\log(z_j)$	0.81 (0.16)	Fréchet scale parameter	Economy total expenditures X_j
τ^s_{hi}	3.32 (3.04) 2.94 (2.32) 5.77 (5.00)	Trade cost	Trade shares (BACI)
κ^s_{ij}	1.54 (1.02) 1.58 (1.16) 1.93 (1.62)	Foreign operation costs	FDI shares (Official FDI and fDi Markets)
ϵ^s	7.61, 6.27, 5.42	Trade elasticities	Trade gravity equation
θ	4.64	Fréchet dispersion parameter	β in adjusted regression (8) in Section 3.3
ρ	0.78	Fréchet correlation parameter	γ in adjusted regression (8) in Section 3.3
$\log(\eta^s_{ij})$	2.29 (3.16) 1.03 (2.92) 2.19 (3.07)	China-alike scale parameter	C_{ij} Proxy

Notes: All data moments are based on year 2017. For sector-specific parameters, values are ordered as follows: (1) agriculture and mining, (2) manufacturing, and (3) services. Parameter values for $\log(z_j)$, τ^s_{hi}, and κ^s_{ij} refer to averages across country pairs for each sector s. The values for $\log(z_j)$ are expressed relative to those for the U.S. Standard deviations are in parentheses. The value of θ is the median estimate from regression (8) for 2023, with the C_{ij} proxy adjusted as detailed in the main text. The value of ρ is the calculated from the same regression estimates.

by firms from j in i in sector s in 2017. Sector-level bilateral FDI stocks from j in i are then constructed as $\frac{N^s_{ij}}{\sum_{s'} N^{s'}_{ij}} \mathrm{FDK}_{ij}$.

Trade shares, π^s_{hi}, are taken from ICIO after aggregating economies and sectors to match calibration level. Bilateral capital stocks are taken from the official bilateral FDI data described in the empirical section for 2017, while domestic capital stocks are taken from the IMF Investment and Capital Stock Dataset (2021 version). Using these two datasets, I compute capital shares across destination countries for each source country.

Since capital is not explicitly modeled, I instead target aggregate profit shares. Specifically, I calibrate $\left\{\kappa^s_{ij}\right\}^{N,N,S}_{i=1,j=1,j\neq i,s}$ so that M^s_{ij} in the model matches $\frac{\mathrm{FDK}^s_{ij}}{\sum_{i'} \mathrm{FDK}^s_{i'j}}$ in the data for all j and s.

Finally, productivity z_j affects total expenditure and income conditional on other endogenous variables, including price indices, as well as fundamentals such as trade costs. Following the identification logic of Waugh (2010), price indices, trade costs, and productivity cannot be separately identified when none are directly observed. Since I observe price indices only at the country level, I normalize productivities to be equal across sectors within each country.

3.2 Trade Elasticities ϵ^s

I estimate trade elasticities using a standard gravity regression with fixed effects, exploiting tariff changes as cost shifters. This approach, however, cannot be applied to the service sector, since most service transactions (e.g., tourism and legal services) do not face tariffs at the border. To circumvent this issue, I follow the literature by using the real exchange rate (RER) as a cost shifter for the service sector. Appendix B.4 provides further details on the data, estimation, and reconciliation across different cost shifters. For the quantitative analysis, I use regression estimates $\epsilon^1 = 7.61, \epsilon^2 = 6.27, \epsilon^3 = 5.42$ for agriculture and mining, manufacturing, and services, respectively.

3.3 FDI Elasticities θ, ρ & η_{ij}^s

For the final set of parameters governing heterogeneous FDI elasticities, there are no conventional estimation methods in the existing literature.[32] I therefore rely on an indirect inference approach for calibration, building on the empirical estimates in Section 2.

The estimates in Table 3 are informative but cannot be used directly to calibrate θ and ρ, because the proxies are plausibly positively correlated with the theoretical C_{ij} while the functional form of this mapping is unknown.

To obtain estimates of the structural parameters θ and ρ for quantitative analysis, I impose the following functional form assumptions. First, I construct an "average" measure of how good a location is as a China-like technology destination and the corresponding average bilateral proxy, defined as $\tilde{C}_{ij} = ((COR_i + GLI_i)/2)\, COR_j$. Next, I assume that

$$C_{ij}(a, b) = \max\left\{ \frac{\left(\tilde{C}_{ij}\right)^a - b}{1 - b}, 0 \right\},$$

where a and b are parameters of this functional form to be determined. A larger value of a makes the mapping from the empirical $\tilde{C}_{ij}$ to the theoretical C_{ij} more convex. A larger value of b makes small values of empirical $\tilde{C}_{ij}$ less relevant, while the denominator $1 - b$ adjusts to keep the largest value of C_{ij} equal to one. The regressions in the empirical section correspond to the special case $a = 1$ and $b = 0$.

I search over grids with $a \in [0.5, 5]$ and $b \in [0, 0.5]$, using a grid size of 0.1 for a

[32] A key challenge is the lack of well-measured cost shifters for FDI (e.g., shifters for κ_{ij}^s) analogous to tariffs in trade.

and 0.01 for b. For each combination of a and b, I use the implied $C_{ij}(a,b)$ to construct the interaction term, run regression (8), and obtain the estimated coefficients $\beta(a,b)$ and $\gamma(a,b)$. I then compute the corresponding structural parameters as $\theta(a,b) = \beta(a,b)$ and $\rho(a,b) = \frac{\gamma(a,b)/\beta(a,b)}{1+\gamma(a,b)/\beta(a,b)}$. I retain only those regressions in which both $\beta(a,b)$ and $\gamma(a,b)$ have $t-$statistics exceeding 2.576 (the 1% significance cutoff) and the Kleibergen–Paap F-statistic exceeds 20.

Figure 1 plots the histograms for θ and ρ for the 2019 and 2023 estimates across different values of a and b. Larger values of a and b lead to larger estimates of θ and smaller estimates

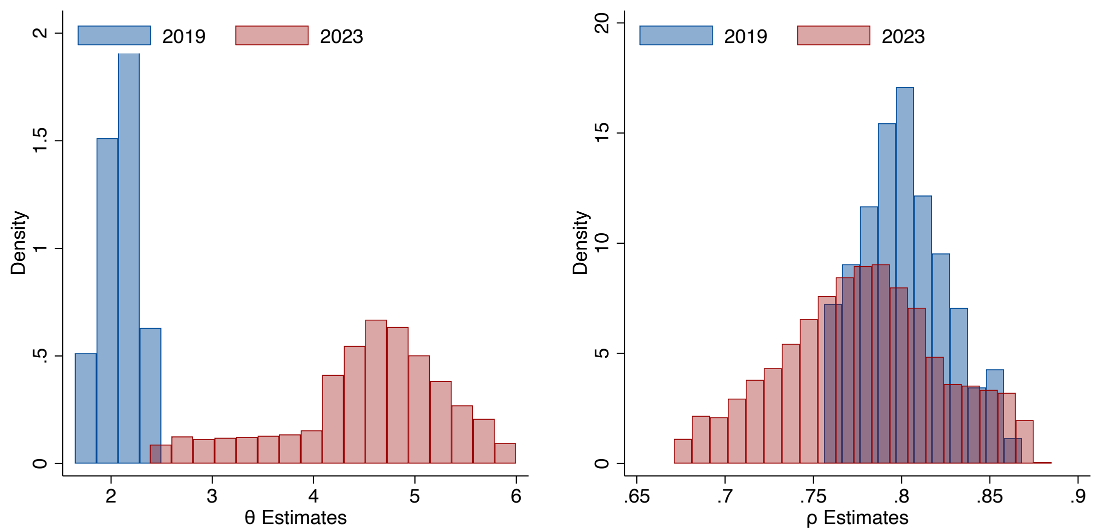

Figure 1: θ, ρ Estimates Histogram

Notes: The histogram sample includes 597 estimates for 2019 and 1498 estimates for 2023 that satisfy all requirements on $t-$statistics and $F-$statistics.

of ρ. In the quantitative analysis, I use the median value of the 2023 estimates, $\theta = 4.64$ and $\rho = 0.78$.[33]

With $C_{ij}(a,b)$, $\theta(a,b)$, and $\rho(a,b)$, I calibrate η_{ij}^s so that the equilibrium model-implied share, $C_{ij} \equiv \frac{\eta_{ij} Z_{ij}^{\rho}}{1+\eta_{ij} Z_{ij}^{\rho}}$, aligns with the empirical proxy $C_{ij}(a,b)$.

4 Quantitative Implications of the Trump Tariffs

I now use the calibrated model to evaluate the quantitative implications of the 2018–2019 Trump tariffs. I implement tariff increases at the sector level (three sectors) on Chinese

[33]The values $a = 4.1$ and $b = 0.1$, which lead to the median estimate of θ, imply $\rho = 0.7805$, which is very close to the median ρ estimate of 0.7781.

exports to the United States. Aggregating product-level tariff changes using 2017 Chinese export values to the U.S. as weights (HS 6-digit level), the implied sectoral tariff increases are 16.3% for agriculture and mining and 19.7% for manufacturing.

The results show that the welfare implications — measured by real consumption responses — change substantially once FDI diversion is taken into account. I further decompose welfare changes to highlight the underlying mechanisms, with particular attention to the relocation effect emphasized in this paper.

I then present results on heterogeneous elasticities of FDI with respect to the value of operating into each destination. Finally, I conduct counterfactuals that vary the "China-alike" measure for the U.S. relative to its empirically observed value and examine how these changes affect the FDI diversion patterns and welfare implications of the Trump tariffs.

4.1 The Importance of FDI Diversion

The left panel of Figure 2 shows aggregate real consumption responses for each economy under the baseline model and the Fixed FDI model. The Fixed FDI model uses the same calibration parameters, fundamentals, and initial equilibrium, but producers are held fixed in their original locations after the tariff shocks. In the baseline model (blue bars),

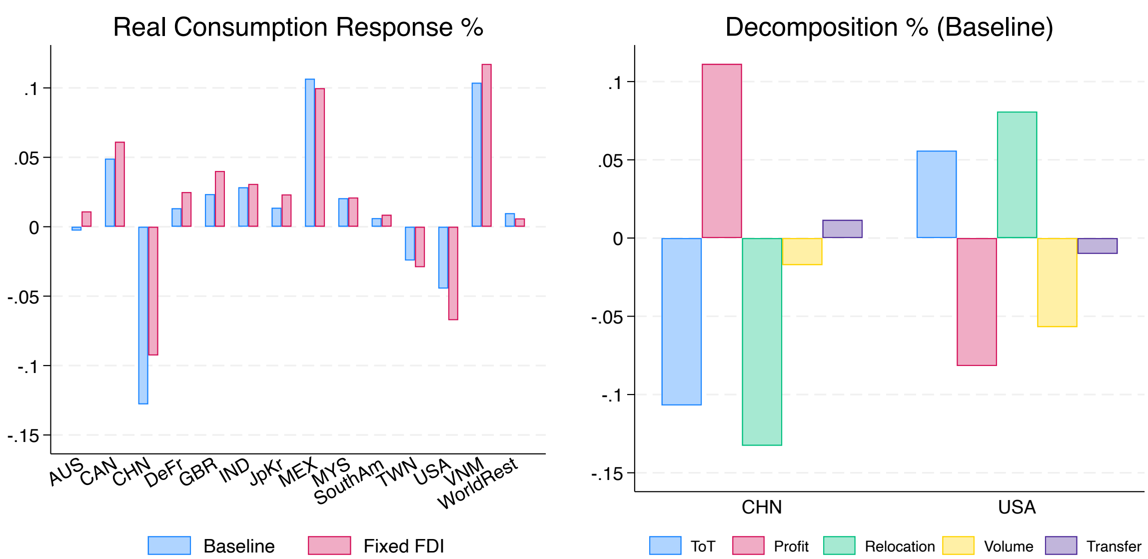

Figure 2: Real Consumption Responses

Notes: The response refers to the percentage change in real consumption for each country following the Trump tariffs on China. The right panel shows the aggregate welfare decomposition for China and the U.S. according to equation (3), based on the Baseline counterfactual with FDI diversion. The precision error of this first-order decomposition averages -7.58% across all economies.

China suffers the largest real consumption loss, at around 0.13%, while the U.S. loses about 0.04%. Economies for which the U.S. is a major export market — such as Canada, Mexico, and Vietnam — benefit significantly from the Trump tariffs. By contrast, economies more dependent on China than on the U.S. for export revenues — such as Taiwan, China — experience welfare losses.

FDI diversion plays a central role in shaping these welfare outcomes. Absent FDI diversion, the welfare implications of the Trump tariffs differ substantially across economies. Comparing the baseline model with the Fixed FDI model, in which producers are held fixed in their original locations but otherwise continue to optimize pricing and production, reveals three key patterns.

First, eliminating FDI diversion substantially alleviates China's welfare losses from the Trump tariffs by about 28% and amplifies the welfare loss for the U.S. by more than 50%.

The right panel plots the decomposition for China and the U.S., showing that the relocation effect — zero in the Fixed FDI model — is the most significant mechanism driving these results. The relocation effect outweighs the traditional terms-of-trade effect emphasized in the existing literature. China's welfare loss is mainly driven by the relocation effect, as some varieties become more costly when they must be produced abroad and re-imported. The relocation effect, as discussed in the model section, reflects changes in price indices due to shifts in producer locations, excluding direct tariff and wage effects that also exist in trade-only models or models with fixed FDI. Thus, it points to a countervailing force affecting price levels in the economy that imposes tariffs on others.

Second, Mexico and Vietnam — the two largest beneficiaries of the Trump tariffs — experience divergent outcomes due to the presence of FDI diversion. Mexico's gains are larger in the baseline model, while Vietnam's are smaller. This difference arises from general equilibrium effects: FDI diversion reduces Chinese income and expenditure, which adversely affects economies like Vietnam that rely heavily on Chinese demand. By contrast, Mexico's export revenues depend much more on the U.S. than on China, so increased U.S. expenditure in the baseline model amplifies Mexico's benefits.

Third, for most economies, the positive trade diversion effects of the Trump tariffs are dampened once FDI diversion is taken into account. This is because FDI diversion draws more investment into the U.S., raising domestic production and thereby limiting export opportunities for other countries.

4.2 FDI Diversion Patterns: Heterogeneous Elasticities

The left panel of Figure 3 shows how changes in Chinese outward FDI to different destination economies correlate with changes in the value of operating in those economies. The tariff shock reduces the value of operating for all economies, with the U.S., Mexico, and Canada benefiting the most in relative terms. Indeed, changes in their value of operating are the largest among all calibrated economies. However, the increase in FDI for these three economies is not the largest among all economies. Instead, Vietnam emerges as a significant destination for Chinese FDI relocation, even though its changes in the value of operating do not stand out relative to others. Similarly, Malaysia; Japan and Korea; and Taiwan, China also shows sizable FDI growth given their changes in the value of operating. The dotted line

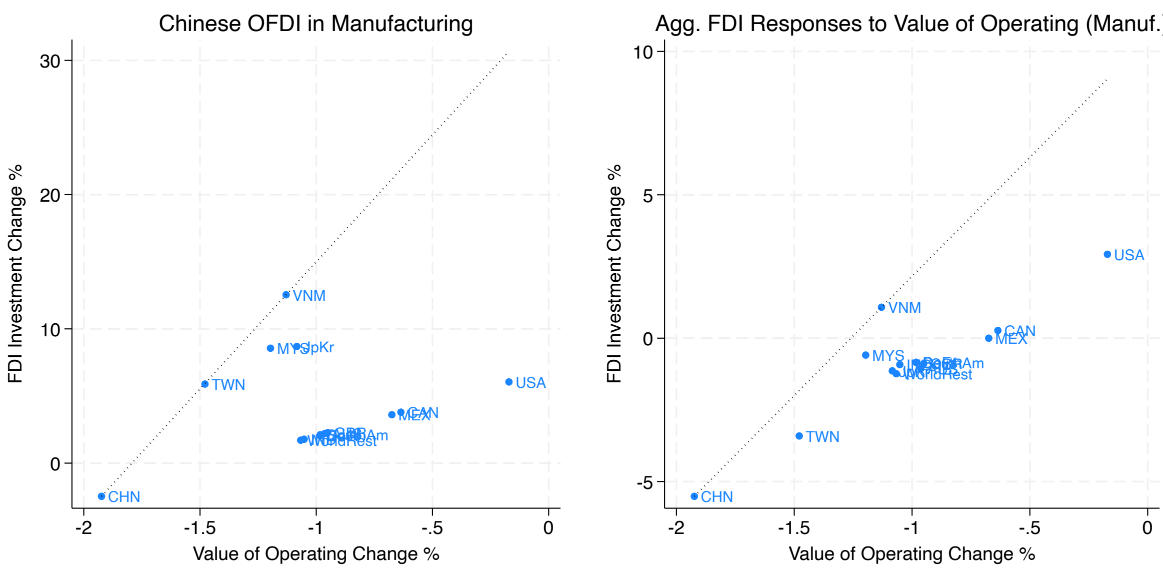

Figure 3: FDI Elasticities

Notes: The figure plots results for the manufacturing sector. The response corresponds to the percentage change in Chinese outward FDI to each destination country ($D_{i,CHN}$) in the left panel and the percentage change in each country's total inward FDI ($\sum_{j\neq i} D_{i,j}$) in the right panel, both in response to the Trump tariffs on China. The x-axis reports the percentage change in v_{ij} for each destination i. The dotted line links CHN and VNM.

links China and Vietnam on the plot; all other economies lie below it, indicating that, for all these economies, the elasticity of China's FDI investment with respect to relative changes in value of operating is smaller than that for Vietnam. This heterogeneity is built in through the calibrated "China-alike" shares C_{ij}, with Vietnam and Taiwan, China having the highest values and thus the largest elasticities.

The right panel of Figure 3 shows changes in aggregate inward FDI across destination economies. The FDI elasticity heterogeneity exhibits the same qualitative pattern but to a smaller extent.

On the other hand, Figure 4 plots how changes in the total exports of the exposed manufacturing sector (net of tariffs and including domestic trade) relate to changes in the value of operating. The dotted line is the 45-degree line. The correlation is clearer and

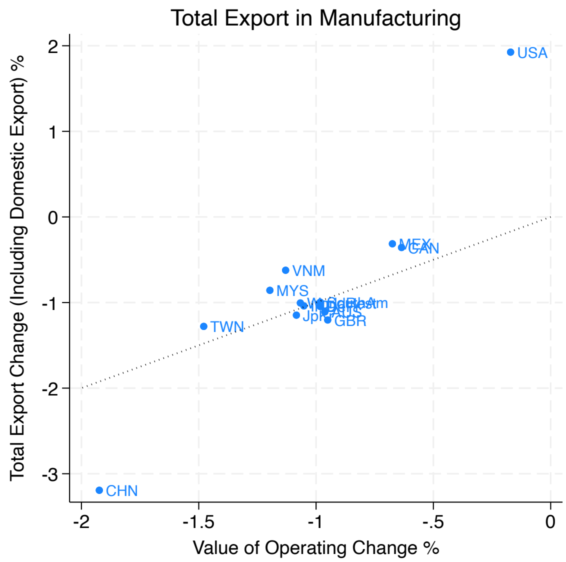

Figure 4: Export Elasticities

Notes: The figure plots results for the manufacturing sector. The response corresponds to the percentage change in total exports by each country in response to the Trump tariffs on China. The x-axis reports the percentage change in the value of operating, v_{ij}, for each destination i. The dotted line is the 45-degree line.

the elasticities are essentially homogeneous, reflecting the fact that the value of operating captures market access as both a production and export location for each destination.[34]

4.3 Varying How China-alike the U.S. Is

A key motivation for the Trump tariffs is the possibility that the U.S. could induce FDI diversion and thereby benefit. Throughout the paper, I argue that the magnitude of such diversion depends on bilateral country characteristics, with the China-alike measure serving

[34] Total exports net of tariffs are $\sum_h X^s_{hi} = \left(\left(\frac{\epsilon^s}{\epsilon^s-1}\right)^{-\epsilon^s} \sum_h Q^s_h \left(P^s_h\right)^{\epsilon^s-1} \left(\tau^s_{hi}\right)^{1-\epsilon^s} \left(t^s_{hi}\right)^{-\epsilon^s}\right) \left(\sum_j M^s_{ij} \tilde{z}^s_j \kappa^s_{ij} w_i\right)$. The first term is exactly the value of operating. Economies above the 45-degree line exhibit positive deviations due to the second term in the export expression, which captures changes in FDI inflows and wage levels.

as a proxy in this context. A natural question is how much the level of U.S. "China-alikeness" matters for the counterfactual results.

Figure 5 plots aggregate welfare changes and their decompositions for three different cases. Each case corresponds to different set of U.S. η_{ij}^s values. The "Baseline" uses η_{ij}^s calibrated to match the proxy C_{ij} in the data. In the "Small η" ("Large η") case, I set $\eta_{\text{US},j}^s$ to the smallest (largest) value across all destinations for each j and sector.

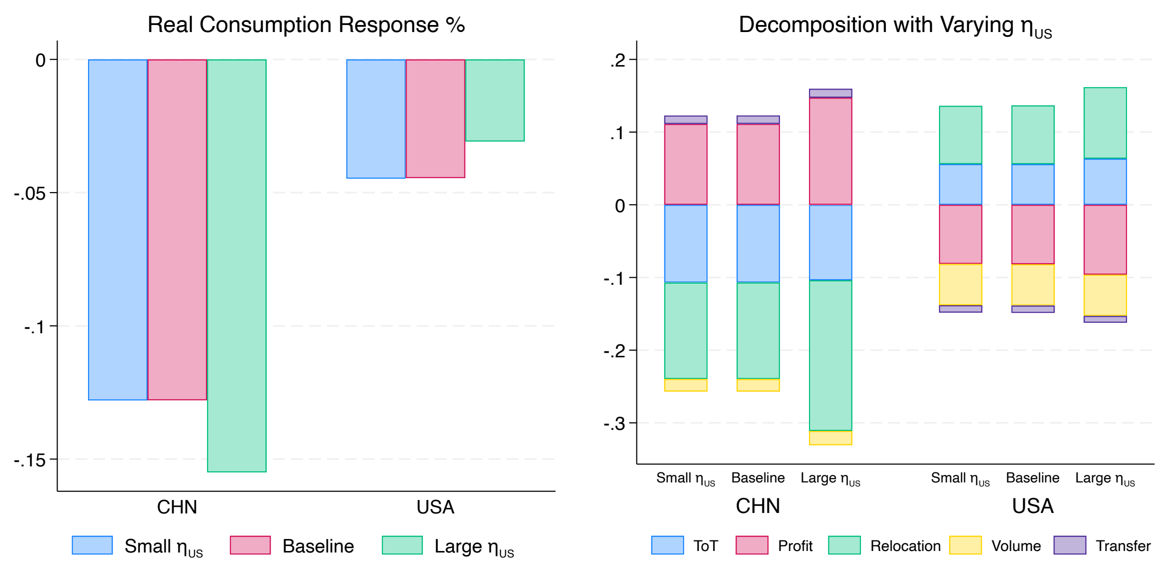

Figure 5: Welfare with Varying US CA Share

Notes: The response refers to the percentage change in real consumption for China and the U.S. following the Trump tariffs on China. The right panel shows the aggregate welfare decomposition for China and the U.S. according to equation (3).

When the U.S. becomes much more China-alike ("Large η" case), China's welfare losses are further amplified by about 22%, while U.S. welfare losses are mitigated by about 30%. The decomposition shows that the main driver of these differences is once again the relocation effect. Figure 6 shows that Chinese and global FDI investment into the U.S. becomes more elastic than into any other destination, almost doubling FDI diversion toward the U.S. relative to the baseline in Figure 3. Chinese FDI diversion to Vietnam, Malaysia, Japan, Korea, and Taiwan, China falls by more than half relative to the baseline, and aggregate FDI diversion to these economies becomes almost zero. By contrast, decreasing how China-alike the U.S. is ("Small η" case) does not change the results much, since the U.S. is already among the least China-alike economies according to my proxy measures.

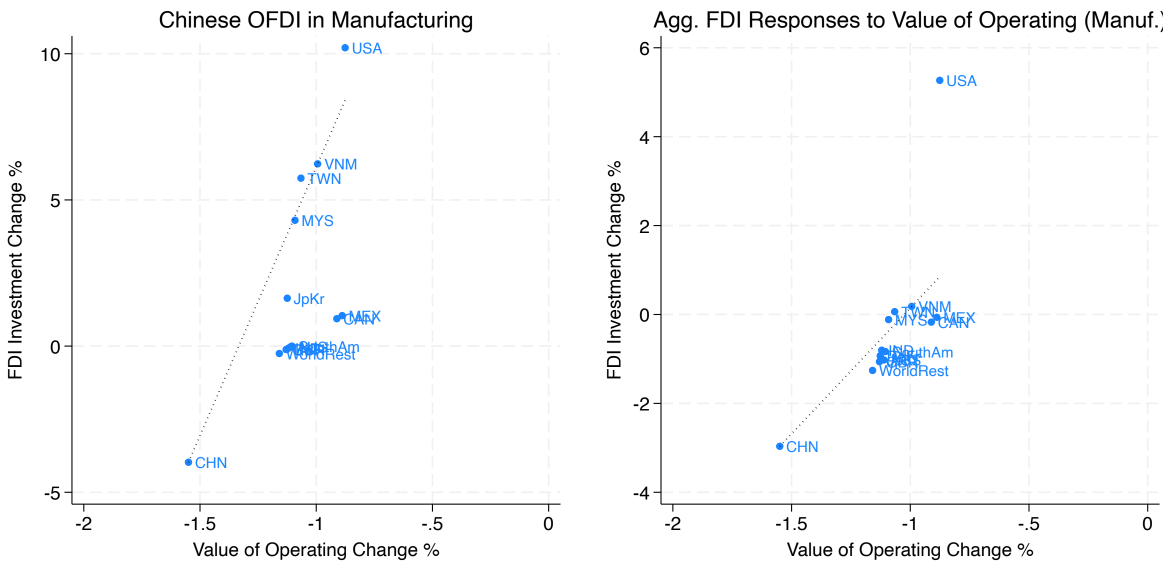

Figure 6: FDI Elasticities under "Large US η" Counterfactuals

Notes: The figure plots results for the manufacturing sector. The response corresponds to the percentage change in Chinese outward FDI to each destination country ($D_{i,CHN}$) in the left panel and the percentage change in each country's total inward FDI ($\sum_{j\neq i} D_{i,j}$) in the right panel, both in response to the Trump tariffs on China. The x-axis reports the percentage change in v_{ij} for each destination i. The dotted line links CHN and VNM.

5 Conclusion

This paper underscores the importance of accounting for FDI diversion — both its magnitude and its systematic heterogeneity — when examining the effects of trade policies on welfare and global economic outcomes. The recent China–U.S. trade war provides a relevant and timely case study in today's highly interconnected global economy.

Whereas much of the existing literature documents FDI relocation patterns and their potential drivers in a largely descriptive manner, this paper offers a systematic, generalizable, and theory-consistent framework to test and quantify FDI diversion in response to trade policies shocks, such as the China–U.S. trade war. The analysis sheds light on why certain economies, such as Vietnam, have emerged as major destinations for diverted FDI, and on the extent to which U.S. reshoring efforts are likely to succeed.

The proxies used to test the hypothesis and gauge why some economies attract FDI with larger elasticities than others during the China–U.S. trade war are admittedly imperfect, and the mechanisms they capture are not the only possible explanations in this context or more broadly. Nevertheless, the framework and empirical approach developed here provide a flexible platform for studying alternative mechanisms driving FDI diversion, and can be extended to more detailed modeling of specific channels as richer sectoral or micro-level data become available.

A Model Appendix

A.1 Model Derivation

I suppress the sector superscript when it is not essential.

Pricing. The producer solves the following pricing and production problem conditional on the production location i:

$$\begin{aligned} \max \sum_h \frac{p_{hij}(a) q_{hij}(a)}{t_{hi}} - w_i l_{ij}(a), \\ \text{s.t. } q_{ij}(a) = \frac{a^{\frac{1}{\epsilon-1}}}{\kappa_{ij}} l_{ij}(a) = \sum_{h=1}^{N} \tau_{hi} q_{hij}(a), \\ q_{hij}(a) = \left(\frac{p_{hij(a)}}{P_h}\right)^{-\epsilon} Q_h. \end{aligned}$$

Thus, the optimal pricing and production decisions satisfy

$$\begin{aligned} p_{hij}(a) &= \frac{\epsilon}{\epsilon-1} \frac{t_{hi}\tau_{hi} w_i}{a^{\frac{1}{\epsilon-1}}/\kappa_{ij}} \\ d_{ij}(a) &= \underbrace{\frac{1}{\epsilon-1} A_i \left(w_i \kappa_{ij}\right)^{1-\epsilon}}_{\equiv v_{ij}} a \\ l_{ij}(a) &= q_{ij}(a) / \frac{a^{\frac{1}{\epsilon-1}}}{\kappa_{ij}} = w_i^{-\epsilon} A_i \frac{a}{\kappa_{ij}^{-\epsilon-1}}, \\ \text{where } A_i &\equiv \sum_h \left(\tau_{hi}\right)^{-\epsilon} \left(t_{hi}\right)^{1-\epsilon} \left(\frac{\epsilon}{\epsilon-1}\right)^{-\epsilon} P_h^{\epsilon} Q_h. \end{aligned}$$

Location Choice. Since $\{a_{ij}\}$ follows a multivariate max-stable Fréchet distribution with scale parameter z_j, shape parameter θ, correlation function G, correlation parameter ρ, and weights $\{\eta_{ij}\}$, the transformed variables $\{d_{ij} = v_{ij} a_{ij}\}$ also follow a multivariate max-stable Fréchet distribution, with weights $\{\eta_{ij} v_{ij}^{\theta}\}$. Hence, conditional on location i being chosen, the distributions of d_{ij} and a_{ij} are given by

$$\begin{aligned} \mathbb{P}\left(d_{ij}(a_{ij}) \leq d \,|\, d_{ij}(a_{ij}) = \max_{i'} d_{i'j}(a_{i'j})\right) &= \mathbb{P}\left(\max_{i'} d_{i'j}(a_{i'j}) \leq d\right) \\ &= \exp\left(-z_j G\left(v_{1j}^{\theta}, \ldots, v_{Nj}^{\theta}\right) d^{-\theta}\right), \end{aligned}$$

$$\mathbb{P}\left(a_{ij} \leq a \,|\, d_{ij}(a_{ij}) = \max_{i'} d_{i'j}(a_{i'j})\right) = \exp\left(-z_j \frac{G\left(v_{1j}^\theta, \ldots, v_{Nj}^\theta\right)}{v_{ij}^\theta} a^{-\theta}\right) \equiv G_{ij}(a).$$

Aggregate Variables. I now derive the aggregate variables. The sector-level price index is given by

$$P_h^s = \left(\sum_{j=1}^N \sum_{i=1}^N \int_{M_{ij}^s} p_{hij}^s(\omega)^{1-\epsilon^s} \,\mathrm{d}\omega\right)^{\frac{1}{1-\epsilon^s}} = \left(\sum_j \sum_i M_{ij}^s \int_0^\infty p_{hij}^s(a)^{1-\epsilon^s} \,\mathrm{d}G_{ij}^s(a)\right)^{\frac{1}{1-\epsilon^s}}.$$

Similarly, aggregate profits are given by

$$D_{ij}^s = \int_{M_{ij}^s} d_{ij}^s(\omega) \,\mathrm{d}\omega = M_{ij}^s \int_0^\infty d_{ij}^s(a) \,\mathrm{d}G_{ij}^s(a)\,,$$

and the trade share is given by

$$\pi_{hi}^s = \frac{X_{hi}^s}{X_h^s} = \frac{\sum_j \int_{M_{ij}^s} p_{hij}^s(\omega) q_{hij}^s(\omega) \,\mathrm{d}\omega}{P_h^s Q_h^s} = \frac{\sum_j M_{ij}^s \int p_{hij}^s(a) q_{hij}^s(a) \,\mathrm{d}G_{ij}^s(a)}{P_h^s Q_h^s}.$$

Substituting M_{ij}^s, $p_{hij}^s(a)$, $d_{ij}^s(a)$, $q_{hij}^s(a)$, and $G_{ij}^s(a)$ yields the price indices, aggregate profits, and trade shares reported in the main text.

FDI Technology Class Shares. The location choice probability — which also corresponds to the FDI share for producers from j — is

$$M_{ij}^s = \frac{v_{ij}^\theta G_i(v_{1j}^\theta, \ldots, v_{Nj}^\theta)}{G(v_{1j}^\theta, \ldots, v_{Nj}^\theta)}.$$

Substituting the correlation function, the FDI share can be decomposed as follows:

$$\begin{aligned} M_{ij}^s &= \frac{v_{ij}^\theta + \eta_{ij}\left(\frac{\left(\eta_{ij} v_{ij}^\theta\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j} v_{i'j}^\theta\right)^{\frac{1}{1-\rho}}}\right)^\rho v_{ij}^\theta}{\sum_{i'} v_{i'j}^\theta + \left(\sum_{i'}\left(\eta_{i'j} v_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}} \\ &= \sum_{k=1,2} M_{ij}^{sk} = \underbrace{\frac{v_{ij}^\theta}{\sum_{i'} v_{i'j}^\theta}}_{\equiv M_{ij}^{sW1}} \underbrace{\frac{\sum_{i'} v_{i'j}^\theta}{\sum_{i'} v_{i'j}^\theta + \left(\sum_{i'}\left(\eta_{i'j} v_{i'j}^\theta\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv M_j^{sB1}} \end{aligned}$$

$$
+ \underbrace{\frac{\eta_{ij}\left(\frac{\left(\eta_{ij}\upsilon_{ij}^{\theta}\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j}\upsilon_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}}\right)^{\rho}\upsilon_{ij}^{\theta}}{\left(\sum_{i'}\left(\eta_{i'j}\upsilon_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv M_{ij}^{sW2}} \underbrace{\frac{\left(\sum_{i'}\left(\eta_{i'j}\upsilon_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}{\sum_{i'}\upsilon_{i'j}^{\theta}+\left(\sum_{i'}\left(\eta_{i'j}\upsilon_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv M_{j}^{sB2}},
$$

Here, M_{ij}^{sW1} and M_{ij}^{sW2} denote the within-class shares for the technology class without correlation ($k = 1$ or "location-specific") and with correlation ρ ($k = 2$ or "China-alike"), respectively. Similarly, M_j^{sB1} and M_j^{sB2} denote the between-class shares. Note that the following relationship holds:

$$
\frac{M_{ij}^{s2}}{M_{ij}^{s}} = \frac{\eta_{ij}Z_{ij}^{\rho}}{G_{ij}}.
$$

Therefore, $\frac{\eta_{ij}Z_{ij}^{\rho}}{G_{ij}}$ measures the share of FDI in location i that operates using the technology class with positive correlation, the "China-alike" technologies.

A.2 Welfare Decomposition

Aggregate expenditure, inclusive of tariff payments, is

$$
\begin{aligned}
X_j &= w_j L_j + D_j + T_j - \Gamma_j \\
&= w_j L_j + \sum_i \sum_s D_{ij}^s + \sum_i \sum_s \left(t_{ji}^s - 1\right)\mathcal{T}_{ji}^s - \Gamma_j .
\end{aligned}
$$

The aggregate price index is

$$
P_h^s = \left(\sum_{j=1}^{N}\sum_{i=1}^{N} \tilde{M}_{ij}^s \tilde{z}_j \left(P_{hij}^s\right)^{1-\epsilon^s}\right)^{\frac{1}{1-\epsilon^s}} .
$$

Substituting P_{hij}^s and assuming that the only shocks are the tariff changes, the log deviations of aggregate expenditure and the price index are

$$
\mathrm{d}\ln X_j = \frac{w_j L_j}{X_j}\,\mathrm{d}\ln w_j + \sum_i\sum_s \frac{D_{ij}^s}{X_j}\,\mathrm{d}\ln D_{ij}^s + \sum_i\sum_s \frac{\left(t_{ji}^s-1\right)\mathcal{T}_{ji}^s}{X_j}\left(\mathrm{d}\ln t_{ji}^s + \mathrm{d}\ln \mathcal{T}_{ji}^s\right) - \frac{\Gamma_j}{X_j}\,\mathrm{d}\ln\Gamma_j\,,
$$

$$
\mathrm{d}\ln P_j = \sum_i\sum_s \left(\frac{t_{ji}^s\mathcal{T}_{ji}^s}{X_j}\,\mathrm{d}\ln w_i + \frac{\left(t_{ji}^s-1\right)\mathcal{T}_{ji}^s}{X_j}\,\mathrm{d}\ln t_{ji}^s + \frac{1}{1-\epsilon^s}\frac{t_{ji}^s\mathcal{T}_{ji}^s}{X_j}\sum_{j'}\omega_{ij'}\,\mathrm{d}\ln\tilde{M}_{ij'}^s\right).
$$

Reorganizing these two log deviations yields the welfare decomposition in equation (3):

$$
\begin{aligned}
\mathrm{d}\ln C_j \approx\ & \frac{w_j L_j}{X_j}\,\mathrm{d}\ln w_j + \sum_i \sum_s \frac{D_{ij}^s}{X_j}\,\mathrm{d}\ln w_i - \sum_i \sum_s \frac{\mathcal{T}_{ji}^s}{X_j}\,\mathrm{d}\ln w_i \\
& + \sum_i \sum_s \frac{D_{ij}^s}{X_j}\left(\mathrm{d}\ln D_{ij}^s - \mathrm{d}\ln w_i\right) \\
& + \sum_i \sum_s \frac{1}{\epsilon^s - 1}\frac{t_{ji}^s \mathcal{T}_{ji}^s}{X_j} \sum_{j'} \omega_{ij'}^s\,\mathrm{d}\ln \tilde{M}_{ij'}^s \\
& + \sum_i \sum_s \frac{\left(t_{ji}^s - 1\right)\mathcal{T}_{ji}^s}{X_j}\left(\mathrm{d}\ln \mathcal{T}_{ji}^s - \mathrm{d}\ln w_i\right) - \frac{\Gamma_j}{X_j}\,\mathrm{d}\ln \Gamma_j\,,
\end{aligned}
$$

where $\mathcal{T}_{ji}^s \equiv \frac{\pi_{ji}^s}{t_{ji}^s} X_j^s$ denotes the factual trade value exported from i to j in sector s, and $\omega_{ij'}^s \equiv \frac{D_{ij'}^s}{\sum_j D_{ij}^s}$ is the share of FDI stocks in i and sector s by producers from j'.

A.3 Microfoundations for Productivity Draw Distribution

A.3.1 China-alike Production

The microfoundation adapts Lind and Ramondo (2023*a*, 2024) to the context of FDI studied in this paper. For each producer, and thus each variety ω from j, there exists an infinite but countable set of production ideas indexed by $n = 1, 2, \ldots$. Each idea has a quality R_n, a most suitable environment (location) i_n, and belongs to a production technology class k. I assume that, in the context of the Trump tariffs, there are two types of technology class. The first is "location-specific" (LS) technology, and the second is "China-alike" (CA) technology. A CA idea naturally has $i_n = CN$ and can be interpreted, for example, as a production method relying heavily on cheap, disciplined labor and good infrastructure. The LS technology class aggregates all "non-China-alike" technologies, and i_n denotes the location whose specific environment is most suitable for implementing that idea.

Formally, ideas are discovered according to a Poisson process with intensity $\theta r^{-\theta-1}\Lambda_{ij}^k\,\mathrm{d}r$. Thus, the expected number of production ideas of technology class k for this variety in i with quality above r is $r^{-\theta}\Lambda_{ij}^k$.

To be implemented in actual production, an idea must be combined with local applications. For CA technologies, an idea can be applied in all possible production locations. When a location's production environment is more similar to China — that is, more China-alike — such ideas are more likely to achieve high application efficiency there. Formally, given idea quality R_n and $k_n = CA$, the set $\{Z_{nm}, \ell_{nm}\}$ consists of the points of a Poisson process with intensity $\Gamma\left(1 - \theta/\sigma\right)^{-\sigma/\theta} \sigma z^{-\sigma-1} T_\ell^{\mathrm{CA}}\,\mathrm{d}z$, where $T_\ell^{\mathrm{CA}} > 0$.

If the firm applies CA applications for a CA idea n in location ℓ_{nm}, it uses the best available application:

$$Z_{n\ell}^{\text{CA}*} \equiv \max_{m=1,2,\ldots} Z_{nm} \mathbb{1}\{\ell_{nm} = \ell\}.$$

Since applications are independent of idea quality, the distribution of $Z_{n\ell}^{\text{CA}*}$ across application locations for CA ideas, denoted by $M_{CN}^{\text{CA}}(z_1, \ldots, z_N)$, is also independent of quality. This distribution is given by:

$$M_{CN}^{\text{CA}}(z_1, \ldots, z_N) = \exp\left[-\Gamma(\rho)^{-\frac{1}{1-\rho}} \sum_{\ell=1}^{N} T_\ell^{\text{CA}} z_\ell^{-\frac{\theta}{1-\rho}}\right].$$

To derive this,

$$\begin{aligned}
&\mathbb{P}\left[Z_{n1}^{\text{CA}*} \leq z_1, \ldots, Z_{nN}^{\text{CA}*} \leq z_N | R_n = r, i_n = CN\right] \\
&= \mathbb{P}\left[\max_{m=1,2,\ldots} Z_{nm} \mathbb{1}\ell_{nm} = \ell \leq z_\ell, \forall \ell = 1, \ldots, N \,|\, R_n = r, i_n = CN\right] \\
&= \mathbb{P}\left[Z_{nm} \mathbb{1}\ell_{nm} = \ell \leq z_\ell, \forall \ell = 1, \ldots, N, \forall m \,|\, R_n = r, i_n = CN\right] \\
&= \mathbb{P}\left[Z_{nm} \leq z_{\ell_{nm}}, \forall m \,|\, R_n = r, i_n = CN\right] = \mathbb{P}\left[Z_{nm} > z_{\ell_{nm}}, \text{ for no } m \,|\, R_n = r, i_n = CN\right] \\
&= \exp\left[-\sum_{\ell=1}^{N} \int_{z_\ell}^{\infty} \Gamma(1 - \theta/\sigma)^{-\sigma/\theta} T_\ell^{\text{CA}} \sigma z^{-\sigma-1} \, \mathrm{d}z\right].
\end{aligned}$$

The last line follows from the void probability, since $\{Z_{nm}, \ell_{nm}\}$, conditional on $R_n = r, i_n = CN$, forms a Poisson process with intensity $\Gamma(1 - \theta/\sigma)^{-\sigma/\theta} \sigma z^{-\sigma-1} T_i^{CS} \, \mathrm{d}z$.

For LS technologies, only applications at the most suitable location i_n are available. Denote the location of the m-th application of an LS idea n by ℓ_{nm}, with efficiency Z_{nm}.[35] Formally, conditional on idea quality R_n and location i_n, $\{Z_{nm}, \ell_{nm}\}$ consists of the points of a Poisson process with intensity $\Gamma(1 - \theta/\sigma)^{-\sigma/\theta} \sigma z^{-\sigma-1} T_\ell^{\text{LS}} \mathbb{1}\{i_n = \ell_{nm}\} \, \mathrm{d}z$, where $\sigma > \theta, T_\ell^{\text{LS}} > 0$.

If the firm uses LS applications for idea n in location $i_n = \ell_{nm}$, it adopts the best available application:

$$Z_{n\ell}^{\text{LS}*} \equiv \max_{m=1,2,\ldots} Z_{nm} \mathbb{1}\{\ell_{nm} = \ell\}.$$

Since applications are independent of idea quality and LS applications exist only for the same production location, the distribution of $Z_{n\ell}^{\text{LS}*}$, denoted by $M_i^{\text{LS}}(z_i)$, is independent of

[35] An alternative interpretation is that the application efficiency is extremely low when $k_n = LS$ and $\ell_{nm} \neq i_n$.

idea quality and location-specific:

$$M_i^{\mathrm{LS}}(z_i) = \exp\left[-\Gamma(\rho)^{-\frac{1}{1-\rho}} T_i^{\mathrm{LS}} z^{-\frac{\theta}{1-\rho}}\right],$$

where $\rho \equiv 1 - \theta/\sigma$, and the derivation is similar to the one for M_{CN}^{CA}.

Finally, the productivity a firm uses in production at location i is

$$A_i \equiv \max_{\substack{n=1,2,\dots \\ k=\mathrm{LS},\,\mathrm{CA}}} R_n Z_{ni}^{k*}.$$

The implied productivity distribution across locations is given by

$$\begin{aligned}
\mathbb{F}(a_1,\dots,a_N) = \mathbb{P}[A_1 \le a_1,\dots,A_N \le a_N] &= \mathbb{P}\left[\max_{\substack{n=1,2,\dots \\ k=LS,CS}} R_n Z_{ni}^{k*} \le a_i, i=1,\dots,N\right] \\
&= \mathbb{P}\left[R_n Z_{ni}^{k*} a_i^{-1} \le 1, \forall i = 1,\dots,N, \forall n, \forall k\right] \\
&= \mathbb{P}\left[R_n \max_{\substack{i=1,\dots,N \\ k=LS,CS}} Z_{ni}^{k*} a_i^{-1} \le 1, \forall n\right] \\
&= \mathbb{P}\left[R_n \max_{\substack{i=1,\dots,N \\ k=LS,CS}} Z_{ni}^{k*} a_i^{-1} > 1, \text{ for no } n\right].
\end{aligned}$$

Since $\{R_n, i_n\}$ follows a Poisson process with intensity $\theta r^{-\theta-1}\Lambda_{ij}^k \,\mathrm{d}r$, and $\left\{Z_{ni}^{k*}\right\}_{i=1,\dots,N}$ is a random vector with distribution $M_i^k(z_1,\dots,z_N)$ conditional on $R_n = r, i_n = i, k$, the marking theorem for Poisson processes implies that $\left\{R_n, i_n, \left\{Z_{ni}^{k*}\right\}_{i=1,\dots,N}\right\}_{n=1,2,\dots}$ forms a Poisson process with intensity $\mathrm{d}M_i^k(z_1,\dots,z_N)\,\theta r^{-\theta-1}\Lambda_{ij}^k\,\mathrm{d}r$. Thus, the corresponding void probability is

$$\begin{aligned}
\dots &= \exp\left[-\sum_{\substack{i=1,\dots,N \\ k=\mathrm{LS},\mathrm{CA}}} \int_0^\infty \int_{\mathbb{R}_+^N} \mathbb{1}\{r \max_{i'} z_{i'} a_{i'}^{-1} > 1\}\,\mathrm{d}M_i^k(z_1,\dots,z_N)\,\theta r^{-\theta-1}\,\mathrm{d}r\,\Lambda_{ij}^k\right] \\
&= \exp\left[-\sum_{\substack{i=1,\dots,N \\ k=\mathrm{LS},\mathrm{CA}}} \int_{\mathbb{R}_+^N} \int_{\left(\max_{i'} z_{i'} a_{i'}^{-1}\right)^{-1}}^\infty \theta r^{-\theta-1}\,\mathrm{d}r\,\mathrm{d}M_i^k(z_1,\dots,z_N)\,\Lambda_{ij}^k\right].
\end{aligned}$$

The inner integral with respect to r evaluates to

$$\max_{i'=1,\dots,N} z_{i'}^\theta a_{i'}^{-\theta}.$$

Since $\left\{Z_{ni}^{\mathrm{LS}*}\right\}$ follows a Fréchet distribution, the second integral for $k = \mathrm{LS}$ is

$$\int_{\mathbb{R}_+^N} \max_{i'=1,\ldots,N} z_{i'}^{\theta} a_{i'}^{-\theta}\, \mathrm{d}M_i^{\mathrm{LS}}(z_i) = \mathbb{E}\left[\max_{i'=1,\ldots,N} \left(Z_{ni'}^{\mathrm{LS}*}\right)^{\theta} a_{i'}^{-\theta} \mid R_n = r, i_n = i, k = \mathrm{LS}\right]$$
$$= \left[\left(\Gamma(\rho)^{-\frac{1}{1-\rho}} T_i^{\mathrm{LS}}\right)\left(a_i^{-\theta}\right)^{\frac{1}{1-\rho}}\right]^{1-\rho} \Gamma(\rho) = \left(T_i^{\mathrm{LS}}\right)^{1-\rho} a_i^{-\theta}.$$

Since $\left\{Z_{ni}^{\mathrm{CA}*}\right\}$ follows a Fréchet distribution and is independent across i, the second integral for $k = \mathrm{CA}$ is

$$\int_{\mathbb{R}_+^N} \max_{i'=1,\ldots,N} z_{i'}^{\theta} a_{i'}^{-\theta}\, \mathrm{d}M_i^{\mathrm{CA}}(z_1,\ldots,z_N) = \mathbb{E}\left[\max_{i'=1,\ldots,N} \left(Z_{ni'}^{\mathrm{CA}*}\right)^{\theta} a_{i'}^{-\theta} \mid R_n = r, i_n = \mathrm{CA}, k = \mathrm{CA}\right]$$
$$= \left[\Gamma(\rho)^{-\frac{1}{1-\rho}} \sum_i T_i^{\mathrm{CA}} \left(a_i^{-\theta}\right)^{\frac{1}{1-\rho}}\right]^{1-\rho} \Gamma(\rho) = \left[\sum_{i=1}^{N} T_i^{\mathrm{CA}} a_i^{-\frac{\theta}{1-\rho}}\right]^{1-\rho}.$$

To impose discipline on the parameters, I assume $\Lambda_{ij}^{\mathrm{LS}} = z_j$ and $\Lambda_{ij}^{\mathrm{CA}} = z_j \Lambda_j^{\mathrm{CA}}$, so that Λ_j^{CA} reflects the relative productivity of CA technologies relative to LS technologies for firms from j. I also normalize LS application efficiencies by setting $T_i^{\mathrm{LS}} = 1$ for all i. Under these assumptions, the joint productivity distribution across locations is

$$\mathbb{F}_j\left(a_1,\ldots,a_N\right) = \exp\left(-z_j\left[\sum_i a_i^{-\theta} + \left(\sum_i \left(\underbrace{\Lambda_j^{\mathrm{CA}}\left(T_i^{\mathrm{CA}}\right)^{1-\rho}}_{\equiv \eta_{ij}} a_i^{-\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}\right]\right).$$

Replacing $\Lambda_j^{\mathrm{CA}}\left(T_i^{\mathrm{CA}}\right)^{1-\rho}$ with η_{ij} yields the reduced-form productivity distribution reported in the main text.

A.3.2 Alternative Microfoundation: Production with Chinese Key Suppliers

I offer an alternative microfoundation that builds on the role of intermediate inputs in multinational production — such as headquarter inputs in Ramondo and Rodriguez-Clare (2013) and sourcing decisions in Antras, Fort and Tintelnot (2017) — which are arguably important determinants of FDI diversion in the context of the China–U.S. trade war. It also illustrates how the same productivity distribution can be used to study alternative mechanisms underlying FDI diversion. Implementing this alternative microfoundation would require more detailed data, such as data on intermediate input trade, which are outside the scope of this paper.

Each production idea is paired with a supplier of intermediate inputs. Conditional on the choice of production location i, the production function for variety ω from j incorporates intermediate inputs, relative to the baseline model in the main text:

$$q_{ij}(\omega) = \frac{z(\omega)^{\frac{1}{\epsilon-1}}}{\kappa_{ij}} \left(\tilde{r}(\omega)^{\frac{1}{\epsilon-1}} l_{ij}(\omega)\right)^{1-\alpha} (m_{ij}(\omega))^{\alpha},$$

where $m_{ij}(\omega)$ and $z(\omega)$ denote, respectively, the quantity and match-specific quality of the intermediate input, and $\tilde{r}(\omega)$ is the labor-augmented productivity of the production idea.

Let the price of the intermediate input be p^m. The producer solves

$$\max_{\{p_{hij}\}, l_{ij}, m_{ij}} \sum_h \frac{p_{hij} q_{hij}}{t_{hi}} - w_i l_{ij} - p^m m_{ij}.$$

Under CES demand, the optimal pricing rule yields

$$p_{hij}(\tilde{r}, p^m, z) = \frac{\epsilon}{\epsilon - 1} \frac{t_{hi} \tau_{hi} w_i^{1-\alpha}}{\left(\tilde{r}^{1-\alpha} \frac{z}{(p^m)^{\alpha(\epsilon-1)}}\right)^{\frac{1}{\epsilon-1}} / \kappa_{ij}}.$$

It follows that the producer's effective productivity is $a \equiv \underbrace{\tilde{r}^{1-\alpha}}_{\equiv r} \frac{z}{(p^m)^{\alpha(\epsilon-1)}}$.

The labor-augmented productivity $\tilde{r}(\omega)$ is assumed to follow a Fréchet distribution, independently across production locations, with scale parameter z_j and shape parameter θ:

$$M_j(\tilde{r}_1, \ldots, \tilde{r}_N) = \exp\left(-z_j \sum_i \tilde{r}_i^{-\theta}\right).$$

Hence, the implied joint distribution of r_i is

$$M_j(r_1, \ldots, r_N) = \exp\left(-z_j \sum_i r_i^{-\frac{\theta}{1-\alpha}}\right).$$

Suppliers of intermediate inputs arrive randomly. Their prices depend on the distribution of supplier sources, while input quality reflects randomness in the matching process, similar to Buera and Oberfield (2020). More formally, when a potential supplier arrives, the supplier's combined productivity is drawn from the source distribution $G(a')$, while the match-specific quality component z is drawn from an exogenous distribution. I assume that the arrival rate of quality exceeding z, denoted $B(z)$, follows a power law:

$$B(z) = z^{-\theta}.$$

There are two technology types, distinguished by supplier source. The first is local suppliers (LS), i.e., firms located in the production country i. The second is Chinese suppliers

(CS), i.e., varieties produced in China by Chinese firms. Given any supplier productivity a', the optimal pricing rule continues to apply, so that

$$
\begin{aligned}
& p^m(a') = \frac{\epsilon}{\epsilon-1}\frac{t_{hi}\tau_{hi}w_i^{1-\alpha}}{(a')^{\frac{1}{\epsilon-1}}/\kappa_{ij}}, \\
\Rightarrow \quad & \underbrace{p^m(a')^{-(\epsilon-1)\alpha} = \left(\frac{\epsilon}{\epsilon-1}w_i^{1-\alpha}\right)^{-(\epsilon-1)\alpha}(a')^{\alpha}}_{\equiv \tilde{p}_i^m(a')}\underbrace{(t_{ii'}\tau_{ii'})^{-(\epsilon-1)\alpha}}_{\equiv f_{ii'}^k};
\end{aligned}
$$

Assume that productivity a' for suppliers in i' follows a Fréchet distribution, i.e., $a' \sim$ Fréchet $\left(\tilde{T}_{i'}, \theta\right)$, which I verify later. Then, the scaled f.o.b. intermediate input price in i, denoted $\tilde{p}_i^m(a')$, also follows a Fréchet distribution with parameters $\left(\tilde{T}_i\left(\frac{\epsilon}{\epsilon-1}w_i^{1-\alpha}\right)^{-(\epsilon-1)\theta}, \frac{\theta}{\alpha}\right)$.

Given any $\tilde{p}_i^m$, the arrival rate of match-specific quality that, in combination with that price, yields $z\tilde{p}_i^m > x$ is $B\left(x/\tilde{p}_i^m\right)$. Integrating over possible prices gives $\int B_i^k\left(x/\tilde{p}^m\right)dG_i^{\tilde{p}^m,k}(\tilde{p}^m)$, which is the arrival rate of intermediate-input productivity components exceeding x:

$$
\begin{aligned}
& \int B\left(x/p\right)\mathrm{d}\exp\left(-\tilde{T}_i\left(\frac{\epsilon}{\epsilon-1}w_i^{1-\alpha}\right)^{-(\epsilon-1)\theta}p^{-\frac{\theta}{\alpha}}\right) \\
& = \Gamma(1-\alpha)\left(\tilde{T}_i\left(\frac{\epsilon}{\epsilon-1}w_i^{1-\alpha}\right)^{-(\epsilon-1)\theta}\right)^{\alpha}x^{-\theta} \equiv \Lambda_i x^{-\theta}.
\end{aligned}
$$

Equivalently, the infinite but countable set of intermediate-input productivity components $\{X_n, i_n\}$, where i_n denotes the supplier's origin, forms a Poisson process with intensity $\Lambda_i\theta x^{-\theta-1}\,\mathrm{d}x$.

Finally, the combined productivities across locations follow

$$
\begin{aligned}
\mathbb{F}\left(a_1,\ldots,a_N\right) = \mathbb{P}\left[A_1 \le a_1,\ldots,A_N \le a_N\right] &= \mathbb{P}\left[\max_{\substack{n=1,2,\ldots\\ k=LS,CS}} X_n r_{ni'} f_{ni'}^k \le a_{i'}, i'=1,\ldots,N\right] \\
&= \mathbb{P}\left[X_n r_{ni'} f_{ni'}^k a_{i'}^{-1} \le 1, \forall i'=1,\ldots,N, \forall n, k=LS,CS\right] \\
&= \mathbb{P}\left[X_n \max_{i'=1,\ldots,N} r_{ni'} f_{ni'}^k a_{i'}^{-1} \le 1, \forall n, k=LS,CS\right] \\
&= \mathbb{P}\left[X_n \max_{i'=1,\ldots,N} r_{ni'} f_{ni'}^k a_{i'}^{-1} > 1, \text{ for no } n, k=LS,CS\right].
\end{aligned}
$$

Note that $\{r\}_{i=1,\ldots,N}$ is a random vector whose distribution, conditional on $X_n^k = x$ and $i_n = i$, is $M_j(r_1,\ldots,r_N)$. Similarly, $\left\{f_i^k\right\}_{i=1,\ldots,N}$ can be viewed as a degenerate random vector that equals 1 when $k = LS$, and equals $(t_{ii'}\tau_{ii'})^{-(\epsilon-1)\alpha}$ when $k = CS$. By the marking theorem for Poisson processes, $\left\{X_n, i_n, \left\{r_i, f_i^k\right\}_{i=1,\ldots,N}^{k=LS,CS}\right\}_{n=1,2,\ldots}$ are the points of a Poisson process with intensity $\mathrm{d}M_j\left(r_1,\ldots,r_N\right)\Lambda_i\theta x^{-\theta-1}\,\mathrm{d}x$. Thus, the corresponding void probability is

$$\begin{aligned}\ldots &= \exp\left[-\sum_{\substack{i=1,\ldots,N\\k=LS,CS}}\int_0^\infty\int_{\mathbb{R}_+^N}\mathbb{1}x\max_{i'}r_{i'}f_{i'}^k a_{i'}^{-1}>1\,\mathrm{d}M_j\left(r_1,\ldots,r_N\right)\Lambda_i\theta x^{-\theta-1}\,\mathrm{d}x\right]\\ &= \exp\left[-\sum_{\substack{i=1,\ldots,N\\k=LS,CS}}\int_{\mathbb{R}_+^N}\int_{\left(\max_{i'}r_{i'}f_{i'}^k a_{i'}^{-1}\right)^{-1}}^\infty\Lambda_i\theta x^{-\theta-1}\,\mathrm{d}x\,\mathrm{d}M_j\left(r_1,\ldots,r_N\right)\right].\end{aligned}$$

For $k=LS$ and location i,

$$\begin{aligned}&\int_{\mathbb{R}_+^N}\max_{i'=1,\ldots,N}r_{i'}^\theta a_{i'}^{-\theta}\,\mathrm{d}M_j(\mathtt{q}_1,\ldots,\mathtt{q}_N)=\int_{\mathbb{R}_+}r_i^\theta a_i^{-\theta}\,\mathrm{d}M_j(r_i)\\ &=\mathbb{E}\left[r_i^\theta a_i^{-\theta}\,|\,i_n=i,k=LS\right]=\left[z_j\left(a_i^{-\theta}\right)^{\frac{1}{1-\alpha}}\right]^{1-\alpha}\Gamma(\alpha)=\Gamma(\alpha)z_j^{1-\alpha}a_i^{-\theta}.\end{aligned}$$

For $k=CS$ and $i=CN$,

$$\begin{aligned}&\int_{\mathbb{R}_+^N}\max_{i'=1,\ldots,N}r_{i'}^\theta f_{i'}^{CS}a_{i'}^{-\theta}\,\mathrm{d}M_j(r_1,\ldots,r_N)\\ &=\mathbb{E}\left[\max_{i'=1,\ldots,N}r_{i'}^\theta f_{i'}^{CS}a_{i'}^{-\theta}\,|\,i=CN,k=CS\right]=\Gamma(\alpha)z_j^{1-\alpha}\left[\sum_i\left(\frac{a_i}{f_i^{CS}}\right)^{-\frac{\theta}{1-\alpha}}\right]^{1-\alpha}.\end{aligned}$$

Putting these together:

$$\mathbb{F}_j\left(a_1,\ldots,a_N\right)=\exp\left(-\Gamma(\alpha)z_j^{1-\alpha}\left[\sum_i\Lambda_i a_i^{-\theta}+\left(\sum_i\left(\Lambda_{CN}\left(f_i^{CS}\right)^\theta a_i^{-\theta}\right)^{\frac{1}{1-\alpha}}\right)^{1-\alpha}\right]\right).$$

It remains to verify the earlier assumption regarding the marginal distribution. Specifically, this requires that $\{\tilde{T}_i,\Lambda_i\}$ satisfy the system of joint equations for $i=1,\ldots,N$:

$$\begin{aligned}\Gamma(\alpha)z_i^{1-\alpha}\left(\Lambda_i+\Lambda_{CN}\left(f_i^{CS}\right)^\theta\right)&=\tilde{T}_i,\\ \Gamma(1-\alpha)\left(\tilde{T}_i\left(\frac{\epsilon}{\epsilon-1}w_i^{1-\alpha}\right)^{-(\epsilon-1)\theta}\right)^\alpha&=\Lambda_i.\end{aligned}$$

In summary, this alternative microfoundation requires a slight modification of the production function (and, correspondingly, of trade shares and goods market-clearing conditions), as well as adjustments to the scale parameters in the correlation function of the productivity draw distribution. Nevertheless, the same structure applies, leading to a similar reduced-form specification.

A.4 Simplifying Model Assumption: One-Location Firms

I assume that each producer is restricted to operating in a single location in the main text, thereby ruling out the possibility that a variety is produced in multiple locations to serve different markets. Alternatively, Arkolakis et al. (2018) adopt the opposite assumption: they replace firm-level fixed operating costs with fixed marketing costs for each export destination, allowing firms to serve each market independently from potentially different production locations. In this section, I show that adopting this alternative assumption has only minimal implications for the results in the main text.

Consider a producer ω from source economy j serving market h. The producer chooses a production location i from among all possible destinations. The production function is $q_{hij}(a) = a^{\frac{1}{\epsilon-1}} l_{hij}(a)/\kappa_{ij}$, and the joint productivity distribution is the same as in the main text, $\mathbb{F}_j(\{a_i\})$. For each destination market h, the producer selects the cheapest production location from which to serve that market, and sets the corresponding price:

$$p_{hij} = \frac{\epsilon}{\epsilon - 1} \frac{t_{hi}\tau_{hi}w_i}{a_{ij}^{\frac{1}{\epsilon-1}}/\kappa_{ij}} \quad \Rightarrow \quad p_{hj} = \min_{i'} p_{hi'j}.$$

The profit from selling to h by producing in i, excluding tariffs, is

$$\frac{d_{hij}(a)}{t_{hi}} = \left(\frac{\epsilon}{\epsilon - 1}\right)^{1-\epsilon} \frac{1}{\epsilon} \left(t_{hi}\tau_{hi}\kappa_{ij}\right)^{1-\epsilon} w_i^{1-\epsilon} P_h^{\epsilon} Q_h \frac{1}{t_{hi}} a \equiv v_{hij} a.$$

Following similar calculations, the probability that location i is the optimal production site to serve h is $M_{hij} \equiv \frac{v_{hij}^{\theta} G_{ji}\left(v_{h1j}^{\theta},\ldots,v_{hNj}^{\theta}\right)}{G_j\left(v_{h1j}^{\theta},\ldots,v_{hNj}^{\theta}\right)}$. The corresponding conditional productivity distribution is $G_{hij}(a) \equiv \exp\left(-z_j \left(\frac{G_j\left(v_{h1j}^{\theta},\ldots,v_{hNj}^{\theta}\right)}{v_{hij}^{\theta}}\right) a^{-\theta}\right)$. The total revenue of firms from j producing in i to sell in h is

$$D_{hij} = M_{hij} \int_0^{\infty} v_{hij} a \, \mathrm{d}G_{hij}(a) = \tilde{z}_j \left(\frac{G_{ji}}{G_j}\right)^{\frac{\theta-1}{\theta}} v_{hij}^{\theta},$$

and the total revenue of firms from j producing in i across all markets is $D_{ij} = \sum_h D_{hij} = \tilde{z}_j \left(\frac{G_{ji}}{G_j}\right)^{\frac{\theta-1}{\theta}} \sum_h v_{hij}^{\theta}$. Define $v_{ij} \equiv \left(\sum_h v_{hij}^{\theta}\right)^{\frac{1}{\theta}}$, and substitute for v_{hij}:

$$v_{ij} \equiv \left(\sum_h v_{hij}^{\theta}\right)^{\frac{1}{\theta}} = \frac{1}{\epsilon - 1} \left(w_i \kappa_{ij}\right)^{1-\epsilon} A_i,$$

where $A_i \equiv \left(\sum_h \left[\left(\frac{\epsilon}{\epsilon-1}\right)^{-\epsilon} t_{hi}^{-\epsilon} \tau_{hi}^{1-\epsilon} P_h^{\epsilon} Q_h\right]^{\theta}\right)^{\frac{1}{\theta}}$. Thus, the only difference from the framework in the main text is the definition of v_{ij} and A_i. From a theoretical perspective, this modification does not materially alter the main results.

Empirically, since the paper relies on aggregate data and focuses on aggregate implications, the two modeling assumptions are effectively equivalent. When the U.S. imposes tariff increases on Chinese exports, a producer may choose to relocate only the operations serving the U.S. market while retaining production for China and other destinations within China. This implies smaller producer outflows from China conditional on relocation, and a higher probability of movement for each producer. Without more detailed firm-level data on relocation decisions, it is not possible to distinguish between these different margins of FDI diversion. While it would certainly be interesting to study how finite operating fixed costs alter the elasticity of FDI diversion and its implications, my calibration targets aggregate FDI diversion elasticity at the country level. Hence, the aggregate implications of my model should be similar to those of a richer model with multiple FDI diversion margins, mitigating concerns about this simplification for the questions addressed here.

The main advantage of this simplifying assumption is that it rules out firms' joint decision-making across multiple locations, which would otherwise introduce a complex combinatorial problem, as in Tintelnot (2017); Morales, Sheu and Zahler (2019); Alfaro-Urena et al. (2023). Frameworks that incorporate such mechanisms — like Tintelnot (2017) — speak directly to another important driver of heterogeneous FDI diversion elasticities: proximity to key markets. Mexico provides a salient example. When firms can operate in several — but costly and therefore limited — production sites, proximity to major markets becomes a critical determinant of location choice. In this context, tariff shocks that worsen China's attractiveness as a production base can induce firms to select only one new location; Mexico is then likely the preferred alternative and exhibits high FDI diversion elasticities.

A.5 Trade Diversion Index: Model and Empirics

In the empirical analysis, I use country-level aggregate data to construct the trade diversion index. Accordingly, the corresponding model variables are

$$\sum_s \omega_{ij}^s \partial \ln M_{ij}^s, \quad \sum_s \omega_{i'j}^s \partial \ln M_{i'j}^s, \text{ and } \sum_s \omega_{ij}^s \partial \ln v_{ij}^s,$$

where ω_{ij}^s denotes the share of sales (and equivalently the FDI share) of firms from j operating in i for sector s. Empirically, this share is not available, and I approximate it using $r_i(\nu)$ from the empirical trade diversion index when sector s corresponds to product ν.

Since $v_{ij}^s \equiv \frac{1}{\epsilon^s-1} A_i^s (w_i \kappa_{ij}^s)^{1-\epsilon^s}$, the market access part of the relevant changes is given by

$$\sum_s \omega_{ij}^s \, \mathrm{d}\ln A_i^s$$

$$= \sum_s \omega_{ij}^s \sum_h \frac{(\tau_{hi}^s)^{-\epsilon^s} (t_{hi}^s)^{1-\epsilon^s} \left(\frac{\epsilon^s}{\epsilon^s-1}\right)^{-\epsilon^s} (P_h^s)^{\epsilon} Q_h^s}{\sum_{h'} (\tau_{h'i}^s)^{-\epsilon^s} (t_{h'i}^s)^{1-\epsilon^s} \left(\frac{\epsilon^s}{\epsilon^s-1}\right)^{-\epsilon^s} (P_{h'}^s)^{\epsilon} Q_{h'}^s} \left(-\epsilon^s \, \mathrm{d}\ln \tau_{hi}^s + (1-\epsilon^s) \, \mathrm{d}\ln t_{hi}^s + \mathrm{d}\ln (P_h^s)^{\epsilon} Q_h^s\right).$$

Because the analysis focuses on how changes in U.S. demand affect outcomes, only the case $h = \text{US}$ matters here. The corresponding share is $r_{hi}^s \equiv \frac{(\tau_{hi}^s)^{-\epsilon^s} (t_{hi}^s)^{1-\epsilon^s} \left(\frac{\epsilon^s}{\epsilon^s-1}\right)^{-\epsilon^s} (P_h^s)^{\epsilon} Q_h^s}{\sum_{h'} (\tau_{h'i}^s)^{-\epsilon^s} (t_{h'i}^s)^{1-\epsilon^s} \left(\frac{\epsilon^s}{\epsilon^s-1}\right)^{-\epsilon^s} (P_{h'}^s)^{\epsilon} Q_{h'}^s}$ with $h = \text{US}$. This corresponds to $r_{\text{US},i}(\nu)$ in the empirical trade diversion index.

Thus, the relevant variation becomes

$$\sum_s \omega_{ij}^s r_{\text{US},i}^s \, \mathrm{d}\ln (P_{\text{US}}^s)^{\epsilon} Q_{US}^s \,.$$

I assume that across sectors s, the relevant elasticity is $\tilde{\epsilon}$. Hence, $\mathrm{d}\ln (P_{\text{US}}^s)^{\epsilon} Q_{\text{US}}^s = (\epsilon - \tilde{\epsilon}) \, \mathrm{d}\ln P_{\text{US}}^s + \tilde{\epsilon} \, \mathrm{d}\ln X_{US}$. The variation in the U.S. sectoral price index arises from tariff changes across all U.S. source countries:

$$\mathrm{d}\ln P_{\text{US}}^s = \sum_{i'} \pi_{\text{US},i'}^s \, \mathrm{d}\ln P_{\text{US},i'j}^s \,.$$

Since I study U.S. tariffs on China, only the case $i' = \text{CN}$ is relevant. Because firms from different j face the same change in tariffs on Chinese exports to the U.S., $\mathrm{d}\ln P_{\text{US,CN},j}^s = \mathrm{d}\ln t_{\text{US,CN}}^s + \mathrm{d}\ln w_{\text{CN}}$, assuming that the trade costs and foreign operation frictions remain unchanged. Putting everything together, the relevant exposure of j's investment in i to U.S. tariffs on China is

$$\sum_s \omega_{ij}^s r_{\text{US},i}^s \pi_{\text{US,CN}}^s \, \mathrm{d}\ln t_{\text{US,CN}}^s \,,$$

which maps directly to the empirical trade diversion index in (5).

B Empirics Appendix

B.1 FDI Data Details

The OECD FDI data are based on statistics provided by 38 OECD member countries. The data are public and can be accessed here: `https://stats.oecd.org/index.aspx?DataSetCode=FDI_FLOW_PARTNER`. The OECD defines FDI as: "FDI statistics cover all entities in an FDI relationship. An FDI relationship is established when an investor in one country acquires 10% or more of the voting power in a business enterprise in another country. The 10 percent criterion is used to establish that the direct investor has a significant degree of influence over the operations of the direct investment enterprise."

A key issue with FDI data for economic analysis is the complex financing structure of investing firms, including the use of special purpose entities (SPEs) to channel investments. My objective is to capture the actual production capacity deployed in a host country and ultimately owned by a source country. In the OECD database, each reporting country provides different measures of FDI values. The domestic entities related to FDI can be classified as either SPEs or non-SPEs, and the counterpart country can be measured by immediate or ultimate sources/destinations. I prioritize using the host country's reported inward FDI from non-SPE entities and ultimate source countries whenever available. When these are not available, I use total (SPEs and non-SPEs) or immediate source country data. If the host country does not report the information, I use mirror data from partner countries.

The OECD database is limited in terms of country coverage. Coverage is more complete when at least one country in the pair is an OECD member, and less so when neither is (e.g., China and Vietnam).

I use the Coordinated Direct Investment Survey (CDIS) compiled by the International Monetary Fund (IMF) to complement the OECD database. As with the OECD data, I prioritize reporting countries' inward FDI positions and fill missing information using alternative sources when necessary.

The reliability of these datasets and thus their priority in my empirical analysis depend on how effectively they address issues such as complex financing structures. The OECD and CDIS datasets make concerted efforts to tackle these problems.

B.2 "China-alike" Proxies: Histogram

Figure A1 plots the histograms of the two proxies for C_{ij} in (6).

B.3 Empirical Evidence: Robustness Checks

B.3.1 Pre-shock Regressions

This section reports results from regressions (7) and (8) for pre-shock periods as placebo robustness checks.

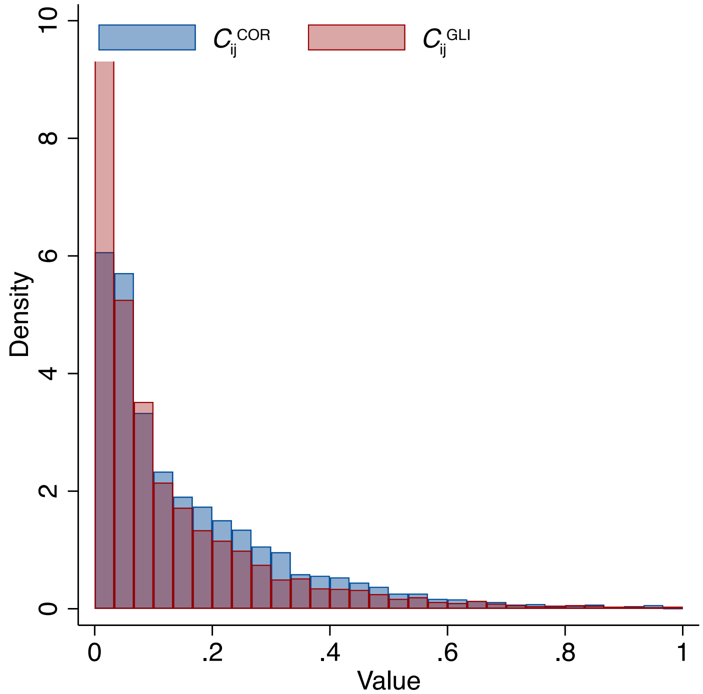

Figure A1: Proxy Histogram

Notes: The sample for both proxies includes 3,369 economy pairs, covering 138 destination economies and 73 investing economies.

B.3.2 Control for GDP per capita and Employment

Table A3 repeats the regressions in Tables 2 and 3, adding two controls for the destination country i: 2017 log GDP per capita and 2017 log employment (number of persons engaged), both from the Penn World Table (version 10.01). In the baseline (non-interaction) specifications, ΔEX_i is instrumented by DI_i, while $\ln \text{GDPpc}_i$ and $\ln \text{Emp}_i$ are treated as included instruments. The coefficients on ΔEX_i remain consistently positive and significant, and they increase over longer horizons. The coefficients on $\ln \text{GDPpc}_i$ are also consistently positive and significant, indicating that more advanced economies generally experience faster inward FDI growth relative to less advanced economies.

In the interaction specifications, all interaction terms with ΔEX_i are instrumented by the corresponding interaction terms with DI_i, capturing systematic variation in FDI diversion elasticities. The results remain consistent with the baseline for the two proxies, but also suggest higher elasticities for richer economies (with higher $\ln \text{GDPpc}_i$) and for larger economies (with higher $\ln \text{Emp}_i$, especially in later years). Overall, while there are additional systematic patterns in FDI diversion, the proxies emphasized in the main text remain

Table A1: Pre-shock: IV Estimates of $\bar{\beta}$ by Year

	2013	2014	2015	2016
ΔEX_i	-0.263	0.597	2.791	0.580
	(2.929)	(2.681)	(1.877)	(1.111)
Kleibergen–Paap F		11.12		
# Obs.		3435		

Notes: All regressions include investing economy fixed effects. The sample is restricted to economies with the largest inward FDI stocks in 2017, excluding those typically classified as tax havens. The regressions cover 74 investing economies and 138 destination economies. Standard errors are clustered at the investing economy level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

important.

B.3.3 FDI Diversion Patterns and Industry Composition

To explore how sectoral composition affects heterogeneity in FDI diversion elasticities, Table A4 extends the interaction regressions in Table A3 by adding $\Delta\text{EX}_i \times \text{Sector Share}_i$, alongside the main interaction terms $\Delta\text{EX}_i \times C_{ij}^{P}$, for $P \in \{COR, GLI\}$. Sector shares are measured as the sector's value-added share of total economy-wide value-added, as reported in the OECD ICIO for 2017. All sector shares are normalized to range from zero to one. Manufacturing (code C) aggregates all manufacturing subsectors. I report results for 2019 and 2023, covering all available ISIC (Rev. 4) two-digit tradable sectors. The interaction terms $\Delta\text{EX}_i \times \text{Sector Share}_i$ are instrumented using the corresponding interaction terms with DI_i.

Almost all coefficients on $\Delta\text{EX}_i \times C_{ij}^{COR}$ and $\Delta\text{EX}_i \times C_{ij}^{GLI}$ remain significantly positive, indicating that no single industry fully accounts for the systematic heterogeneity captured by the proxies C_{ij}^{COR} or C_{ij}^{GLI}.

A few sectors stand out as particularly important in attracting FDI diversion in response to the Trump tariffs: "Chemicals", "Computer, electronic & optical", "Machinery & equipment n.e.c.", and "Other transport equipment". In contrast, sectors associated with lower FDI diversion elasticities include mining and "Food, beverages & tobacco," which consistently yield negative coefficients. In general, sectors with larger elasticities tend to be technologically complex manufacturing industries, while sectors highly dependent on geography or natural resources exhibit smaller or negative elasticities.

Table A2: Pre-shock: IV Estimates of β, γ by Year

Panel A. Proxy C_{ij}^{COR}				
	2013	2014	2015	2016
ΔEX_i	-1.847	-0.990	0.157	0.158
	(1.131)	(0.897)	(0.662)	(0.503)
$\Delta \text{EX}_i \times C_{ij}^{COR}$	2.084	2.178	3.901*	0.502
	(3.872)	(3.563)	(2.200)	(1.432)
Kleibergen–Paap F		20.82		
# Obs.		3369		
Panel B. Proxy C_{ij}^{GLI}				
	2013	2014	2015	2016
ΔEX_i	-0.857	-0.293	1.123*	0.440
	(0.957)	(0.808)	(0.612)	(0.464)
$\Delta \text{EX}_i \times C_{ij}^{GLI}$	1.076	2.083	4.532	0.136
	(6.599)	(6.175)	(3.940)	(2.733)
Kleibergen–Paap F		30.87		
# Obs.		3369		

Notes: All regressions include investing economy fixed effects. The sample is restricted to economies with the largest inward FDI stocks in 2017, excluding those typically classified as tax havens. The regressions cover 74 investing economies and 138 destination economies. Standard errors are clustered at the investing economy level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.4 Estimation of Trade Elasticities ϵ^s

Using the trade share expression (2) and the prices P_{hij}^s,

$$X_{hi}^s = \left(X_h^s \left(P_h^s\right)^{\epsilon^s - 1}\right) \left(\frac{\epsilon^s}{\epsilon^s - 1} \sum_j \tilde{M}_{ij}^s \tilde{z}_j \kappa_{ij}^s w_i\right) \left(\tau_{hi}^s t_{hi}^s\right)^{1-\epsilon^s}.$$

The partial trade elasticities in the model are governed solely by the preference parameters ϵ^s. This is because the model assumes no firm entry and that each firm operates a single production location and exports to all destinations. Consider tariffs between importing countries h and h' and exporting country i. Changes in t_{hi} and $t_{h'i}$ jointly affect firm location decisions for producers from all source countries j. As a result, cross-country trade differences arise only along the intensive margin, which is governed solely by the trade elasticities ϵ^s.

Although the mapping from empirical estimates to model parameters depends on the model assumptions, the resulting estimates fall within the range of the trade elasticities estimated in the literature. For example, estimated elasticities for Agriculture and Mining are larger than those for Manufacturing, consistent with Caliendo and Parro (2015), who do not estimate trade elasticities for the service sector.

I begin with BACI trade data from 1995 to 2017 prior to the Trump tariffs, collapsed to the ISIC (Rev. 3.1) 2-digit level. I merge these data with the most-favored-nation (mfn) tariffs from the Global Tariff Database and then further collapse them into two broad sectors: $s = 1$, agriculture and mining, and $s = 2$, manufacturing. Tariffs at the broad-sector level are computed as trade-value-weighted averages of ISIC 2-digit tariffs.

For each of the two sectors, I estimate:

$$\ln \mathrm{EX}^s_{hit} = \mathrm{FE}^s_{ht} + \mathrm{FE}^s_{it} + \mathrm{FE}^s_{hi} + (1 - \epsilon^s)\ln(1 + \mathrm{mfn}^s_{hit}) + u^s_{hit},$$

where the implied coefficient $\hat{\epsilon}^s$ is used for calibration, and time-invariant trade costs are absorbed by importer–exporter fixed effects FE^s_{hi}.

This standard tariff-based approach is not applicable to services, since service trade (e.g., tourism, legal service) generally does not incur tariffs. To address this, I instead follow the literature and use the real exchange rate (RER) as a cost shifter. For sector 3, I substitute $\ln \tau^s_{hit}$ in the regression with $\ln \mathrm{RER}_{hit}$. Because the real exchange rate satisfies $\mathrm{RER}_{hit} = \mathrm{RER}_{hjt}\mathrm{RER}_{jit}$, importer−time and exporter−time fixed effects would absorb all variation. I therefore estimate with importer−exporter fixed effects FE^s_{hi} and time fixed effects FE^s_t:

$$\ln \mathrm{EX}^3_{hit} = \mathrm{FE}^3_{hi} + \mathrm{FE}_t - \epsilon^3_{\mathrm{RER}} \ln \mathrm{RER}_{hit} + u^3_{hit}.$$

For the service sector, I use total bilateral service trade values from ICIO for the available countries over 2008–2017. Real exchange rates are calculated using official exchange rates and PPP from the World Development Indicators (WDI).

It is well known that the trade elasticities estimated from RER shifters are typically lower than those estimated from tariff shifters. See Burstein and Gopinath (2014) for a survey. To make the elasticity for the service sector comparable to those for goods, I assume that the underlying factors causing the discrepancy between RER and tariff pass-throughs affect all sectors similarly. Consequently, I scale the RER-based estimates for services by the ratio of tariff-based to RER-based estimates in manufacturing. Specifically, the estimated coefficients using tariff shifters are $\hat{\epsilon}^1_{\text{tariff}} = 7.61$ and $\hat{\epsilon}^2_{\text{tariff}} = 6.27$, while the estimated coefficients using RER shifters for sectors 2 and 3 are $\hat{\epsilon}^2_{\text{RER}} = 0.076$ and $\hat{\epsilon}^3_{\text{RER}} = 0.066$. I therefore infer the service-sector elasticity as $\hat{\epsilon}^3_{\text{RER}} \times \frac{\hat{\epsilon}^2_{\text{tariff}}}{\hat{\epsilon}^2_{\text{RER}}} = 5.42$. Thus, the calibrated values are $\epsilon^1 = 7.61, \epsilon^2 = 6.27, \epsilon^3 = 5.42$.

Table A3: Robustness Check: Control for Other Systematic FDI Diversion Patterns

	2019			2020			2021			2022			2023		
	Base	C_{ij}^{COR}	C_{ij}^{GLI}	Base	C_{ij}^{COR}	C_{ij}^{GLI}	Base	C_{ij}^{COR}	C_{ij}^{GLI}	Base	C_{ij}^{COR}	C_{ij}^{GLI}	Base	C_{ij}^{COR}	C_{ij}^{GLI}
$\Delta \mathrm{EX}_i$	5.970***	-14.075***	-15.894***	3.501**	-11.274**	-11.710**	6.401***	-15.789***	-18.964***	8.291***	-18.920***	-23.790***	11.844***	-26.601***	-33.921***
	(1.522)	(4.135)	(3.591)	(1.512)	(4.885)	(4.435)	(2.069)	(5.456)	(5.077)	(2.735)	(7.085)	(6.839)	(3.512)	(8.350)	(8.163)
$\ln \mathrm{GDPpc}_i$	0.145***			0.131***			0.193***			0.228***			0.316***		
	(0.043)			(0.039)			(0.055)			(0.079)			(0.102)		
$\ln \mathrm{Emp}_i$	0.003			0.002			0.008			0.012			0.026		
	(0.021)			(0.014)			(0.022)			(0.028)			(0.038)		
$\Delta \mathrm{EX}_i \times C_{ij}^{COR}$		5.135**			3.210			7.616***			9.575***			14.683***	
		(2.258)			(2.702)			(2.762)			(3.193)			(3.616)	
$\Delta \mathrm{EX}_i \times C_{ij}^{GLI}$			8.904***			6.769**			12.390***			14.070***			21.830***
			(2.436)			(2.785)			(3.792)			(4.612)			(5.237)
$\Delta \mathrm{EX}_i \times \ln \mathrm{GDPpc}_i$		1.507***	1.700***		1.146**	1.176***		1.597***	1.945***		1.927**	2.479***		2.709***	3.536***
		(0.446)	(0.376)		(0.509)	(0.443)		(0.564)	(0.511)		(0.736)	(0.695)		(0.875)	(0.833)
$\Delta \mathrm{EX}_i \times \ln \mathrm{Emp}_i$		0.381**	0.384***		0.230	0.175		0.338*	0.381**		0.585**	0.710***		0.938***	1.117***
		(0.156)	(0.120)		(0.181)	(0.131)		(0.189)	(0.156)		(0.230)	(0.193)		(0.269)	(0.243)
Kleibergen–Paap F	19.74	40.03	50.06	19.74	40.03	50.06	19.74	40.03	50.06	19.74	40.03	50.06	19.74	40.03	50.06
# Obs.	3415	3349	3349	3415	3349	3349	3415	3349	3349	3415	3349	3349	3415	3349	3349

Notes: All regressions include investing economy fixed effects. The sample is restricted to economies with the largest inward FDI stocks in 2017, excluding those typically classified as tax havens. The regressions cover 74 investing economies and 138 destination economies. Standard errors are clustered at the investing economy level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Robustness Check: Systematic FDI Diversion Patterns due to Industry Composition

Code	Industry	Panel A: C_{ij}^{COR}				Panel B: C_{ij}^{GLI}			
		2019		2023		2019		2023	
		$\Delta EX_i \times C_{ij}^{COR}$	$\Delta EX_i \times$ Sec. Sh.	$\Delta EX_i \times C_{ij}^{COR}$	$\Delta EX_i \times$ Sec. Sh.	$\Delta EX_i \times C_{ij}^{GLI}$	$\Delta EX_i \times$ Sec. Sh.	$\Delta EX_i \times C_{ij}^{GLI}$	$\Delta EX_i \times$ Sec. Sh.
A01to02	Agriculture, hunting, forestry	6.718***	-11.547***	19.471***	-19.194***	13.786***	-10.725***	33.893***	-24.157***
A03	Fishing and aquaculture	11.479***	-7.414***	27.677***	-12.983***	21.878***	-7.378***	53.141***	-17.630***
B05to06	Mining & quarrying, energy	6.708***	-19.693***	19.121***	-37.187***	10.540***	-24.579***	26.846***	-53.706***
B07to08	Mining & quarrying, non-energy	7.276***	-17.953**	20.621***	-25.427***	12.784***	-14.272**	32.830***	-21.913**
B09	Mining support services	21.088***	-18.748***	43.734***	-31.711***	44.361**	-27.450**	100.595**	-59.839***
C	Manufacturing	9.717***	-2.553	27.426***	-9.179*	25.734***	-10.906**	65.792***	-29.382***
C10to12	Food, beverages & tobacco	14.149***	-13.470***	29.110***	-16.266**	22.298***	-12.906***	45.515***	-16.655**
C13to15	Textiles, leather & footwear	11.217***	-6.938***	27.312***	-12.362***	21.428***	-7.161***	52.366***	-17.419***
C16	Wood & cork products	7.336***	-1.684	21.097***	-1.607	11.921***	-2.930**	30.974***	-5.113**
C17to18	Paper products & printing	8.716***	3.077	21.495***	-2.355	13.270***	-4.797*	31.213***	-16.999***
C19	Coke & refined petroleum	7.942***	-1.531	20.686***	-7.776*	12.952***	-5.487	31.449***	-14.442***
C20	Chemicals	-14.111	125.881**	-12.939	196.754**	-42.142*	173.258*	-81.888	359.051*
C21	Pharmaceuticals	8.218***	0.405	22.060***	1.760	14.359***	-0.632	35.441***	0.425
C22	Rubber & plastics	10.841**	29.192*	25.243***	36.655	16.151***	14.831	38.087***	23.532
C23	Other non-metallic minerals	7.062***	-2.912**	19.441***	-6.404***	10.859***	-5.592***	27.392***	-12.456***
C24	Basic metals	6.410***	-8.728***	18.843***	-15.079***	10.575***	-9.520***	27.342***	-19.772***
C25	Fabricated metal products	12.155***	7.808	23.511***	3.158	14.625***	0.200	31.602***	-4.253
C26	Computer, electronic & optical	-6.011*	25.533***	5.651	29.239**	-4.070	20.365***	6.146	32.154***
C27	Electrical equipment	8.273***	-0.275	23.012***	-3.362	17.272***	-5.750***	40.892***	-11.214***
C28	Machinery & equipment n.e.c.	9.458***	30.488***	23.926***	48.329***	16.785***	31.015***	40.368***	66.122***
C29	Motor vehicles, trailers	13.248***	-3.087*	24.822***	-1.778	13.817***	0.257	25.038***	4.219**
C30	Other transport equipment	-5.362*	40.611***	-0.242	66.408***	-20.329**	55.350***	-36.556**	114.501***
C31to33	Manufacturing n.e.c.; repair & install	8.721***	1.853	21.991***	0.298	13.242***	-2.739	31.752***	-8.253***

Notes: The two cells in each row under the same panel and year report coefficients estimated from the IV regression (8), augmented with the interaction term $\Delta EXi \times$ Sector Share$i$ for a particular sector. Sector shares are measured as the sector's value-added share of total economy-wide value-added, as reported in the OECD ICIO for 2017. All sector shares are normalized to range from zero to one. Manufacturing (code C) aggregates all manufacturing subsectors. I report results for 2019 and 2023, covering all available ISIC (Rev. 4) two-digit tradable sectors.
All regressions include investing economy fixed effects. The sample is restricted to economies with the largest inward FDI stocks in 2017, excluding those typically classified as tax havens. The regressions cover 74 investing economies and 138 destination economies. Standard errors are clustered at the investing economy level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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