Trade Wars with FDI Diversion*

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Abstract

This paper shows that accounting for the existence and patterns of foreign direct investment (FDI) diversion, with empirically calibrated elasticities, significantly changes the quantitative implications of trade policies. I show that countries more exposed to trade diversion from the Trump tariffs have relative higher inward FDI stocks following the China-US trade war, and the elasticities of FDI diversion are highly heterogeneous. The quantitative analysis of the Trump tariffs highlights how FDI diversion impacts both aggregate and distributional welfare. The relocation and profit-shifting effects of FDI diversion, rather than the traditional terms-of-trade effect, lead to a tripled welfare loss for China and larger gains for US consumers than losses for US producers.

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A fundamental question in international economics concerns the impacts of trade policies on trade and welfare. Recent literature, particularly invigorated by the China-US trade war since 2018, primarily focuses on trade diversion — the substitution of goods exports across countries. A robust and surprising finding from recent studies is the virtually complete pass-through of tariffs to prices. This implies that US consumers of imported goods have borne the brunt of the tariffs through higher prices, although this has been potentially offset by gains to US producers (Fajgelbaum et al. 2021; Khandelwal and Fajgelbaum 2022). However, the China-US trade war also underscores the link between changes in trade patterns and significant movements of productive capital. The potential relocation of manufacturers to the US and the substantial increase in FDI in countries like Vietnam by producers from worldwide are showcase examples. In this paper, I extend a benchmark model of trade diversion to show that accounting for the existence and patterns of FDI diversion would overturn these implications and significantly changes the implications and quantitative evaluations of the Trump tariffs.

The analysis includes three parts. First, I present evidence of significant FDI diversion in the context of the Trump tariffs, and highlight a distinct pattern of heterogeneous FDI responsiveness across country pairs. This evidence also provides crucial moments for model calibration, influencing the magnitude of the quantitative results. Second, I develop a general equilibrium framework where trade shocks lead to both trade and FDI diversion. I decompose the aggregate welfare deviations into multiple income sources or theoretical channels that shed light on the distributional welfare implications of tariff changes. Third, I employ this framework to illustrate the quantitative importance of FDI diversion in understanding the Trump tariffs. For example, FDI diversion amplifies China's losses from the Trump tariffs while reversing the welfare implication for the US from a net loss to a net gain, driven by larger gains to consumers than losses to producers. Furthermore, FDI diversion increases greatly the incentives for countries to impose tariffs on their trading partners.

To begin, I construct a trade diversion index that measures a country's exposure to trade diversion from the Trump tariffs. I show that countries with higher exposure, meaning those with a greater potential to substitute for China's exports to the US and for whom such export opportunities are important, experienced a relative increase in inward FDI stocks following the China-US trade war. For example, Vietnam's trade diversion index ranks near the 95th percentile in my sample. Consequently, Vietnam's inward FDI stocks are around 8% higher two years after the trade war compared to countries with a trade diversion index around zero, such as Russia.

Having established a causal link between the Trump tariffs and FDI diversion, I proceed to show that the patterns of the observed changes in bilateral FDI stocks do not align with predictions made by most existing FDI models with a gravity structure, which suggest that a source country with a larger increase in total outward FDI stocks should similarly increase their FDI stocks in all destination countries. Contrary to this prediction, in the example of the Trump tariffs, China's FDI stock growth percentage varies greatly across countries, with particularly strong growth in countries like Vietnam. I refer to these observed patterns of bilateral FDI stock changes as "heterogeneous bilateral FDI elasticities".

I show that the heterogeneous bilateral FDI elasticities can be partially explained by observable country-pair characteristics and are not attributable solely to idiosyncratic bilateral shocks. For example, the response of FDI stocks between geographically closer countries is systematically larger, even after controlling for the receiver country's total inward FDI stock change and the source country's total outward FDI stock change. It's important to note that these systematic patterns pertain to the responsiveness of FDI stocks, not just their level, as in the usual gravity models. I argue that accounting for such heterogeneity is quantitatively important when assessing implications of trade policies.

With these empirical findings in mind, I build a multi-country general equilibrium model that captures the connections between trade and FDI, along with heterogeneous FDI elasticities. I think of FDI as domestic producers operating their firms in foreign countries as export platforms, earning repatriated profits and bringing know-how with them. Tariff shocks that lead to trade diversion alter the producers' values of operation in different production locations. Consequently, producers adjust their optimal production locations, resulting in FDI diversion.

To highlight the distributional implications of tariffs, I decompose a country's aggregate welfare change into different income sources, including wages, firms' domestic and foreign profits, and tariff revenues. Alternatively, I conduct a more theoretical decomposition of aggregate welfare changes. With the presence of producer profits (with fixed mass of producers) and foreign production, two important channels arise, in addition to the traditional terms-of-trade effect: the profit-shifting effect and the relocation effect. Since these income sources and model mechanisms are typically connected, to varying extents, with different population groups in reality, these decompositions provide a basic illustration of the distributional implications of the Trump tariffs.

To capture the observed heterogeneity in FDI responses tractably and flexibly, I apply a recently developed method for studying trade elasticity heterogeneity (Lind and Ramondo 2023) and adapt it to my FDI analysis. It also provides a particular interpretation — the idea of the "fit" between technologies with production locations.

I calibrate my model to a world economy of fourteen economies and three sectors with the year before the China-US trade war as the original equilibrium. The reduced form regressions on FDI diversion and heterogeneous elasticities provide crucial moments for model calibration, influencing the magnitude of the quantitative results. In the counterfactual exercises, I perform comparative statics to demonstrate how counterfactual results change with varying elasticity parameters, highlighting the importance of regulating FDI diversion elasticities using empirical evidence for the model's quantitative implications.

After the calibration, I perform a quantitative analysis, subjecting the original equilibrium to the Trump tariffs. I begin by illustrating that neglecting FDI diversion can lead to substantial differences in predicting the welfare implications of the Trump tariffs. This is shown by comparing the predictions derived from the baseline model with those from an exercise that assumes fixed producer locations and, consequently, largely unchanged FDI allocations. For example, incorporating FDI diversion triples the welfare costs of the Trump tariffs on China and reverses the sign of the welfare implication for the US.

I conduct the two decompositions to highlight the significant distributional implications of the Trump tariffs within each country and underscore the role of FDI diversion. The income-based decomposition shows that economies substituting more for Chinese exports, like the US and Vietnam, benefit from higher wage rates and domestic profits due to trade diversion. With FDI diversion, these economies also attract more FDI, further amplifying wage gains. However, FDI diversion often has the opposite effect on producer profits from domestic operations, as increased labor wages raise production costs.

The theory-based decomposition shows that the two new channels — the profit-shifting effect, which relates more to the household's welfare as producers, and the relocation effect, which relates more to the household's welfare as consumers — are significant contributors to welfare changes, greatly outweighting the traditional terms-of-trade effect. FDI-receiving countries like the US primarily benefit from the relocation effect, as more goods are produced domestically, lowering the price index. On the other hand, the profit-shifting effect is negative for the US and positive for China. These findings contrast with existing studies on the welfare implications of the Trump tariffs on the US, such as Fajgelbaum et al. 2020, which generally conclude with losses in consumer surplus and gains in producer surplus for the US.

As FDI diversion greatly changes the welfare implication of trade policies, I numerically show how it substantially changes countries' incentives to impose tariffs on their trading partners. I quantitatively investigate the noncooperative "optimal" tariffs for the US and China through both a uniform increase in tariffs and a Nash tariff exercise. The results show that FDI diversion greatly raises the "optimal" tariff that the US would like to impose on Chinese exports and the equilibrium Nash tariffs between China and the US. This leads to lower welfare outcomes for both countries.

Finally, I highlight the critical role of heterogeneous FDI diversion elasticities in shaping the patterns of FDI diversion and their implications. China's large decrease in its inward FDI stock and increase in its outward FDI investment are highly heterogeneous. For example, the growth of Chinese outward FDI stocks in economies such as Vietnam, Japan, Korea, and Malaysia are much larger than the growth in economies like the US or Mexico, quantitatively changing the FDI diversion and welfare implications for these economies.

Related Literature. My paper contributes to the vast literature on the impact of trade policies. The recent China-US trade tensions have reignited interests in this classic question, with a focus on the price effects of trade policies, including Amiti, Redding and Weinstein (2020); Fajgelbaum et al. (2020); Flaaen, Hortaçsu and Tintelnot (2020); Fajgelbaum et al. (2021); Cavallo et al. (2021). Waugh (2019) goes beyond price effects by looking at employment and consumption implications. Some papers study the trade war implications by allowing for additional elements, such as labor and firms reallocations domestically in Caliendo and Parro (2019) and firm-to-firm supply relationships in Grossman, Helpman and Redding (2023).

My paper highlights the importance of large movements of FDI during the China-US trade war, frequently featured in media headlines and of considerable policy concern (e.g., IMF 2023; Alfaro and Chor 2023). It offers a general equilibrium model that directly links FDI to trade and production fundamentals, demonstrating that FDI diversion greatly changes the implications of the Trump tariffs. Furthermore, I provide empirical evidence on how different countries respond to trade shocks in terms of FDI, whereas the existing literature tends to concentrate on individual countries (e.g., McCaig, Pavcnik and Wong 2022).

My treatment of FDI is closely related to the literature on multinational production (as reviewed by Antràs and Yeaple 2014; Bernard et al. 2018). The classic view on horizontal versus vertical FDI focuses on the substitutability and complementarity of trade and FDI between source and receiver countries (e.g., Helpman 1984; Helpman, Melitz and Yeaple 2004; Ramondo and Rodriguez-Clare 2013; Irarrazabal, Moxnes and Opromolla 2013; Tintelnot 2017; Arkolakis et al. 2018; Li, Nie and Wang 2020). It also relates to the extensive international macroeconomics literature on global capital allocations, including Portes and Rey (2005); Eaton et al. (2016); Alvarez (2017); Alessandria, Choi and Lu (2017); Reyes-Heroles (2017); Anderson, Larch and Yotov (2019); Ravikumar, Santacreu and Sposi (2019); Davis, Valente and van Wincoop (2021); Kleinman et al. (2022); Hu (2023).

Compared to these literature, I emphasize the Trump tariffs, using empirical moments to calibrate (heterogeneous) FDI diversion elasticities, which are crucial for the quantitative implications of the Trump tariffs. I also connect to the theory of optimal tariffs, traditionally focused on terms-of-trade manipulation incentives for imposing tariffs (e.g., Dixit 1985). I incorporate FDI location choice and producer profits, highlighting the significant roles of profit-shifting and relocation effects, through which tariff changes affect a country's aggregate and distributional welfare and alter incentives to impose tariffs (e.g., Venables 1987; Ossa 2011, 2014; Bagwell and Staiger 2012). Relatedly, Ju et al. (2024) shed light on another factor — industrial policy competitions — that influences tariff incentives, particularly in the context of the China-US trade war.

Another key contribution of my treatment of FDI recognizing the large heterogeneous responsiveness of FDI across country pairs, which cannot be accounted for in most FDI models in the literature. Recent studies develop various methods to study heterogeneous trade elasticities through flexible demand systems (e.g., Adao, Costinot and Donaldson 2017; Fajgelbaum et al. 2021) and flexible technologies (e.g., Farrokhi and Pellegrina 2023). I apply the generalized extreme value distribution method from Lind and Ramondo (2023) for my FDI analysis, offering a tractable yet flexible method to generate heterogeneous FDI elasticities governed by data. My quantitative exercises demonstrate that such heterogeneity has significant implications for both FDI diversion patterns and welfare outcomes.

1 The Evidence and Patterns of FDI Diversion

This section presents two empirical analyses of global FDI movements. The first analysis provides evidence that trade policy shocks, such as the Trump tariffs, generate systematic FDI responses, referred to as FDI diversion.[1] Most existing research employs shocks like bilateral trade and investment agreements to empirically analyze FDI responses. For example, McCaig, Pavcnik and Wong (2022) shows that the US-Vietnam Bilateral Trade Agreement, which reduced US import tariffs on exports from Vietnam, led to a significant increase in foreign firms in Vietnam. However, since it focuses on a single FDI receiver country, it is hard to quantify the magnitude of FDI responses with respect to other fundamental changes and answer questions such as the potential increase in FDI Vietnam might receive if the US further reduced import tariffs. Even in a multi-country context, the magnitude of shocks is difficult to compare across different investment agreements. By contrast, the shock of the Trump tariffs complements these empirical studies by offering a substantial shock that has the potential to affect many countries to varying degrees, allowing for comparable quantitative measurement.

[1]This concept of FDI diversion in response to trade and other external shocks is supported by anecdotal evidence. For example, European integration has led to significant relative capital formation and reallocation across economies within Europe, such as in Spain, Portugal, and Estonia following their accession to EU membership (see Baldwin and Wyplosz 2022). Additionally, there have been numerous concerns that China's integration into the world economy has diverted investment away from other developing economies.

After introducing the data, I construct a trade diversion index that gauges a country's exposure to the Trump tariffs. This index measures a country's potential to substitute for Chinese exports to the US in response to the Trump tariffs, and the significance of such export opportunities for that country. I show that countries with higher trade diversion indices tend to experience relatively larger increases in inward FDI stocks following the Trump tariffs. As a direct implication, I show in Online Appendix OA.2 that FDI diversion plays a significant role in a country's export responses to the Trump tariffs.

The second analysis offers suggestive evidence of the heterogeneous responses of FDI from different source countries to changes in FDI attractiveness in a receiver country. During the China-US trade war, some countries, like Vietnam and Mexico, have been regarded as winners due to their notable export and FDI growth. My analysis reveals systematic deviations from the predictions of FDI changes based on standard FDI gravity models and underscores the need to depart from existing benchmarks to account for the FDI movement patterns and welfare implications of the Trump tariffs.

1.1 FDI Data

I use two sources of FDI data. The first is the official data collected and published by governments and international agencies. I start with the OECD International direct investment database, which offers both country-level FDI aggregates, and FDI by partner country or by industry.[2]

[2]FDI data are based on statistics provided by 38 OECD member countries. The data is public and can be accessed from here: `https://stats.oecd.org/index.aspx?DataSetCode=FDI_FLOW_PARTNER`. The definition for FDI is: "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 criteria is used to establish that the direct investor has a significant degree of influence over the operations of the direct investment enterprise."

One major issue with FDI data for economic analysis is the complex financing structure of firms making these investments, including the use of special purpose entities (SPEs) to channel investments. My objective in analyzing FDI data is to capture the actual production capacity deployed in a receiver country and ultimately owned by a source country. In the OECD database, each reporting country provides different measures of FDI values. The domestic entity related to the FDI investments can be divided into either SPEs or non-SPEs, and the counterpart country can be measured by immediate or ultimate sources/destination. I prioritize using the receiver country's reported non-SPEs entities' FDI from an ultimate source country whenever the information is available. When non-SPEs entity or ultimate source country FDI is not available, I use the total (SPEs and non-SPEs) or immediate source country data. When the reporting country's information is not available, I will use the mirror data from other reporting countries.

The OECD database is limited in terms of available countries.[3] Thus, in addition to the OECD database, I use the Coordinated Direct Investment Survey (CDIS) compiled by the International Monetary Fund (IMF), which offers bilateral FDI positions for many more countries than the OECD database.[4] For certain economies that I need for quantitative exercises but are not fully covered by these databases, I manually collected data from national statistical offices. For aggregate inward FDI stocks still missing values, I further use UNCTADstat's foreign direct investment data on inward and outward stocks.[5][6] In sum, this combined dataset from multiple official FDI datasets offers unilateral inward FDI positions for most countries and bilateral FDI positions for a limited number of countries, from 2013 to 2021.

The second type of FDI data is a micro-project-level database called fDi Markets offered by *Financial Times*, which tracks cross-border greenfield investments globally since 2003. The fDi Markets database has two main advantages. First, it provides information about the industry of each project, allowing me to construct FDI information at a much more granular industry level, broadly at the three-digit NAICS 2012 level. Second, the database records greenfield investments exclusively, thus the complex financing structures (like SPEs) behind official FDI data are less of a concern. However, it is important to note that these advantages also result in a different definition of FDI compared to the official data. The FDI projects recorded through news and business agencies might vary in quality and coverage across countries. Moreover, FDI investments made through mergers and acquisitions are not included. I use the fDi Markets database as an independent and complementary source of information to assess FDI diversion. I will show that despite their different construction criteria, both the fDi Markets database and the official FDI data tell a similar story. To construct the dataset for my empirical analysis, I first extract all FDI projects

[3] It is more complete when one side of the country-pair is an OECD country, less so when neither is (e.g., China and Vietnam).

[4] I again prioritize the reporting country's inward FDI position and fill in using other information when missing.

[5] See `https://unctadstat.unctad.org/wds/TableViewer/tableView.aspx?ReportId=96740`.

[6] The reliability of these datasets, and thus the priority in terms of using these datasets for empirical analysis, depends on how well they measure the FDI stocks by addressing problems such as complicated financing structures. Both the OECD and CDIS datasets make concerted efforts to tackle these measurement issues, whereas other data sources are more prone to being affected by such complications.

from the database for a list of countries, with each country serving as either source or receiver. I then map all projects to their respective sectors and aggregate the projects to the source-destination-sector-year level to serve as a measure of bilateral FDI investment. Three variables are used as proxies for FDI investments: the number of projects, the estimated number of jobs created, and the estimated amount of capital invested, all cumulatively over the years.

1.2 Construction of the Trump Tariffs Trade Diversion Index

In 2018 and 2019, the United States increased tariffs on China that covered about $350 billion in trade flows. Similar to studies on trade diversion in the literature (e.g., Fajgelbaum et al. 2021), I assume that the product-level variations in tariff increases by the US on Chinese exports are not correlated with countries' specialization in goods produced for causal identification. Given that I do not have FDI data at the product level, I construct a trade diversion index at both the country and sector levels, using variation from the Trump tariffs across goods and countries' trade shares. This index is intended to capture the relative potential of each country to substitute for Chinese exports in meeting US demand.[7]

I take the HS 6-digit level tariff increases imposed by the US on China from Fajgelbaum et al. (2020).[8] I then use BACI trade flow data to construct weights for the tariff increases.[9] Intuitively, countries that specialize in goods hit by larger tariff increases from the US on Chinese exports are likely to experience a larger increase in diverted export demand. This potential increase is likely to be stronger if the US is a larger market for that good and for this country. Finally, the diverted export demand is likely to be greater if China was

[7]My construction of the trade diversion index follows a shift-share design, with the tariff variations across products being the shift, and trade share being the share. To identify the effect of this index on inward FDI stocks, the shifters need to be mean-independent of the shares, the potential outcomes (inward FDI stock growth for each country in absence of the Trump tariffs), and the treatment effects per unit of shifters on each country (see Proposition 1 in Adão, Kolesár and Morales 2019).

[8]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 are a series of tariff increases over the period of 2018 and 2019, while I treat it as a single event that happened in 2018. I use the simple average of the 2018 and 2019 scaled tariffs for each variety. Using other measures, such as the maximum tariff increase, does not qualitatively change my results.

[9]BACI provides data on bilateral trade flows for 200 countries at the product level (5000 products). Products correspond to the "Harmonized System" nomenclature (6-digit code). See http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37.

a prominent exporter of this good to the US. Thus, using the BACI trade value data from 2017 (and I suppress the t subscript below), for each good ν, I calculate country i's export revenue share, $r_i(\nu)$, country i's export revenue share from the US, $r_{\text{US},i}(\nu)$, and the US import share from China, $\pi_{\text{US,CN}}(\nu)$.[10]

Denoting the US tariff increase on China for good ν by $\Delta\tau_{\text{US,CN}}(\nu)$, the trade diversion index for country i is defined as:

$$\text{DI}_i = \sum_{\nu} r_i(\nu)\, r_{\text{US},i}(\nu)\, \pi_{\text{US,CN}}(\nu)\, \Delta\tau_{\text{US,CN}}(\nu). \tag{1}$$

When analyzing sector-level FDI responses, I define a similar country-sector level index, DI_{si}, by aggregating over all goods within a sector s.

1.3 FDI Diversion: Event Study Design

I employ an event-study specification, using the Trump tariffs implemented in 2018 as an exogenous shock. Specifically, the baseline specification uses country-level FDI data and runs the following regression

$$\ln \text{FDK}_{it} = \text{FE}_i + \text{FE}_t + \sum_{t'=2013, t'\neq 2017}^{2021} \vartheta_{t'} \mathbb{1}_{t'} \times \text{DI}_i + u_{it}, \tag{2}$$

where FDK_{it} is the inward FDI stock for country i at time t, and $\mathbb{1}_{t'}$ is the time dummy for year t'. I use FDI for general reference and FDK when specifically referring to the stock variable used in the empirical analysis.[11]

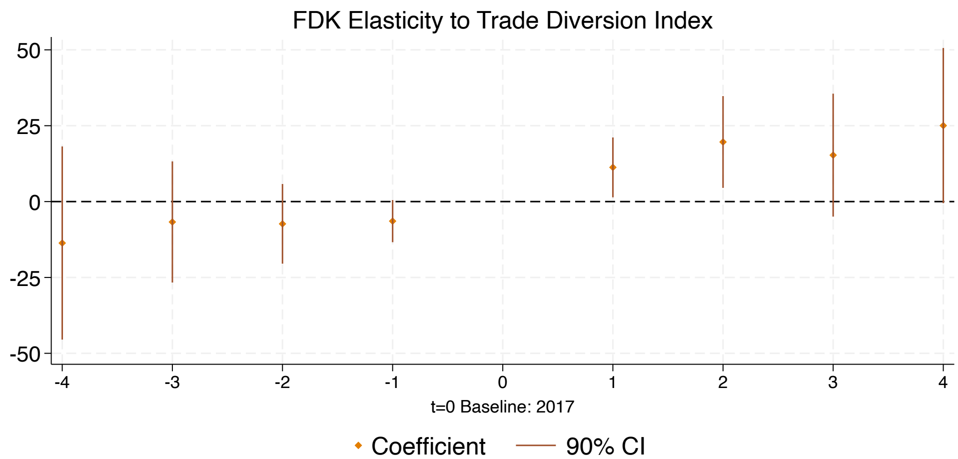
Figure 1 plots the coefficients $\vartheta_{t'}$, providing the baseline evidence for how FDI responds to the constructed trade diversion index. Given that the coefficients for post-event years are approximately 20, and the 95th percentile trade diversion index is around 0.004 (which

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

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

[11] I use FDK_{it}, the stock variable, instead of flow variable for empirical analysis because stocks are the originally reported number, and because flows are often negative and thus lead to many missing values.

is Vietnam), it suggests that the Trump tariffs led to a relative increase of roughly 8% in Vietnam's inward FDI stock compared to a country with a near-zero trade diversion index, such as Russia. Online Appendix OA.1.1 presents four different specifications of a similar regression, employing exchange-rate-adjusted FDK values, constructing the trade diversion index at the ISIC 2-digit level tariff changes[12], using bilateral FDK, and directly using the observed export growth as the explanatory variable instead of the trade diversion index. Across these alternative specifications used as robustness checks, I find a consistent positive relative effect of the trade diversion index on the post-shock inward FDK.



Notes: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax havens. This results in 117 countries included in the regression (2). The trade diversion index is constructed using equation (1), with ν at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 1: FDI Diversion and Trade Diversion Index

Figure 2 presents a similar result from a regression at the sectoral level, using fDi Markets data. The dependent variable is the cumulative estimated number of jobs created.[13] Online

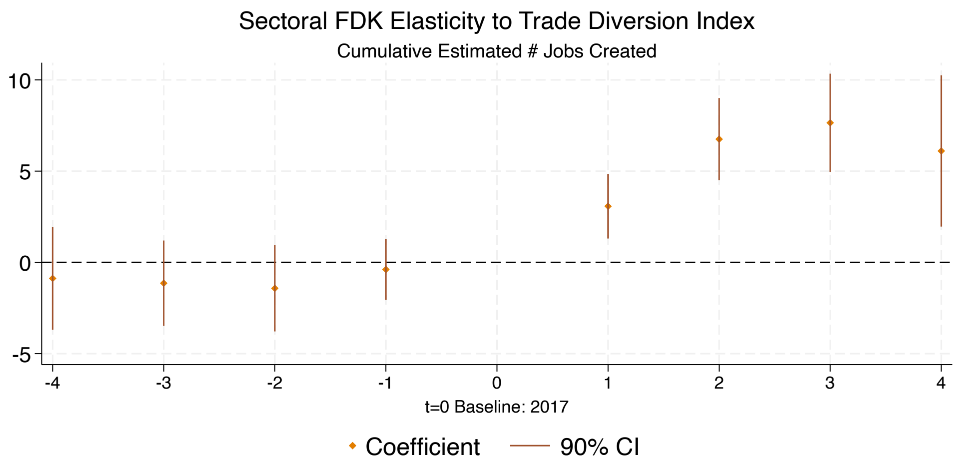
[12] This captures the idea that a country may be an ideal production location for a certain good, attracting FDI inflows not solely by specializing in that specific good, but also by being proficient in producing similar goods. For example, when dining tables are tariffed by the US, Vietnam doesn't need to be a good alternative solely based on its export of dining tables. If it specializes in other furniture's production, it could adjust its production capacity accordingly, making it a likely destination for increased FDI.

[13] More specifically, the regression is

$$\ln \mathrm{J}_{sit} = \mathrm{FE}_{it} + \mathrm{FE}_{st} + \mathrm{FE}_{si} + \sum_{t'=2013, t'\neq 2017}^{2021} \vartheta_{t'} \mathbb{1}_{t'} \times \mathrm{DI}_{si} + u_{sit},$$

where I control for the receiver-country-year, source-country-year, and sector-year fixed effects.

Appendix OA.1.2 shows the results of the other two dependent variables used to measure FDI investments, which are the cumulative number of projects and the cumulative estimated value of capital invested. All of these results point to the conclusion that the Trump tariffs divert FDI to more exposed countries.



Notes: The FDI data used are the fDi Markets database measure of greenfield FDI investments. The dependent variable is the cumulative estimated number of jobs created by these projects, aggregated at the source-receiver-sector level. The sectors are broadly categorized according to the NAICS 2012 3-digit level. I constrain the sample to include those receiver-sector pairs with at least 10 projects before 2017, and service sectors are excluded. This results in a sample of 31 receiver countries and 24 sectors. The regression controls for the receiver-year, receiver-sector, and sector-year fixed effects. The trade diversion index is constructed similarly to equation (1) at the country-sector level, with ν at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 2: Sectoral FDI Diversion and Trade Diversion Index

1.4 Heterogeneous Bilateral FDI Responsiveness

This section argues that the patterns of bilateral FDI changes exhibit a clear deviation from the predictions of most existing models of bilateral FDI with a gravity structure.[14] These models typically suggest that the changes of bilateral FDK have the following structure[15]

$$\mathrm{d}\ln \mathrm{FDK}_{ij} = \mathrm{d}\ln \mathrm{FE}_i + \mathrm{d}\ln \mathrm{FE}_j + \mathrm{d}\ln u_{ij}\,.$$

[14] In addressing the question of the patterns of FDI diversion, I consider my analysis to extend beyond the scope of the Trump tariffs as the sole drivers of FDI movement across economies.

[15] For example, see Ramondo and Rodriguez-Clare (2013) when there is no imports of home inputs associated with multinational production and no correlation across productivity in different locations, and Irarrazabal, Moxnes and Opromolla (2013) with constant headquarter input shares.

For example, the Trump tariffs might lead to a positive $\mathrm{d}\ln\mathrm{FE}_i$ for Vietnam and a positive $\mathrm{d}\ln\mathrm{FE}_j$ for China. However, the deviations from this benchmark model are evident in the following example.

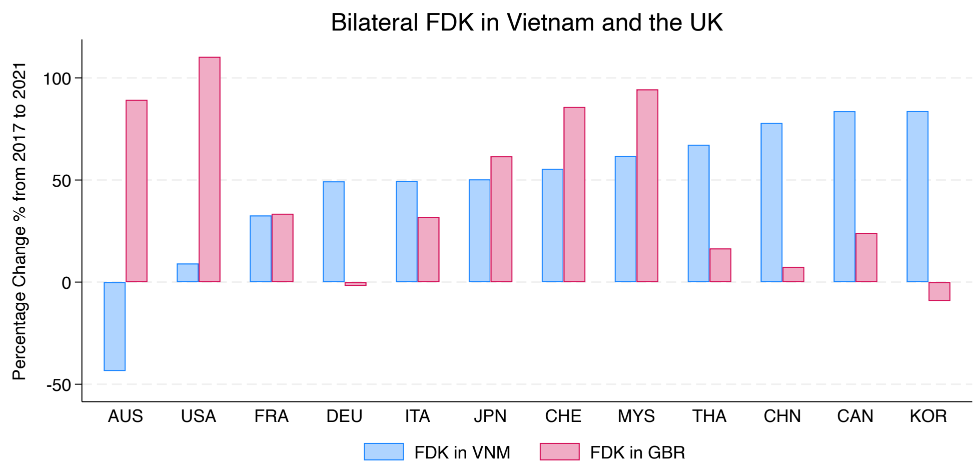


Figure 3: Deviation to Most Existing FDK Models

Vietnam and the UK experienced similar growth in their total inward FDI stocks from 2017 to 2021, indicating comparable receiver country factors. However, as illustrated in Figure 3, the source countries increasing their investments in Vietnam and the UK are notably different. Consider two source countries, such as China and France, with different incentives to increase their outward FDI stocks, the above benchmark model would predict that they increase their bilateral FDI investments either both more in Vietnam or both more in the UK. Any deviation from this prediction needs to be accounted for by the third term, $\mathrm{d}\ln u_{ij}$, which usually represents deviations due to bilateral operation frictions or trade costs.[16]

Importantly, I show that such deviations are systematically correlated with observable bilateral country characteristics, suggesting a systematic country-pair factor rather than purely idiosyncratic factors. In the above example, countries like Korea and China are those increasing their investments most in Vietnam, while countries such as Australia and the US are doing so in the UK, suggesting a systematic variation in FDI responsiveness that aligns with certain country characteristics.

[16]For instance, the two economies might enter a new treaty affecting FDI investments or could be influenced by unforeseen political tensions.

To explore this systematically, Regression (3) looks for factors that can explain the observed heterogeneity in FDI responses across country pairs:

$$\mathrm{d}\ln \mathrm{FDK}_{ij} = \mathrm{FE}_i + \mathrm{FE}_j + \boldsymbol{Z}_{ij}\tilde{\boldsymbol{\psi}} + \left(\mathrm{d}\ln \mathrm{FDK}_i \cdot \boldsymbol{Z}_{ij}\right)\boldsymbol{\psi} + u_{ij}, \tag{3}$$

where $\boldsymbol{Z}_{ij}$ represents a vector of observable bilateral country characteristics. The fixed effect FE_i captures all common factors that affect the bilateral inward FDI stocks in country i, and FE_j captures the changes of the source country's incentives for overall outward FDI investments. The receiver country's total inward FDI change, $\mathrm{d}\ln \mathrm{FDI}_i$, serves as a proxy for the change in the receiver country's attractiveness for FDI. Therefore, the interaction coefficients, $\boldsymbol{\psi}$, reflect how these observed country characteristics correlate with the magnitude of bilateral FDI responses. Table 1 reports results for coefficients $\boldsymbol{\psi}$.

	Outcome: $\mathrm{d}\ln \mathrm{FDK}_{ij}$
$\mathrm{d}\ln \mathrm{FDK}_i \times \ln(\mathrm{Dist}_{ij})$	-0.284**
	(0.122)
$\mathrm{d}\ln \mathrm{FDK}_i \times \ln\left(\mathrm{GDPpc}_j\right)$	0.156**
	(0.065)
$\mathrm{d}\ln \mathrm{FDK}_i \times \mathrm{ComparaAdv}_{ij}$	0.599**
	(0.283)
R^2	0.105
# of Obs.	2735

Notes: The FDI data used are official bilateral FDI stocks from the OECD and CDIS datasets. The dependent variable is the bilateral FDI growth from 2017 to 2019. The sample is limited to source countries with a sufficient number of investment destinations, resulting in 34 source countries and 199 receiver countries included in the regression. Distance between countries is obtained from the CEPII Gravity Database (version 202211). GDP per capita data is sourced from the World Bank's World Development Indicators (WDI). Comparative advantage similarity is calculated based on BACI trade values from the year 2017. Standard errors in parentheses are clustered at the receiver country level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1: Country Characteristics and the Magnitude of Bilateral FDI Responses

The first variable, $\ln(\mathrm{Dist}_{ij})$,[17] suggests that distance is negatively correlated with bilateral FDI *responses*, not levels, given the receiver's and source economy's unilateral FDI change. For example, it's likely that the response of Taiwanese FDI in Vietnam is especially high in part due to the close proximity of Taiwan to Vietnam. $\ln\left(\mathrm{GDPpc}_j\right)$ is the log of the source country's GDP per capita, which serves as a proxy for the general level of development

[17]Distance is the log of population-weighted distance between most populated cities of two economies (harmonic mean).

of the source country. The positive coefficient suggests that a more developed source country tends to have systematically larger FDI responses to a receiver country that attracts more FDI. Finally, ComparaAdv_{ij} is a measure of comparative advantage similarity, calculated as the correlation between two countries' export shares across industries, which correlates with a larger magnitude of FDI responses. For example, the correlation between China's and Vietnam's export shares across industries, and thus the measure of their comparative advantage similarity is 0.92. In contrast, the comparative advantage similarity for China and India is significantly lower, with a correlation of just 0.13.

While I do not claim that these are the only factors influencing bilateral FDI elasticities, the goal is to capture some observable systematic patterns of heterogeneous FDI diversion elasticities in a reduced-form way. I will show later that standard stochastic assumptions about FDI location choices fail to generate such heterogeneity in response to a common shock. One of the contributions of this paper is the application of a simple method to generate endogenous heterogeneous FDI elasticities across country pairs in a tractable way. This approach is also flexible enough to utilize empirical results from Table 1 to regulate the heterogeneity of FDI diversion elasticities in the model. This, in turn, quantitatively improves the model's predictions about FDI diversion. Accounting for such country characteristics is especially important for understanding the implications of the China-US trade war on countries such as Vietnam.

2 Model

I study a world economy consisting of N countries and S sectors. The model is static. Each country j is endowed with exogenous inelastically-supplied efficiency units of labor L_j and an aggregate firm productivity level z_j. For each country and sector, there is a fixed unit mass of producers indexed by ω. Each producer has a technology to produce a differentiated variety. Each ω is constrained to operate in one production country i and sells its variety to all potential importing countries h.[18]

[18] I assume that there is a large enough span-of-control cost such that no producers operate in multiple locations. I will generally index the source country (where the producers are from) by j, the production country by i, and the importing country by h.

I first outline the demand system that combines all varieties for the consumption of the representative household. I then specify the production technology and how producers make their production and location choices. Subsequent to defining the equilibrium, I analyze how shocks lead to FDI diversion, the mechanisms, and how to apply the tools of Lind and Ramondo (2023) that allow for heterogeneous FDI diversion elasticities across country pairs.

I discuss three model simplifying assumptions and their implications at the end of this section. First, I discuss the implications of dynamic transitions and extend the model to a dynamic version. Second, I discuss how the assumption that producers are restricted to one production location affects the elasticity of FDI diversion. Third, I offer some thoughts on extending the model to incorporate heterogeneity in both trade and FDI elasticities.

2.1 Household and Demand

For an importing country h and sector s, there is a producer of the sectoral composite good Q_h^s who supplies it at cost by purchasing and combining all tradable varieties. Let M_{ij}^s denote the set of varieties owned by producers from country j produced in country i in sector s. These tradable varieties are subject to two types of frictions between the production (or exporting) country i and importing country h: (i) iceberg trade costs d_{hi}^s, and (ii) one plus the ad-valorem tariff, denoted by τ_{hi}^s. More 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 $q_{hij}^s(\omega)$ is the quantity of ω in sector s imported by h, produced in i, and owned by a producer from j. ϵ^s is the sector-specific elasticity of substitution across varieties. The variety's corresponding price is $p_{hij}^s(\omega)$.

The sectoral composites are then purchased (at the associated price index P_h^s) and aggregated into the final good for household consumption

$$Q_h = \prod_{s=1}^{S} (Q_h^s)^{\phi_h^s}, \text{ s.t. } \sum_s \phi_h^s = 1,$$

where ϕ_h^s is the exogenous expenditure share for the sectoral composites. The corresponding final good price index is P_h.

The representative household consumes the final good, and the expenditure $P_h C_h$ equals the household's total income $w_h L_h + D_h + T_h - \Gamma_h$, which includes labor income and other incomes that are taken as given, including (i) the aggregate domestic producers' profits D_h, as all firms are ultimately owned by the household, (ii) government-collected tariff revenue T_h, and (iii) an exogenous country-level transfer Γ_h. The transfer could represent reserves or other mechanisms that affect the country's balance of payments but are not endogenously captured within the model.

2.2 Production

Each producer gets a productivity draw for each potential production location. Based on the outcomes of these draws and the respective values of operation in each location, the producer then decides where to establish its firm. Conditional on the production location choice, the producer solves its optimal production and pricing problem.

Let $\mathbf{a}_j^s(\omega) = \left\{a_{ij}^s(\omega)\right\}_{i=1}^N$ be the random vector of productivity draws that a producer ω from j in sector s receives across all potential production locations i. I will suppress the superscript s and the individual producer index ω with the understanding that the following set-up applies independently and symmetrically across all producers and sectors.

I assume that the vector $\{a_{ij}\}_{i=1}^N$ follows a max-stable multivariate Fréchet distribution characterized by a shape parameter θ, a scale parameter z_j, and a correlation function G^j,[19]

$$\mathbb{F}_{ij}(\mathbf{a}_j) \equiv \mathbb{P}\left(a_{1j} \leq a_1, a_{2j} \leq a_2, \ldots, a_{Nj} \leq a_N\right) = e^{-z_j G^j\left(a_1^{-\theta}, a_2^{-\theta}, \ldots, a_N^{-\theta}\right)}.$$

The correlation function G^j allows for a flexible structure for the dependence of productivity draws across different production locations i for producers from a source country j. This flexibility is crucial for generating heterogeneous FDI diversion elasticities across country pairs. To fix ideas, the common assumption in the literature is that productivity draws are independent across countries, as in Eaton and Kortum (2002), which corresponds to an

[19]For an introduction to this class of generalized extreme value distributions, see Lind and Ramondo (2023).

additive correlation function $G^j\left(a_1^{-\theta}, a_2^{-\theta}, \ldots, a_N^{-\theta}\right) = \sum_i a_i^{-\theta}$. In this case, a deviation to the attractiveness of location i as an FDI receiver country results in the same responsiveness from all source countries j, which is inconsistent with the empirical evidence. I will discuss later the specific form of the correlation function G^j and its implications, focusing on the heterogeneous FDI diversion elasticities across country pairs.

Consider a producer from j in sector s, operating in i with a productivity a. Conditional on this productivity, the producer uses a constant returns to scale technology and a single factor of production, namely labor, to produce

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

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

Given the production technology and the CES demand, each producer determines the price at which it sells its variety to importing country $h$and the quantity of labor to hire, subject to the constraint that the total output produced must equal the total quantities sold, taking into account trade costs: $\sum_{h=1}^N d_{hi}^s q_{hij}^s(a) = q_{ij}^s(a)$.

It is important to note that I abstract from fixed costs of exporting. I also abstract from fixed costs of operation by assuming a fixed mass of producers for each source country and sector, and that each producer is constrained to operate in only one location. These fixed costs are important for understanding the different margins of adjustments of trade and FDI as highlighted by Tintelnot (2017) for FDI. However, I will argue in more detail at the end of this section that abstracting from them enhances the model's tractability, and my calibration method matches the country-level aggregate FDI diversion elasticity as shown in the data. This approach is sufficient for the purpose of quantitative analysis, especially when the margins of adjustment is not the primary focus of this paper.

2.3 Equilibrium

Let π^s_{hi} be the import share of goods shipped from i to importer h in sector s. Let D^s_{ij} be the aggregate profits earned by producers from j who operate in i and sector s. Denote $D_j \equiv \sum_i \sum_s D^s_{ij}, \mathcal{D}_j \equiv \sum_i \sum_s D^s_{ji}$ as country j's total inward and outward profits. In this static framework, where capital is not explicitly modeled, profits serve as a proxy for FDI.

The goods market clearing condition is $Y_i = \sum_h \sum_s \frac{\pi^s_{hi}}{\tau^s_{hi}} X^s_h$, where $Y_i \equiv w_i L_i + \mathcal{D}_i$ is the total value of output in country i. The net export for country j is $\text{Net Export}_j \equiv Y_j - X_j$, and the net income is $\text{Net Income}_j \equiv D_j - \mathcal{D}_j$. The budget constraint for each country must be satisfied: $\text{Net Export}_j + \text{Net Income}_j + T_j - \Gamma_j = 0$.

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

2.4 Solution to the Producer's Problem

I solve the producer's problem in two steps. First, I solve the producer's optimal pricing and production problem, given the choice of production location. This gives us the value of operation in each location. Second, producers decide on the location of production, taking into account the values of operation in each location and the random productivity draws.

For a producer from j in sector s, operating in i, and selling to country h, the optimal price $p^s_{hij}(a)$ is set as a markup over marginal cost. The markup is $\frac{\epsilon^s}{\epsilon^s-1}$, depending on the sector-specific elasticity of substitution. The marginal cost depends on the trade costs, tariffs, bilateral operation frictions, the wage rate in the production location, and the producer's productivity. The optimal price is given by:

$$p^s_{hij}(a) = \frac{\epsilon^s}{\epsilon^s - 1} \frac{d^s_{hi} \tau^s_{hi} w_i}{a^{\frac{1}{\epsilon^s-1}} / \kappa^s_{ij}}.$$

The profit from selling to all importing countries h is

$$v_{ij}^{s}(a) \equiv \frac{1}{\epsilon^{s}-1} A_{i}^{s} w_{i}^{1-\epsilon^{s}} \frac{a}{\kappa_{ij}^{s}\,{}^{\epsilon^{s}-1}},$$

where $A_i^s = \sum_h \left(d_{hi}^s\right)^{-\epsilon^s} \left(\tau_{hi}^s\right)^{1-\epsilon^s} \left(\frac{\epsilon^s}{\epsilon^s-1}\right)^{-\epsilon^s} \left(P_h^s\right)^{\epsilon^s} Q_h^s$ captures the market access of country i as a production location for sector s.

Suppressing the superscript s, I derive in Online Appendix OA.3 the probability that a location i is the best choice for a producer from j

$$\mathbb{P}\left(v_{ij}\left(a_{ij}\right) = \max_{i'} v_{i'j}\left(a_{i'j}\right)\right) = \frac{\tilde{v}_{ij}^{\theta} G_i^j(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta})}{G^j(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta})},$$

where $G_i^j \equiv \frac{\partial G^j(x_1, x_2, \ldots, x_N)}{\partial x_i}$, and $\tilde{v}_{ij} = v_{ij}(1)$ is the profit of a producer from j operating in i with a normalized productivity $a = 1$, which I refer to as the value of operation in i for producers from j. The numerator measures how good location i is as a production location. The denominator is the sum of this measure across all locations, i.e., $G^j(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta}) = \sum_i \tilde{v}_{ij}^{\theta} G_i^j(\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta})$.[20]

The correlation function captures the correlation structure of productivity draws across locations. Given the value of operation for a location, if the productivity draw there is more correlated with locations with higher values of operation, it is intuitively less likely to be chosen. I will show later that not only the levels of location choice, but also the responsiveness depend on the correlation structure, which is important for understanding the patterns of FDI diversion in response to trade policies.

Given these firm level decisions, I can derive the aggregate variables, including producers' distributions, price indices, and bilateral trade and FDI flows. See Online Appendix OA.3 for details.

A key property of the model is that the producers' location choices will respond to changes in trade policies. For example, suppose that the US imposes a tariff increase on

[20] 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 $\mathbb{P}\left(v_{ij}\left(a_{ij}\right) = \max_{i'} v_{i'j}\left(a_{i'j}\right)\right) = \frac{\tilde{v}_{ij}^{\theta}}{\sum_{i'} \tilde{v}_{i'j}^{\theta}}$. Here, the choice probability depends solely on the relative value of $\tilde{v}_{ij}$ and the parameter θ.

Chinese exports in sector s: $\mathrm{d}\ln\tau^s_{US,CN}$. Holding the production location for each producer constant, producers will adjust their prices, leading to the standard trade diversion. Moreover, such shocks also bring about FDI diversion, as the production location choice depends on value of operation across locations, and thus trade fundamentals. To see this more clearly, China's market access in sector s, A^s_{CN}, is directly affected by $\mathrm{d}\ln\tau^s_{US,CN}$, which in turn affects the values of operation $\tilde{v}^s_{ij}$, and the equilibrium producer allocations $\tilde{\mathbb{F}}^s_{ij}(a)$.

2.5 Decomposition: Welfare Change Induced by Tariff Changes

To better understand how FDI diversion affects a country's aggregate welfare, namely its real consumption, and distributional welfare, I derive two decompositions. The first decomposition looks at different income sources, which are typically distributed among various population groups in reality (Helpman, Melitz and Yeaple (2004)). Using the country budget constraint:

$$\mathrm{d}\ln C_j \approx \frac{w_j L_j}{X_j}\frac{\mathrm{d}\ln w_j}{\mathrm{d}\ln P_j} + \sum_s \frac{D^s_{jj}}{X_j}\frac{\mathrm{d}\ln D^s_{jj}}{\mathrm{d}\ln P_j} + \sum_{i\neq j}\sum_s \frac{D^s_{ij}}{X_j}\frac{\mathrm{d}\ln D^s_{ij}}{\mathrm{d}\ln P_j} + \frac{T_j}{X_j}\frac{\mathrm{d}\ln T_j}{\mathrm{d}\ln P_j} - \frac{\Gamma_j}{X_j}\frac{\mathrm{d}\ln \Gamma_j}{\mathrm{d}\ln P_j}. \tag{4}$$

The first term can be interpreted as a weighted change in consumer surplus, if one equates the notion of "consumer" with the notion of "worker". Similarly, the second and third term can be interpreted as a weighted change in producer surplus (distinguishing between those from domestic operations and foreign operations), and the final two terms as a weighted change in government surplus.[21]

Next, to highlight the mechanisms due to FDI diversion that make the implications of the Trump tariffs differ from existing papers, one can show by replacing the aggregate price

[21] As discussed in footnote 11 of Ossa (2014).

index:

$$
\begin{aligned}
\mathrm{d}\ln C_j \approx\ & \frac{w_j L_j}{X_j}\,\mathrm{d}\ln w_j + \sum_i \sum_s \frac{D_{ij}^s}{X_j}\,\mathrm{d}\ln w_i - \sum_i \sum_s \frac{\mathcal{T}_{ji}^s}{X_j}\,\mathrm{d}\ln w_i \\
& + \sum_i \sum_s \frac{D_{ij}^s}{X_j}\left(\mathrm{d}\ln D_{ij}^s - \mathrm{d}\ln w_i\right) \\
& + \sum_i \sum_s \frac{1}{\epsilon^s - 1}\frac{\tau_{ji}^s \mathcal{T}_{ji}^s}{X_j}\sum_{j'} \omega_{ij'}^s\,\mathrm{d}\ln \tilde{M}_{ij'}^s \\
& + \sum_i \sum_s \frac{\left(\tau_{ji}^s - 1\right)\mathcal{T}_{ji}^s}{X_j}\left(\mathrm{d}\ln \mathcal{T}_{ji}^s - \mathrm{d}\ln w_i\right) - \frac{\Gamma_j}{X_j}\,\mathrm{d}\ln \Gamma_j\,,
\end{aligned} \tag{5}
$$

where $\mathcal{T}_{ji}^s \equiv \frac{\pi_{ji}^s}{\tau_{ji}^s} X_j^s$ is 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 that are owned by producers from j.

The first line on the right-hand side, the terms-of-trade effect of tariff changes, exists even without FDI diversion. This effect captures the differential changes in world prices of the production and consumption bundles of country j. Compared to a model without FDI, the world price changes of country j's production bundle include not only the price changes of goods produced directly within country j but also those produced in all other countries. The respective weights for these price changes are j's income shares from domestic production and production in another country i. The price change of the consumption bundle is the weighted average of all wage changes with the weights being the factual import value shares.[22]

The second line represents the profit-shifting effect, which captures changes in country j's real income due to changes in its aggregate profits originating from changes in industry output. Notice that the profit deviation term actually includes effects arising from changes in the mass of producers, while the wage deviation term, reflecting production cost, does not. Thus, this term reflects profit-shifting effect averaged over the new mass of producers. I interpret this term as a weighted change in producer surplus.

The third line is the production relocation effect. Household j consumes varieties that are exported from all countries i, while the varieties produced in i are again from all potential

[22] Following existing literature, I define terms-of-trade as the ratio between the ex-factory price of a foreign variety and that of a domestic variety. Since labor is the only production factor and that producers charge a constant markup, wage changes are proportional to changes in the ex-factory prices.

source countries j'. When tariff changes induce producers to relocate to places that are cheaper to serve consumers in j, it leads to a reduction in the aggregate price index for consumers in j, positively impacting their welfare. I interpret this term as a weighted change in consumer surplus.[23]

The fourth term represents the tariff-revenue effect, which comes from changes in import volumes, and the last term captures changes in the values of the exogenous transfer term.

As I will show in the quantitative section, not only does FDI diversion significantly alter the magnitude of welfare implications, but it also changes the channels through which a country is impacted, as per this decomposition. For example, a key finding from existing research on the US-China trade war (e.g., Fajgelbaum et al. 2020) is that the US consumers suffer from higher import prices, while producers benefit from the Trump tariffs. However, when considering FDI diversion, the scenario alters significantly. I will illustrate that US consumers actually experience gains from a substantially lower price index due to the relocation effect. Conversely, US producers face losses due to increased domestic production costs and diminished foreign profits.

2.6 Heterogeneous FDI Diversion Elasticities

I derive in Online Appendix OA.3 an aggregate profit allocation equation,[24] i.e., the aggregate sectoral profits by operating in country i for producers from j equal:

$$D_{ij}^s = \frac{\left(\tilde{v}_{ij}^s\right)^\theta G_i^j}{G^j} D_j^s,$$

where the first term in fraction is the probability that location i is chosen.

I now examine the determinants of the magnitude and heterogeneity of the elasticity of

[23] Ossa (2014) discusses a close mathematical and economic connection between the profit-shifting and relocation effects. Tariffs lead to changes in output at the intensive margin without free entry and at the extensive margin with free entry. The former leads to the profit-shifting effect, while the latter leads to the relocation effect. In my environment with both production location choices and profits (due to a fixed total mass of producers and no entry), both effects are present. Moreover, in an environment with only domestic production, a single sector, and constant markups, a positive profit-shifting effect also implies a positive relocation effect. However, with foreign production or FDI, as in this paper, these two effects might operate in different directions.

[24] In the baseline static model without capital, profit allocations are the same as FDI stock allocations.

the FDI diversion with respect to the values of operation $\tilde{v}_{ij}^s$ due to shocks such as tariffs, which hinge on the assumption of the correlation function G^j. I will start with two examples featuring standard assumptions that have been used in the literature (e.g., Ramondo and Rodriguez-Clare 2013; Arkolakis et al. 2018). An important feature of these assumptions is that they do not generate heterogeneous FDI elasticities.

Example 1: No correlation. Consider a correlation function that implies independence of draws across locations, $G^j(x_1, x_2, \ldots, x_N) \equiv \sum_{i=1}^N x_i$. In this case, the FDI gravity simplifies to $D_{ij} = \frac{(\tilde{v}_{ij})^\theta}{\sum_{i'}(\tilde{v}_{i'j})^\theta} D_j$. Using $\tilde{v}_{ij} = A_i w_i^{1-\epsilon^s} / \kappa_{ij}^{\epsilon^s-1}$, and defining $\tilde{A}_i \equiv A_i w_i^{1-\epsilon^s}$, the first-order deviation of D_{ij} across two equilibria in response to any shocks is

$$\mathrm{d}\ln D_{ij} = \theta \left[\mathrm{d}\ln \tilde{A}_i - (\epsilon^s - 1)\,\mathrm{d}\ln \kappa_{ij} \right] + \mathrm{d}\ln \frac{D_j}{G^j}\,. \tag{6}$$

$\mathrm{d}\ln \tilde{A}_i$ captures the changes in the attractiveness of i as an FDI receiver country (either due to changes in market access or cost of production). There are two observations from this equation on the FDI diversion elasticities. First, the magnitude of the FDI diversion elasticity is governed by the dispersion parameter θ. When θ is larger, the dispersion of productivity draws is smaller, and thus the changes in the values of operation have larger impacts on the producers' location choices, and thus the FDI diversion.

Second, the FDI diversion elasticities are homogeneous in the sense that, conditional on the source and receiver country fixed effects, the only remaining bilateral variation comes from $\mathrm{d}\ln \kappa_{ij}$. In other words, without changes in $\mathrm{d}\ln \kappa_{ij}$, for whatever shocks that lead to $\mathrm{d}\ln \tilde{A}_i$ across i, the bilateral FDI growth from any source country j to two different receiver countries should be proportional to $\mathrm{d}\ln \tilde{A}_i$. In the absence of a predefined relationship between the changes in bilateral operation frictions and country characteristics, this model would fail to find country characteristics that could systematically explain the magnitude of bilateral FDI elasticities across country pairs, in contrast to the empirical evidence.

Example 2: Uniform correlation. As an intermediate step, suppose the correlation function is $G^j(x_1, x_2, \ldots, x_N) = \left(\sum_{i=1}^N x_i^{\frac{1}{1-\rho}}\right)^{1-\rho}$ with $0 < \rho < 1$, which introduces correlation to productivity draws across locations. A higher value of ρ means less dispersion of productivity draws across locations, as draws become more similar. Consequently, producers will be more responsive to substitute across locations when relative values of operation change. To see this more clearly, the first-order deviation of D_{ij} across two equilibria becomes:

$$\mathrm{d}\ln D_{ij} = \frac{\theta}{1-\rho}\left[\mathrm{d}\ln \tilde{A}_i - (\epsilon^s - 1)\,\mathrm{d}\ln \kappa_{ij}\right] + \mathrm{d}\ln \frac{D_j}{(G^j)^{\frac{\rho}{1-\rho}}}.$$

The FDI diversion elasticity is now characterized by $\theta/(1-\rho)$. However, the elasticities are still homogeneous across all country pairs.

Example 3: Bilateral correlations. Finally, I assume G^j is a cross-nested CES (CNCES) correlation function used in this paper, with a specification that combines the above two extreme cases together:

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

One way to understand this correlation function is that there are two latent technology types available for producers by which to operate their firms. Within each technology type, the productivity draws across locations can be correlated. The first latent technology nest, with uncorrelated productivity draws, captures the idea that there are certain technologies where the productivity draws across production locations are idiosyncratic, with no predictability in how effective a technology in one country is in terms of its effectiveness in other places. Instead, the second technology nest represents technologies with such predictability, parametrized by the correlation coefficient ρ. In this case, the quality of a_{ij}^s gives some indication of the quality of $\left\{a_{i'j}^s\right\}_{i' \neq i}$ in other locations.

These latent technology types with different correlations build in the idea of the "fit" between technologies and production locations. For example, the productivity of certain goods might be heavily reliant on the supply chain network, leading to a high correlation in an individual producer's productivity across a set of locations.

A larger η_{ij} indicates that such goods account for a larger fraction of all investments from

j to i.[25] In Online Appendix OA.3, I show the exact formula of how η_{ij} and the correlation parameter ρ determine the cross-substitution elasticities across country pairs, i.e., making the coefficient of $\mathrm{d}\ln \tilde{A}_i$ in the above bilateral profit allocation deviation equation heterogeneous across countries. I paramatrize these heterogeneous coefficients and use observable country characteristics in Section 1 for calibration, which is crucial for aligning the model with the empirical findings presented before.

2.7 Discussion of Simplifying Assumptions

Simplifying Assumption 1: Static Model. The model is formulated as a static framework. However, transition dynamics are interesting and potentially important, as the elasticities of producers' relocation decisions might differ from those in a static framework, and the welfare implications need to take these transitions into account. Furthermore, when there is explicit modeling of capital in a world with FDI, the usual trade-off between investment and consumption becomes more intricate. For example, Vietnam does not need to sacrifice domestic consumption if all the increasing investment in Vietnam is made by foreign producers. Of course, the flipside is that the profits from this increased production capacity go to foreign owners.

In Online Appendix OA.3, I extend the static baseline model to a dynamic version with explicit capital investments. The representative household in each country makes consumption and saving decisions, and the saving are lent to domestic producers for investments. Producers use both capital and labor for production, and the investment for capital is subject to an endogenous interest rate.

Producers make similar production and location choices as in the static model. However, they could choose to move or not. They make relocation decisions only if they find that the expected value from operating in a new location — with new draws of productivities — is greater than the value of operation at the current location. The steady-state equilibrium of

[25] For example, if Chinese technologies in manufacturing exhibit high correlation across production locations in Asia due to a closely integrated supply chain network within the region, and if most of Chinese investments in Asian countries are in the manufacturing sector, the manufacturing sector would map into a latent technology nest with high correlation, and the η_{ij} would be high when j is China and i is an Asian country.

the dynamic model retains the properties in the static baseline model.

Simplifying Assumption 2: One-Location Firms. I assume that each producer is limited to operating in a single location, ruling out the possibility that one variety is produced in multiple locations to serve different markets. The key advantage of this simplifying assumption is that it rules out the joint decision across multiple locations for a firm, which results in a complicated combinatorial problem, as in Tintelnot (2017); Morales, Sheu and Zahler (2019); and Alfaro-Urena et al. (2023).[26]

This assumption, however, has implications for the FDI diversion elasticities. When the US imposes tariff increases on Chinese exports, a producer may choose to only move the operation serving the US market to other locations, while retaining its operation that serves China and other markets within China. This implies a smaller capital movement out of China conditional on moving, but at the same time, a higher likelihood of movement for each producer.

Without more detailed data on firm relocation, I cannot speak to the different margins of FDI diversion for each individual producer. Although it is certainly interesting to explore how finite operation fixed costs would change the elasticity of FDI diversion in the model and its implications, I target the aggregate elasticity of FDI diversion at the country level in my calibration. Thus, the implications of my model at the aggregate level should be similar to a richer model with different margins of FDI diversion, alleviating the concerns when addressing the questions asked in this paper.

Simplifying Assumption 3: Homogeneous Trade Elasticity. Finally, I focus on the heterogeneity of the FDI diversion elasticities, while assuming a homogeneous trade diversion elasticity. Previous works, such as Lind and Ramondo (2023) have underscored the considerable heterogeneity in own- and cross-price elasticities of trade. For example, Chinese goods are estimated to be close substitutes for goods from Turkey for US consumers, but poor substitutes for goods from the US itself. Fajgelbaum et al. (2021) makes similar

[26] Alternatively, Arkolakis et al. (2018) makes the opposite assumption by replacing firm operation fixed costs with marketing fixed costs for each export destination, thereby allowing each market to be independently served from different production locations.

points specifically in the context of the China-US trade war, and highlights the importance of country-specific components in generating heterogeneous trade elasticities.

In the context of this model, the heterogeneity in trade elasticities is pertinent, as the incentives for FDI diversion are intertwined with trade fundamentals. When the US imposes tariff increases on China, Vietnamese exports to the US increase substantially, presumably because the goods that Vietnam produces are close substitutes for Chinese goods, which means that the incentive for increasing production capacity in Vietnam is larger. However, conditional on Vietnam being a much better production location for FDI due to the heterogeneous trade elasticities, it does not necessarily mean that FDI from certain source countries would respond more, which is what this paper focuses on — the heterogeneity of FDI diversion elasticities.

3 Calibration

I now take the model to data by calibrating it to the world economy in 2017 as the original equilibrium. The calibrated model has thirteen economies[27] and a combined rest of the world economy (labelled as WorldRest), and three sectors: (1) agriculture and mining, (2) manufacturing, and (3) service.

To calibrate the original equilibrium, I categorize the model's parameters into three groups. The first group of parameters is externally calibrated by direct measurement in the data, including $L_i, \phi_h^s, \tau_{hi}^s$. The second group includes fundamentals recovered by solving the model to match country-specific and bilateral observables, including $d_{hi}^s, \kappa_{ij}^s, z_j$. The last group of parameters includes elasticities for both trade and FDI. Trade elasticities ϵ^s are calibrated using a standard gravity regression with fixed effects. The FDI elasticities are calibrated using indirect inference, including θ, ρ, and η_{ij} that govern the country-pair magnitude and heterogeneity of FDI diversion elasticities.

[27] The calibrated economies include Australia, Canada, China, Germany and France (combined and labelled as DeFr), the UK, India, Japan and Korea (combined and labelled as JpKr), Mexico, Malaysia, South America, Taiwan, the US, and Vietnam.

External Calibration. I measure efficiency units of labor L_i by the product of employers (*emp*: number of persons engaged, in millions) and human capital (*hc*: human capital index, based on years of schooling and returns to education) from Penn World Table (PWT, version 10.01). I measure sectoral expenditure shares ϕ_h^s using the 2017 Inter-Country Input-Output (ICIO) Tables (OECD, 2021 edition). I also have PPP-adjusted total expenditures for each country from PWT. Together with nominal expenditures from ICIO, I can infer the price index P_i for each country. I use the ad-valorem equivalents of most-favored nation tariffs (AVEMFN) from WITS TRAINS for each HS 6-digit product. To get the sectoral level tariffs, I use the 2017 BACI bilateral trade data to get weighted tariffs between each country-pair and the three sectors.

Recover Original Steady State Fundamentals. With the externally calibrated parameters above, and conditional on the set of elasticities to be specified later, I find $\{z_j\}_{j=1}^{N}$, $\{d_{hi}^s\}_{h=1,i=1,h\neq i,s}^{N,N,S}$, $\left\{\kappa_{ij}^s\right\}_{i=1,j=1,j\neq i,s}^{N,N,S}$ to exactly match $\{X_j\}_{j=1}^{N}$, $\{\pi_{hi}^s\}_{h=1,i=1,h\neq i,s}^{N,N,S}$, $\left\{\lambda_{ij}^s\right\}_{i=1,j=1,j\neq i,s}^{N,N,S}$ for the 14 economies and 3 sectors for the year 2017.[28] The trade shares π_{hi}^s are from ICIO, by combining countries and sectors to my level of calibration. The bilateral capital stocks are from the official bilateral FDI data described in the empirical section for year 2017. I then get domestic capital stocks from the IMF Investment and Capital Stock Dataset (2021 version). With these two datasets, I calculate the capital shares across all receiver countries for each source country.

Since I don't have capital in the model, I target the corresponding aggregate profit shares. Specifically, I find $\left\{\kappa_{ij}^s\right\}_{i=1,j=1,j\neq i,s}^{N,N,S}$ such that λ_{ij}^s in my model equals $\frac{\mathrm{FDK}_{ij}^s}{\sum_{i'}\mathrm{FDK}_{i'j}^s}$ in the data, for all j and s.

Finally, productivity z_j intuitively affects total expenditure and income, conditional on other endogenous variables including price indices and fundamentals such as trade costs. Price indices, trade costs, and productivity cannot be separately identified if none of them can be measured directly (following the logic of Waugh 2010). Since I only have country

[28] The bilateral FDI stocks are only available at the country level. To get bilateral FDI stocks at the sector level, I use the fDi Markets to calculate the investment share of each sector for each country-pair in 2017. Specifically, using the cumulative number of projects invested from country j in country i in sector s in year 2017, denoted as N_{ij}^s, the sector bilateral FDI stocks from j in i in sector s is then $\frac{N_{ij}^s}{\sum_{s'}N_{ij}^{s'}}\mathrm{FDK}_{ij}$.

level measures of price indexes, I normalize the productivities to be the same across sectors for each country.

Trade Elasticities ϵ^s. Online Appendix OA.3 shows that the partial trade elasticities in the model are governed by the preference parameters ϵ^s alone, and we have a similar trade gravity equation to a model without FDI, despite the presence of FDI. Thus, I can use the standard regression method with fixed effects to estimate the trade elasticities using tariff changes as cost shifters (for sector 1 and 2). However, this standard method using tariff variations is not applicable to the service sector, as service trade (e.g., tourism, legal service) generally does not incur tariffs at customs. To circumvent this issue, I use another cost shifter in the literature, namely the real exchange rate (RER), for sector 3. See Online Appendix OA.4.1 for details, including specific regressions, the data used, and reconciliation across estimates using different shifters.

3.1 FDI Elasticities θ, ρ, η_{ij}

For the last set of parameters that govern FDI elasticities, there are no conventional methods of estimation in the existing literature. One of the challenges is the lack of well-measured cost shifters for FDI (e.g., shifters for κ_{ij}^s), akin to tariffs for trade. Based on the empirical estimations in Section 1, I use the following indirect inference method for calibration.

Intuitively, both θ, ρ and η_{ij} play a crucial role in determining the average level of the FDI diversion elasticities. The first two dictate the FDI elasticities corresponding to the two latent nests, while η_{ij} defines the weights between the two nests. Moreover, ρ and η_{ij} are directly related to the heterogeneity of the FDI diversion elasticities. (2) and (3) are the empirical regressions that capture the magnitude and heterogeneity of the FDI diversion elasticities and are thus used as targets for calibration.

To establish a direct connection between the parameters η_{ij} and the data, I parameterize η_{ij} using observable bilateral variables that have shown a significant correlation with the magnitude of the FDI responses in the empirical section. More specifically, I assume a functional form

$$\eta_{ij} = \frac{e^{\boldsymbol{Z}_{ij}\boldsymbol{\zeta}}}{1 + e^{\boldsymbol{Z}_{ij}\boldsymbol{\zeta}}}$$
$$\text{and } \boldsymbol{Z}_{ij}\boldsymbol{\zeta} = \zeta_0 + \zeta_1 \ln \text{dist}_{ij} + \zeta_2 \ln \text{GDPpc}_j + \zeta_3 \text{ComparaAdv}_{ij}. \tag{7}$$

As a result, the parameters to be calibrated are θ, ρ, and $\boldsymbol{\zeta}$. The targets for calibration come from the following regressions based on empirical data

$$\mathrm{d} \ln \text{FDK}_i = \vartheta \text{DI}_i + u_i, \tag{8}$$
$$\mathrm{d} \ln \text{FDK}_{ij} = \text{FE}_i + \text{FE}_j + \boldsymbol{Z}_{ij}\tilde{\boldsymbol{\psi}} + (\mathrm{d} \ln \text{FDK}_i \cdot \boldsymbol{Z}_{ij})\, \boldsymbol{\psi} + u_{ij}, . \tag{9}$$

The changes are calculated using data for 2017 and 2019. All regressions are run at the country level. For the corresponding regressions using simulated model data, I use profits in place of capitals.

To generate model moments, I need to take a stand on the specific shock processes that account for changes between the two periods, as different shocks would affect the estimates of coefficients.[29] To proceed, consider a set of shocks that are possible within the model, $L_j, \phi_h^s, d_{ij}^s, z_j, \tau_{ij}^s, \kappa_{ij}^s$, which hit the original equilibrium. For $L_j, \phi_h^s, \tau_{ij}^s$, I can directly measure the values in both 2017 and 2019. For $z_j, d_{ij}^s, \kappa_{ij}^s$, I first calibrate similarly the 2019 equilibrium to deduce the necessary values for these shocks, given the directly measurable shocks and parameters, including θ, ρ, and $\boldsymbol{\zeta}$. I then decompose the bilateral operation frictions into $\mathrm{d} \ln \kappa_{ij}^s = \mathrm{d} \ln \kappa_i^{s,\text{inward}} + \mathrm{d} \ln \kappa_j^{s,\text{outward}} + \mathrm{d} \ln \tilde{\kappa}_{ij}^s$, where $\mathrm{d} \ln \kappa_i^{s,\text{inward}}$ and $\mathrm{d} \ln \kappa_j^{s,\text{outward}}$ represent the deviations in the receiver's and the source country's unilateral inward- and outward-operation frictions, respectively. I assume that $\mathrm{d} \ln z_j$, $\mathrm{d} \ln d_{ij}^s$, $\mathrm{d} \ln \kappa_i^{s,\text{inward}}$, $\mathrm{d} \ln \kappa_j^{s,\text{outward}}$ are deterministic, while $\mathrm{d} \ln \tilde{\kappa}_{ij}^s$ follows an i.i.d. distribution. The actual data is then considered as the result of one realization of this stochastic process.

The calibration process is as follows. Given an initial guess of the parameters to be calibrated, $\theta, \rho, \boldsymbol{\zeta}$, I can get a non-parametric distribution of $\mathrm{d} \ln \tilde{\kappa}_{ij}^s$. I then simulate the

[29] This can be seen more clearly by examining the bilateral FDI deviation equation in Online Appendix OA.3, which suggests that the error terms are correlated with the regressors in equation (9).

realization of $\mathrm{d}\ln\tilde{\kappa}_{ij}^{s}$ many times, and run regressions (8) and (9), and calculate the median of estimates for $\zeta_1, \zeta_2, \zeta_3, \vartheta$ and standard error of estimates for ϑ. I adjust parameter guesses to minimize the discrepancy between the empirical and simulated estimates.

The parameters θ and ρ are intrinsically linked to the estimate of ϑ. The simulated shocks using the backed-out distribution of $\mathrm{d}\ln\tilde{\kappa}_{ij}^{s}$ give us a set of regression coefficients θ. It turns out that ρ exerts a considerable influence on the median of the ϑ estimates, while θ has large impacts on the standard error of the ϑ estimates in the model. Hence, I adjust θ, ρ to target for the point estimate and standard error of ϑ in regression (8) in the data.

The parameters $\boldsymbol{\zeta}$ in the model are directly linked to the corresponding estimates $\hat{\boldsymbol{\psi}}$. Although $\boldsymbol{\zeta}$ encompasses four parameters, with an extra one on the constant ζ_0, the empirical estimates have only three moments $\hat{\psi}_1, \hat{\psi}_2, \hat{\psi}_3$. However, the parameters $\boldsymbol{\zeta}$ only affect the η_{ij} in the model. Given a set of $\boldsymbol{\zeta}$, and a different value for ζ_0, I can always find another set of $\zeta_1, \zeta_2, \zeta_3$ that yield very similar η_{ij}.

Fitting of the Indirect Inference. Table 2 displays the calibration results for θ and ρ using regression (8), and Table 3 shows the calibration results for $\boldsymbol{\zeta}$ using regression (9). Figure OA.10 in Online Appendix OA.4.2 shows the resulting heatmap for η_{ij}.

	Outcome: $\mathrm{d}\ln\mathrm{FDK}_i$		Calibration	
	Data	Model	Parameter	Value
DI_i	18.67 **	18.29	ρ	0.82
	(7.83)	(7.60)	θ	5.79
R^2	0.471			
# of Obs.	117			

Notes: The first column reports empirical regression coefficient for ϑ. I constrain the sample to include the largest FDI receivers, while excluding those typically considered tax havens, which results in 117 receiver countries. The second column reports the median and standard error of regression coefficients from 10 model simulation runs. Finally, the last column reports the corresponding parameter values. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Calibration for FDI Elasticities: θ, ρ

	Outcome: $\mathrm{d}\ln\mathrm{FDK}_{ij}$		Calibration	
	Data	Model	Parameter	Value
$\mathrm{d}\ln\mathrm{FDK}_i \times \ln(\mathrm{Dist}_{ij})$	-0.169*	-0.176	ζ_1	-7
	(0.090)			
$\mathrm{d}\ln\mathrm{FDK}_i \times \ln(\mathrm{GDPpc}_j)$	0.117**	0.116	ζ_2	5
	(0.059)			
$\mathrm{d}\ln\mathrm{FDK}_i \times \mathrm{ComparaAdv}_{ij}$	0.576***	0.521	ζ_3	19
	(0.219)			
			ζ_0	-9.5
R^2	0.111			
# of Obs.	2621			

Notes: The first column reports empirical regression estimates of the interaction coefficients $\boldsymbol{\psi}$. I constrain the sample to include investors with sufficient large number of receivers, while excluding those typically considered tax havens, which results in 36 investor and 193 receiver countries. The second column reports the median of regression coefficients from 10 model simulation runs. Finally, the last column reports the corresponding parameter values. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Calibration for FDI Elasticities: $\boldsymbol{\zeta}$

4 Quantitative Implications of the Trump Tariffs

I now use the calibrated model to evaluate the quantitative implications of the Trump tariffs. I implement tariff increases at the sector level on Chinese exports to the US.[30] Aggregating over product-level tariff changes, weighted by the 2017 export values of goods from China to the US at the HS 6-digit level, the tariff increases at the sector level are 16.3% for agriculture and mining, and 19.7% for manufacturing.

I show that the aggregate welfare implications for each country, i.e., the real consumption responses, change significantly due to FDI diversion. This is illustrated by comparing the outcomes in the baseline model to those in which producers are held fixed in their original locations (the Fixed FDI model). I conduct two decompositions of the aggregate welfare changes to clarify the mechanisms and the distributional implications of the Trump tariffs. Given the substantial impact of FDI diversion on welfare outcomes of trade policies, I investigate the noncooperative "optimal" tariffs for the US and China. I show numerically

[30]The effects of the Trump tariffs may have extended beyond what is captured in the quantitative analysis here. In fact, many believe that the China-US trade war marked the beginning of a broader shift in globalization, potentially leading to the implementation of related policies targeting various aspects such as investment and technology control, and anticipatory effects. Acknowledging the potentially more complicated nature of the Trump tariffs, the exercise here is limited to the direct effects of a tariff shock.

how FDI diversion substantially raises countries' incentives to impose tariffs on their trading partners. I conduct comparative statics exericses to show how these results change with varying FDI elasticity parameters, highlighting the importance of FDI diversion elasticity calibration for the quantitative implications.

I present the model's predictions regarding the unilateral and bilateral FDI responses, which underscore the importance of heterogeneity in FDI diversion elasticities in shaping the patterns of FDI diversion. These predictions are compared with those from a model assuming homogeneous FDI diversion elasticities, where I set $\rho = 0$, maintain the values of $\theta, \epsilon^s, L_i, \phi_h^s, \tau_{hi}^s$ identical to their values in the baseline model, but recalibrate $z_j, d_{hi}^s, \kappa_{ij}^s$ to match the 2017 equilibrium observables.

Finally, although I focus on how FDI diversion changes the welfare implications of tariff changes, I also study the role of FDI diversion in a country's export responses in Online Appendix OA.4.6. Consistent with empirical results, I show that FDI contributes significantly to a country's export growth to the US in response to the Trump tariffs. Interestingly, there are large heterogeneities in the relative contributions from FDI and domestic production capacity across economies in the quantitative counterfactuals. I elucidate why FDI might be a more significant factor in influencing export responses in certain economies (e.g., Vietnam and Mexico) compared to others.

4.1 The Importance of FDI Diversion

Figure 4 shows the responses of the aggregate real consumption for each economy in the baseline model and in the Fixed FDI model. Let's first focus on the predictions across countries in the baseline model (blue bars). China experiences a real consumption loss of around 0.2% while the US experiences a gain of about 0.05%. Economies for which the US is a major export market, such as Canada, Mexico, and Vietnam, benefit significantly from the Trump tariffs. Conversely, economies more dependent on China than the US for export revenues, e.g., Taiwan and the Rest of the World, face negative impacts.

FDI diversion is a critical factor in these welfare outcomes. Absent FDI diversion, the welfare implications of the Trump tariffs differ markedly, with varying effects across different economies. When contrasting the implications from the baseline model with those from the

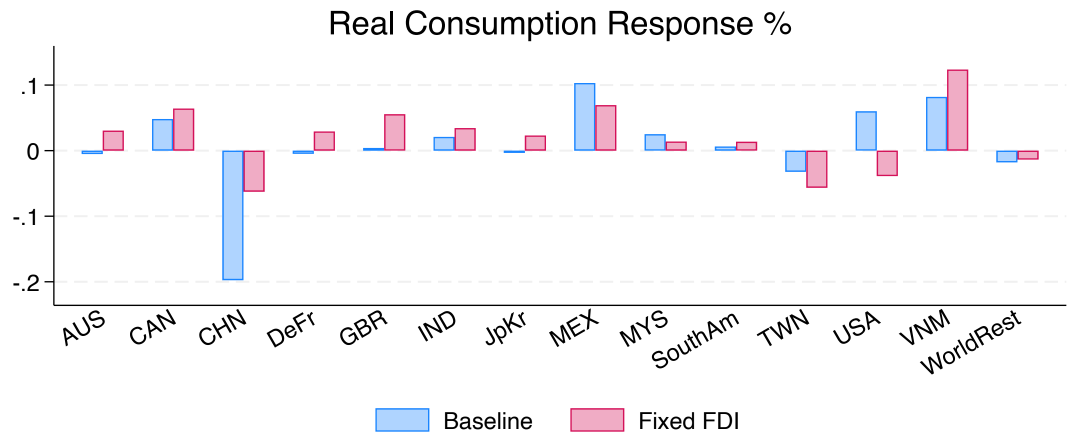


Figure 4: Real Consumption Responses: Baseline vs. Fixed FDI

Fixed FDI model, where producers are free to adjust their pricing and production decisions, while the producers are held fixed at their original locations, three key patterns emerge from this comparison.

First, eliminating FDI diversion significantly underestimates the welfare costs of the Trump tariffs on China, and reverses the sign of the welfare implication for the US. As I will show later when I decompose the aggregate welfare impacts into different sources, this is mainly due to the large wage rate effects driven by significant FDI outflow from China and inflow to the US.

Second, Mexico and Vietnam, the economies that gain the most from the Trump tariffs, experience divergent effects due to the presence of FDI diversion. Mexico's gains are larger in the baseline model than in the Fixed FDI model, whereas Vietnam sees the opposite effect. This is surprising given that both economies receive more FDI following the Trump tariffs (as will be demonstrated later). This difference stems from the general equilibrium effects of FDI diversion, which have adverse impacts on the real consumption of economies that heavily export to China, such as Vietnam, due to reduced income and expenditure in China. In contrast, Mexico's export revenues depend much more on the US than on China, and the increased US expenditure in the baseline model amplifies Mexico's benefits.

Third, for most economies, the impacts of the Trump tariffs are dampened in the baseline model, as FDI diversion provides additional leeway for the global economy to adjust. Several economies that are predicted to benefit from the Trump tariffs in a world without FDI diversion, such as Germany/France and Japan/Korea, experience slight negative effects in the baseline model.

4.2 Distributional Implications

Turning to the distributional implications in response to the Trump tariffs, I first break down the aggregate welfare changes into various incomes sources according to equation (4): wages, profits from producers operating domestically, profits from producers operating abroad, and the sum of tariff revenues and transfers.

Figure 5 presents the real consumption responses of China and the US, along with their decompositions. As previously discussed, FDI diversion leads to significant losses for China

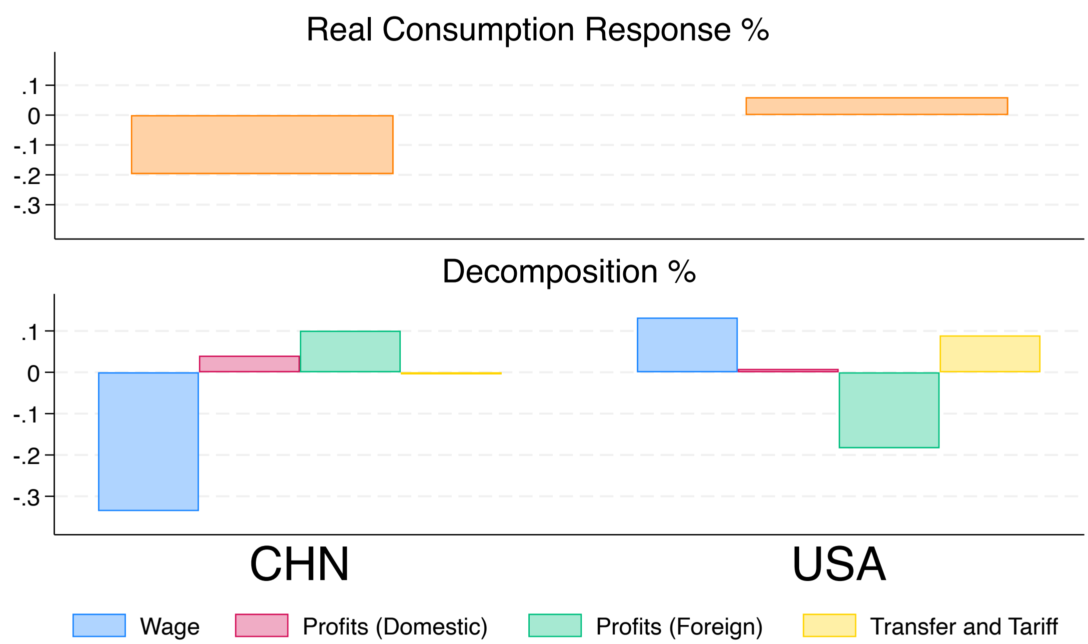


Figure 5: Real Consumption Implications for China and US

and gains for the US. In a world with FDI, the US attracts more FDI because of the Trump tariffs, which leads to an increase in domestic wages. In fact, one of the motivations behind the Trump tariffs, as argued by policymakers, is to encourage the return of manufacturing, thereby benefiting labor. US producers reduce their investments abroad, with some returning to the US. This shift results in a large decrease in US foreign profits and a slightly positive effect on domestic profits.

On the other hand, China's losses primarily come from a large decrease in its domestic wage rate due to decreased US import demand and FDI outflows. As producers from China relocate production to foreign economies, China earns higher foreign profits. Domestic profits also increase for Chinese producers. As foreign producers exit China, the domestic wage rate in China experiences an even more substantial decrease. This, in turn, results in a lower production cost for Chinese producers who continue to operate domestically.

Figure OA.11 in Online Appendix OA.4.3 presents the corresponding aggregate and distributional welfare implications for the two other economies that are significantly affected by the Trump tariffs, Mexico and Vietnam. Both economies experience an approximate 0.1% increase in aggregate consumption, primarily driven by increases in wage rates, while domestic profits for both countries decrease slightly. Instead, in a world without FDI or with Fixed FDI, both of the income sources would be positively affected. Figure OA.12 in Online Appendix OA.4.3 presents the corresponding results for the remaining calibrated economies.

The second decomposition, based on equation (5), offers a more theoretical perspective on the distributional implications of the Trump tariffs. Figure 6 highlights that for both the US and China, the most significant welfare implications of the Trump tariffs arise from the profit-shifting and relocation effects, outweighing the traditional terms-of-trade effect associated with tariff changes studied in the literature. The relocation effect, which reflects the changes in consumer prices due to shifts in producer locations, is argubly mostly relevant for the welfare of households as consumers. On the other hand, the profit-shifting effect, indicates how tariffs influence producer welfare.[31]

Contrary to the US case, China's losses from the Trump tariffs are mainly driven by

[31] Similar to a counterfactual exercise in Ossa (2014) (his Table 2), where a 50 percentage point increase in US apparel tariff, a high elasticity sector, leads to a negative overall profit-shifting effect, as it cuases a larger negative effect on other more profitable industries with higher markups, such as chemicals. In the above Trump tariffs example, the profit shifting effect is positive for the US in the manufacturing sector, but negative in other two sectors. Moreover, in an economy with FDI, producers from all economies who increase their operations in the US push up the wage rate in the US. Although the wage increase has the same effect on every producer, there are more US producers to begin with. Thus, the average profit-shifting effect for US firms, including those already there, and those relocating, is also more negative than firms from most other economies.

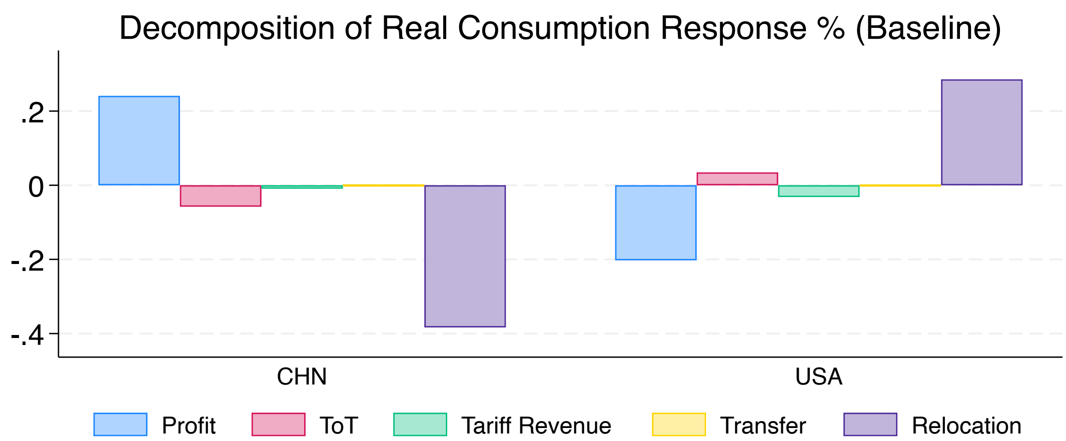


Figure 6: Decomposition of Real Consumption Responses: Baseline

the relocation effect. This is because some varieties become more costly when they need to be produced in and imported from foreign countries. However, the profit-shifting effect mitigates these losses due to lower domestic production costs. Additionally, the option for producers to relocate provides Chinese producers with some means to lessen the impact of the Trump tariffs.

These decompositions suggests that the Trump tariffs have very different implications for the consumer and producer sides, and thus distributional welfare implications, in the US and China compared to existing literature, such as Fajgelbaum et al. (2020). Figure OA.13 in Online Appendix OA.4.4 illustrates the real consumption response decomposition in a scenario with fixed FDI, where the relocation effect is absent. In this fixed FDI context, the profit-shifting effects are markedly smaller, and the predominant channel becomes the traditional terms-of-trade effect.

4.3 "Optimal" Tariffs

Given the significant impact of FDI diversion on the welfare implications of trade policies, a natural question arises: how does FDI diversion affect the incentives of countries to impose tariffs on their trading partners? In this section, I quantitatively explore the noncooperative "optimal" tariffs by the US and China through two exercises.

First, Figure 7 plots the welfare changes for the US and China as the US imposes a uniform tariff increase over Chinese goods from 0 to 80%, starting from the original equilibrium. The red line represents the welfare implications under the Baseline model, which includes FDI diversion, and the blue line under the Fixed FDI model, where FDI locations are held fixed.

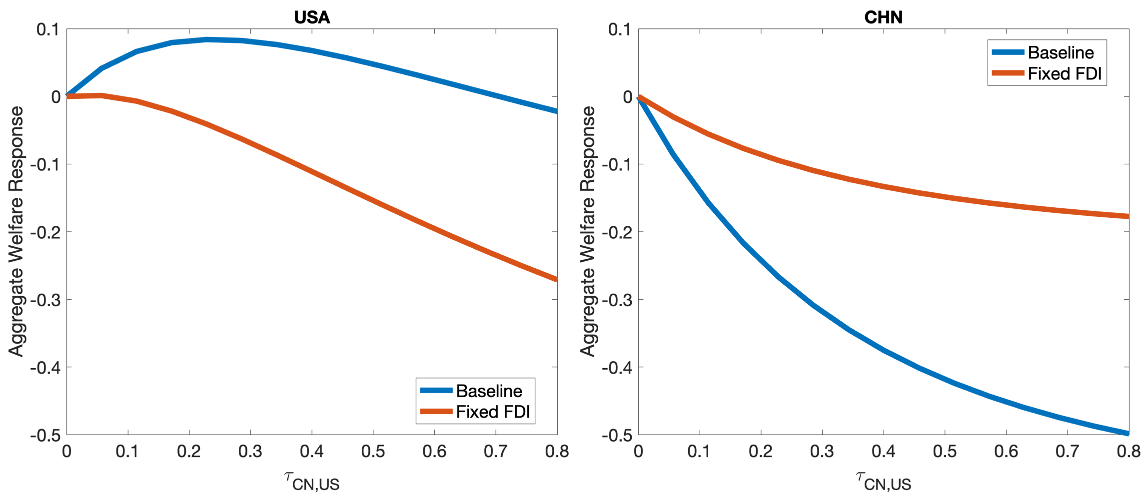


Figure 7: Optimal Tariffs by the US on Chinese Exports

This analysis assumes that China and all other countries do not respond to the US's tariff increases. FDI diversion greatly raises the "optimal" tariff level the US would prefer to impose on Chinese exports, by comparing the tariff increase that maximizes US welfare gains in cases both with and without FDI diversion. Conditional on the tariff increase, the Baseline case always implies a more beneficial role of the Trump tariffs to the US and larger negative impacts on China. For the US, the optimal level is significantly higher than in the Fixed FDI model, where even minor tariff increases start to have negative welfare implications.

Second, I turn to an analysis of Nash tariffs, where both China and the US increase tariffs on each other's exports, maintaining the assumption that other countries remain passive. When both countries respond optimally, taking each other's decisions as given,[32] the Nash

[32]Figure OA.14 and OA.15 in Online Appendix OA.4.5 show the best tariff response functions for both countries, under the Baseline and Fixed FDI models.

equilibrium tariff increases are numerically illustrated in Figure 8. This figure compares the Nash equilibrium tariff increases by the US and China under both the Baseline and Fixed FDI models. The key takeaway from these exercises is the significant increase in incentives

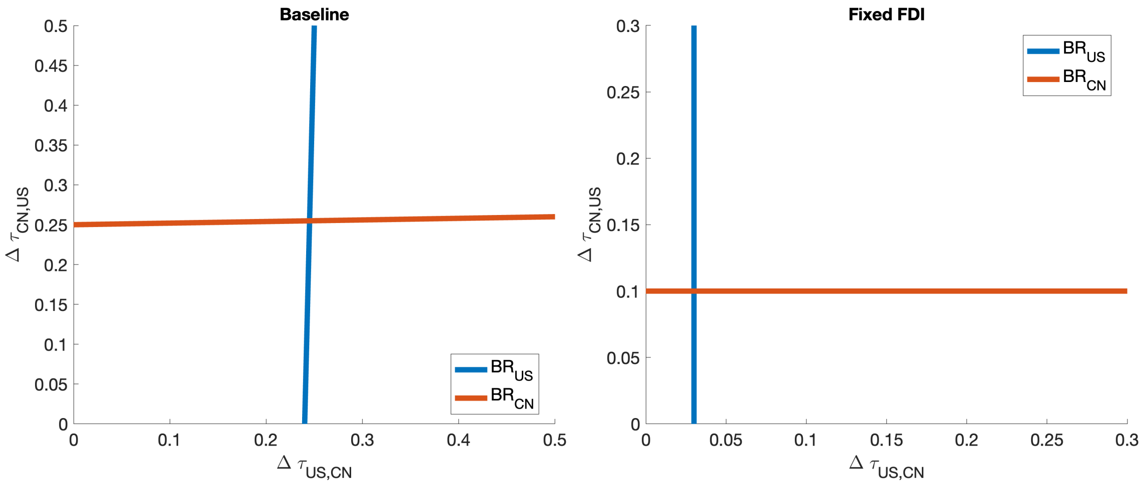


Figure 8: Nash Optimal Tariffs

for both countries to impose tariffs on each other due to FDI diversion, with equilibrium tariff levels rising from around 3% to 25% for the US on Chinese exports, and from around 10% to 25% for China on US exports.

4.4 Quantitative Importance of FDI Diversion Elasticity: θ

To show that the quantitative implications of the Trump tariffs largely depend on the magnitude of FDI diversion elasticities, which I regulate using empricial moments presented in Section 1, I now conduct comparative statics exericses to show how the above results change with varying elasticity parameter values. I focus on the role of θ, setting $\rho = 0$ (i.e., FDI diversion with homogeneous elasticities), to make the exercise more transparent.

In the left plot of Figure 9, I vary the value of θ on the x-axis, and conduct the Trump tariffs counterfactuals with a recalibrated baseline model, and show the aggregate welfare and the second decomposition (profit-shifiting, terms-of-trade, relocation) for the US and China. As θ gets larger, or FDI diversion becomes more elastic, the profit-shifiting and relocation effects are much larger, while the terms-of-trade effect remains relatively unchanged. On the right, I plot the numerical best response functions for China and the US for two values of θ

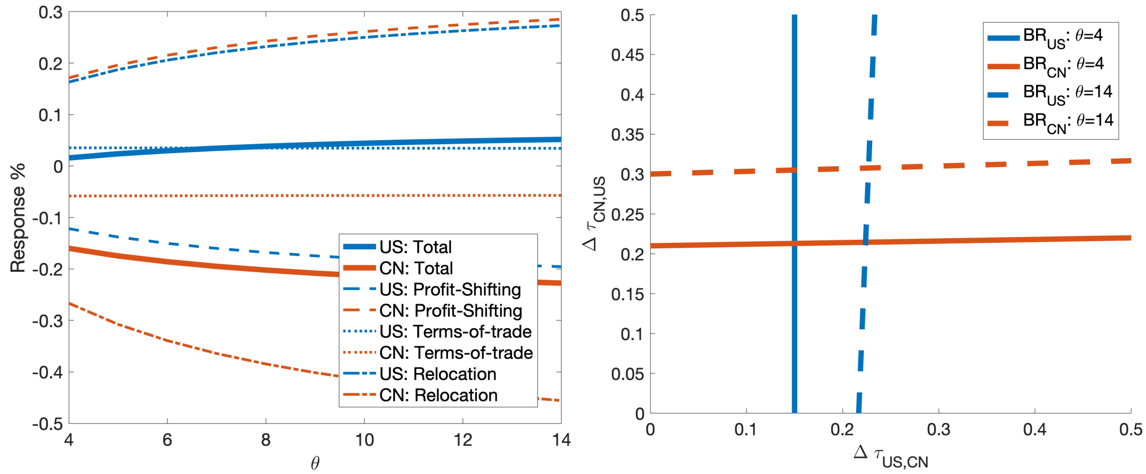


Figure 9: Varying θ: Welfare Decomposition & Nash Optimal Tariffs

(again, both with recalibrated models). The equilibrium Nash tariffs are significantly higher when θ is larger.

4.5 FDI Diversion: Homogeneous vs. Heterogeneous Elasticities

Finally, I present the model's predictions about FDI diversion and highlight the importance of taking heterogeneous FDI diversion elasticities into account. Figure 10 shows the inward FDI stock responses under the homogeneous and heterogeneous FDI elasticity models. Vietnam exhibits particularly different predictions between the two models. In

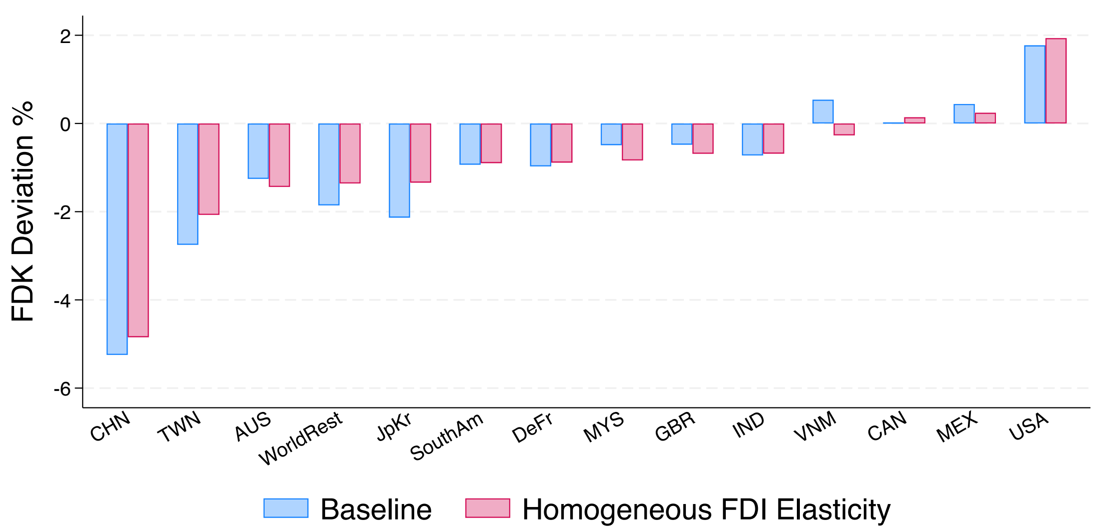


Figure 10: FDK Response: Baseline vs. Homogeneous FDI Elasticity

the Baseline model with heterogeneous FDI diversion elasticities, the increases in FDI investment from China to Japan/Korea and Vietnam are around 20%, while the increases are nearly zero for most other locations. In comparison, in the homogeneous FDI elasticity model, the increases of Chinese outward FDI are rather uniform and around 5% across all receiver economies. As a result, the overall increase of FDI for Vietnam is much larger in the heterogeneous model..[33]

The differences in FDI diversion patterns between the two models also extend to the welfare implications. Figure OA.18 in Online Appendix OA.4.7 shows the welfare responses and the decomposition for Vietnam under three different cases: the Fixed FDI model, the baseline model, and the model with homogeneous FDI diversion elasticities. By comparing models with homogeneous and heterogeneous FDI elasticities, the much larger increase in FDI in Vietnam in the heterogeneous model leads to a much larger increase in the wage rates, while a decrease in producer profits from domestic operations. Ignoring the heterogeneity in FDI elasticities would lead to markedly different conclusions about the distributional welfare implications, especially for countries like Vietnam.

5 Conclusion

This paper underscores the significance of accounting for FDI diversion, with empirically calibrated magnitude and heterogeneity of elasticities, when examining the effects of trade policies on trade and welfare. The recent China-US trade war serves as a pertinent case study in the context of today's highly interconnected global economy.

China, the US, and third-party countries are greatly affected by the Trump tariffs, and their experiences vary widely. FDI diversion changes both the mechanisms and the magnitude of the welfare implications of the Trump tariffs, leading to significant distributional implications. While China can mitigate some of the losses through outward FDI investments,

[33]In Figure OA.17 in Online Appendix OA.4.7, I provide a comparison between the bilateral FDI diversion predictions from the baseline and the homogeneous FDI elasticities model. The key difference between the two models is that, in the homogeneous FDI elasticity model, the source and receiver economy fixed effects explain most of the bilateral FDI responses, as in equation (6), and the pattern of FDI diversion is rather uniform across receiver economies for each source economy, and vice versa. Such predictions fail to capture the complexities of how the Trump tariffs are impacting economies, exemplified by the situation in Vietnam.

FDI diversion exacerbates concerns for the well-being of domestic labor and consumers. In the case of the US, the counterfactual scenarios suggest the potential to attract capital for reshoring. For other economies, it is important to understand the country-specific potential to attract FDI diversion for both the aggregate and distributional implications. Future research could delve deeper into empirical evidence and examine potential policy measures aimed at addressing these dimensions of the issue.

I demonstrate the critical role of heterogeneous FDI elasticities in understanding the patterns of FDI diversion. While this paper focuses on certain economic outcomes like wage rates and producer profits, the broader implications of FDI, such as technology diffusion, further emphasize the significance of this heterogeneity. Therefore, accurately capturing the varied responses of FDI to trade policies is crucial for a comprehensive understanding of their effects. Examining the microfounded mechanisms that lead to such heterogeneity is an area for future research.

References

Adao, Rodrigo, Arnaud Costinot, and Dave Donaldson. 2017. "Nonparametric Counterfactual Predictions in Neoclassical Models of International Trade." *American Economic Review*, 107(3): 633–89.

Adão, Rodrigo, Michal Kolesár, and Eduardo Morales. 2019. "Shift-Share Designs: Theory and Inference." *The Quarterly Journal of Economics*, 134(4): 1949–2010.

Alessandria, George, Horag Choi, and Dan Lu. 2017. "Trade Integration and the Trade Balance in China." *IMF Economic Review*, 65(3): 633–674.

Alfaro, Laura, and Davin Chor. 2023. "Global Supply Chains: The Looming "Great Reallocation"." National Bureau of Economic Research, Inc NBER Working Papers 31661.

Alfaro-Urena, Alonso, Juanma Castro-Vincenzi, Sebastian Fanelli, and Eduardo Morales. 2023. "Firm Export Dynamics in Interdependent Markets." National Bureau of Economic Research, Inc NBER Working Papers 31610.

Alvarez, Fernando. 2017. "Capital accumulation and international trade." *Journal of Monetary Economics*, 91: 1–18.

Amiti, Mary, Stephen J. Redding, and David E. Weinstein. 2020. "Who's Paying for the US Tariffs? A Longer-Term Perspective." *AEA Papers and Proceedings*, 110: 541–46.

Anderson, James, Mario Larch, and Yoto Yotov. 2019. "Trade and investment in the global economy: A multi-country dynamic analysis." *European Economic Review*, 120(C).

Antràs, Pol, and Stephen R. Yeaple. 2014. "Chapter 2 - Multinational Firms and the Structure of International Trade." In *Handbook of International Economics.* Vol. 4 of *Handbook of International Economics*, , ed. Gita Gopinath, Elhanan Helpman and Kenneth Rogoff, 55–130. Elsevier.

Arkolakis, Costas, Natalia Ramondo, Andres Rodriguez-Clare, and Stephen Yeaple. 2018. "Innovation and Production in the Global Economy." *American Economic Review*, 108(8): 2128–73.

Bagwell, Kyle, and Robert Staiger. 2012. "The economics of trade agreements in the linear Cournot delocation model." *Journal of International Economics*, 88(1): 32–46.

Baldwin, Richard, and Charles Wyplosz. 2022. *EBOOK The Economics of European Integration 7e.* McGraw Hill.

Bernard, Andrew B., J. Bradford Jensen, Stephen J. Redding, and Peter K. Schott. 2018. "Global Firms." *Journal of Economic Literature*, 56(2): 565–619.

Caliendo, Lorenzo, and Fernando Parro. 2019. "The Quantitative Effects of Trade Policy on Industry and Labor Locations." Society for Economic Dynamics 2019 Meeting Papers 1575.

Cavallo, Alberto, Gita Gopinath, Brent Neiman, and Jenny Tang. 2021. "Tariff Pass-Through at the Border and at the Store: Evidence from US Trade Policy." *American Economic Review: Insights*, 3(1): 19–34.

Davis, Jonathan, Giorgio Valente, and Eric van Wincoop. 2021. "Global drivers of gross and net capital flows." *Journal of International Economics*, 128(C): S0022199620301124.

Dixit, Avinash. 1985. "Tax policy in open economies." In *Handbook of Public Economics.* Vol. 1. 1 ed., , ed. A. J. Auerbach and M. Feldstein, Chapter 06, 313–374. Elsevier.

Eaton, Jonathan, and Samuel Kortum. 2002. "Technology, Geography, and Trade." *Econometrica*, 70(5): 1741–1779.

Eaton, Jonathan, Samuel Kortum, Brent Neiman, and John Romalis. 2016. "Trade and the Global Recession." *American Economic Review*, 106(11): 3401–38.

Fajgelbaum, Pablo D, Pinelopi Goldberg, Patrick J Kennedy, and Amit Khandelwal. 2020. "The Return to Protectionism." *The Quarterly Journal of Economics*, 135(1): 1–55.

Fajgelbaum, Pablo, Pinelopi Goldberg, Patrick Kennedy, Amit Khandelwal, and Daria Taglioni. 2021. "The US-China Trade War and Global Reallocations." Working Papers.

Farrokhi, Farid, and Heitor S. Pellegrina. 2023. "Trade, Technology, and Agricultural Productivity." *Journal of Political Economy*, 131(9).

Flaaen, Aaron, Ali Hortaçsu, and Felix Tintelnot. 2020. "The Production Relocation and Price Effects of US Trade Policy: The Case of Washing Machines." *American Economic Review*, 110(7): 2103–27.

Grossman, Gene, Elhanan Helpman, and Stephen Redding. 2023. "When Tariffs Disrupt Global Supply Chains." Working Papers.

Helpman, Elhanan. 1984. "A Simple Theory of International Trade with Multinational Corporations." *Journal of Political Economy*, 92(3): 451–71.

Helpman, Elhanan, Marc Melitz, and Stephen Yeaple. 2004. "Export Versus FDI with Heterogeneous Firms." *American Economic Review*, 94(1): 300–316.

Hu, Chenyue. 2023. "General Equilibrium Analysis of Multinational Financial and Trade Linkages."

IMF. 2023. "World Economic Outlook: A Rocky Recovery." International Monetary Fund.

Irarrazabal, Alfonso, Andreas Moxnes, and Luca David Opromolla. 2013. "The Margins of Multinational Production and the Role of Intrafirm Trade." *Journal of Political Economy*, 121(1): 74 – 126.

Ju, Jiandong, Hong Ma, Zi Wang, and Xiaodong Zhu. 2024. "Trade wars and industrial policy competitions: Understanding the US-China economic conflicts." *Journal of Monetary Economics*, 141(C): 42–58.

Khandelwal, Amit, and Pablo D. Fajgelbaum. 2022. "The Economic Impacts of the US–China Trade War." *Annual Review of Economics*, 14(1): 205–228.

Kleinman, Benny, Ernest Liu, Stephen Redding, and Motohiro Yogo. 2022. "Neoclassical Growth in an Interdependent World."

Lind, Nelson, and Natalia Ramondo. 2023. "Trade with Correlation." *American Economic Review*, 113(2): 317–53.

Li, Wei, Guangyu Nie, and Zi Wang. 2020. "Trade, FDI, and Global Imbalances." *Journal of International Money and Finance*, 105(C): S0261560620301443.

McCaig, Brian, Nina Pavcnik, and Woan Foong Wong. 2022. "FDI Inflows and Domestic Firms: Adjustments to New Export Opportunities." CESifo Working Paper Series 10168.

Morales, Eduardo, Gloria Sheu, and Andrés Zahler. 2019. "Extended Gravity." *The Review of Economic Studies*, 86(6): 2668–2712.

Ossa, Ralph. 2011. "A "New Trade" Theory of GATT/WTO Negotiations." *Journal of Political Economy*, 119(1): 122 – 152.

Ossa, Ralph. 2014. "Trade Wars and Trade Talks with Data." *American Economic Review*, 104(12): 4104–46.

Portes, Richard, and Helene Rey. 2005. "The determinants of cross-border equity flows." *Journal of International Economics*, 65(2): 269–296.

Ramondo, Natalia, and Andres Rodriguez-Clare. 2013. "Trade, Multinational Production, and the Gains from Openness." *Journal of Political Economy*, 121(2): 273 – 322.

Ravikumar, B, Ana Maria Santacreu, and Michael Sposi. 2019. "Capital accumulation and dynamic gains from trade." *Journal of International Economics*, 119(C): 93–110.

Reyes-Heroles, Ricardo. 2017. "The Role of Trade Costs in the Surge of Trade Imbalances." Society for Economic Dynamics 2017 Meeting Papers 212.

Tintelnot, Felix. 2017. "Global Production with Export Platforms." *The Quarterly Journal of Economics*, 132(1): 157–209.

Venables, Anthony. 1987. "Trade and Trade Policy with Differentiated Products: A Chamberlinian-Ricardian Model." *Economic Journal*, 97(387): 700–717.

Waugh, Michael. 2010. "International Trade and Income Differences." *American Economic Review*, 100(5): 2093–2124.

Waugh, Michael. 2019. "The Consumption Response to Trade Shocks: Evidence from the US-China Trade War." National Bureau of Economic Research, Inc NBER Working Papers 26353.