# Trade Wars with FDI Diversion*

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**Abstract**

This paper shows that taking into account the existence and patterns of foreign direct investment (FDI) diversion would significantly change the quantitative implications of trade policies, as exemplified by the Trump tariffs. I provide evidence of FDI diversion: 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. I build a multi-country general equilibrium model incorporating FDI diversion with heterogeneous elasticities and apply it to evaluate the impact of the Trump tariffs. The analysis highlights how FDI diversion leads to significantly different aggregate and distributional welfare implications, both in terms of scale and mechanisms. Additionally, FDI diversion creates more incentives for countries to implement tariffs. Finally, accounting for the heterogeneous bilateral FDI elasticities is important to fully understand the patterns of FDI diversion and the quantitative effects of the Trump tariffs.

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# 1 Introduction

One of the classic questions in international economics concerns the impacts of trade policies on trade and welfare. Recent literature, partly revived by the China-US trade war since 2018, focuses primarily on trade diversion — the substitution of goods exports across countries (e.g., Fajgelbaum et al. 2021). However, the China-US trade war also highlights the connection between changes in trade patterns and significant movements of productive capital. A showcase example is Vietnam, which is often portrayed as a winner from the China-US trade war. This is not only because Vietnam exports a lot more to the US replacing Chinese exports, but also because it attracts a large amount of foreign direct investment (FDI). In this paper, I extend a benchmark model of trade diversion to show that accounting for the existence and patterns of FDI diversion would significantly change the quantitative implications of trade policies such as the Trump tariffs.

The analysis proceeds in three steps. First, I present evidence of FDI diversion in the context of the Trump tariffs and document a salient feature of FDI stocks responsiveness across country-pairs. Then I develop a general equilibrium framework where trade shocks lead to both trade and FDI diversion. Finally, I offer this framework as an illustration of the mechanisms through which FDI affects trade and welfare, emphasizing the quantitative importance of these mechanisms in understanding the Trump tariffs.

I find that FDI responds to the Trump tariffs: countries more exposed to trade diversion from the Trump tariffs have relative higher inward FDI stocks following the China-US trade war. The patterns of FDI responses across country-pairs are highly heterogeneous, with elasticities systematically correlating with observable bilateral country characteristics. FDI diversion introduces multiple channels through which the Trump tariffs affect countries, significantly altering both the aggregate and distributional welfare implications. For example, FDI diversion amplifies China's losses resulting from the Trump tariffs, while flipping the welfare implication for the US from a net loss to a net gain. FDI diversion also increases the incentives of countries to impose tariffs on their trading partners. Finally, the heterogeneous bilateral FDI elasticities are crucial in accounting for the patterns of FDI diversion and the quantitative effects of the Trump tariffs.

To start, I construct a trade diversion index that captures 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, the inward FDI stocks for Vietnam is around 8% higher two years after the trade war than 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. For example, between 2017 and 2021, Vietnam and the UK both saw a similar growth rate in total inward FDI stocks. In the absence of idiosyncratic bilateral shocks, like trade cost or foreign operation frictions, most existing FDI models would predict that a source country with a larger increase in total outward FDI stocks should similarly increase their FDI stocks in both Vietnam and the UK. Contrary to this, countries like Korea and China significantly increased their FDI stocks in Vietnam but only marginally in the UK, while the reverse trend is observed for countries like Australia and the US. I call these observed patterns of bilateral FDI stock changes "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 are systematically larger, 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 standard FDI models in existing literature are inadequate for generating heterogeneous FDI responses, yet 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. The model highlights two key features that depart from most of the existing literature.

First, I think of FDI as domestic producers operating their firms in foreign countries, earning profits that are repatriated 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. I show through quantitative exercises that FDI diversion greatly changes not only the aggregate welfare implications of the Trump tariffs but also the distributional welfare implications. I decompose the aggregate welfare changes into different channels. With the presence of producer profits (with fixed mass of producers) and foreign production, two important welfare change channels arise, in addition to the traditional terms-of-trade effect: the profit-shifting effect and the relocation effect. The profit-shifting effect focuses on the impact on producer profits, whereas the relocation effect pertains to how consumer price indices are influenced by tariff changes.

Second, I apply a recently developed method to study trade elasticity heterogeneity (Lind and Ramondo 2023) and adapt it to my FDI problem. This approach provides a tractable yet flexible method to capture the observed heterogeneity in FDI responses. It also provides a particular interpretation — the idea of the "fit" between technologies with production locations — for the empirical patterns documented. As I will demonstrate in the quantitative exercises, the heterogeneity of FDI diversion elasticities greatly changes the pattern of FDI diversion, and thus the aggregate and distributional welfare implications of trade policies.

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. I perfectly match the country expenditures, bilateral trade shares, and FDI stock shares across countries. I use a standard gravity regression with fixed effects to recover parameters governing trade elasticities, and use indirect inference to calibrate the parameters that govern the magnitude and heterogeneity of FDI elasticities.

There are three bilateral country characteristics that I find to be correlated with the magnitude of FDI responses, which I use for calibration. The first is bilateral distance, a standard gravity variable impacting the level of trade flows and FDI in the literature. Here, bilateral distance also affects FDI responsiveness. When two countries are geographically closer, the FDI elasticity with respect to the value of operation is larger. The second is the source country's GDP per capita, reflecting its development level. More developed countries' FDI investments are systematically more responsive in the data. The final characteristic is a measure of comparative advantage similarity using the correlation between countries' export portfolios across industries. When two economies share similar comparative advantages, such as Vietnam and China, the FDI response is systematically larger.

While I do not claim that these are the only factors influencing bilateral FDI elasticities, this calibration procedure captures some observable systematic patterns of heterogeneous FDI elasticities in a reduced-form way. 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.

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 two decompositions to show the large distributional implications of the Trump tariffs within each country and to underscore the role of FDI diversion. The first decomposition is based on different income sources, primarily labor wages and producer profits from both domestic and foreign operations. Since these income sources are typically distributed among various population groups in reality, this decomposition offers a basic illustration of the distributional implications of the Trump tariffs. Economies that substitute more for Chinese exports 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 second decomposition is based on the theoretical channels of welfare changes due to tariff changes. I show that the two new channels — the profit-shifting effect, which relates more to a country's welfare as producers, and the relocation effect, which relates more to a country's welfare as consumers — are significant contributors to welfare changes. 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 show numerically 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 two exercises.

First, I explore the implications for US welfare following a uniform increase in tariffs on all sectors for imports from China, starting from the original equilibrium. This is based on the assumption that China and all other countries do not respond to the US's tariff changes. I show that FDI diversion greatly raises the "optimal" tariff that the US would like to impose on Chinese exports, by comparing the tariff increase that maximizes US welfare gains both with and without FDI diversion. Second, I turn to an analysis of Nash tariffs, where I assume that both China and the US increase tariffs on each other, while still assuming that other countries remain passive. The results indicate that the equilibrium Nash tariffs between China and the US are significantly higher in a scenario with FDI diversion compared to a scenario without it. This leads to lower welfare outcomes for both countries.

I further study the role of FDI diversion in a country's export responses to the Trump tariffs. Most economies increase their exports to the US, replacing Chinese exports. The contribution of FDI to export growth is particularly important for economies such as Mexico, Vietnam, Malaysia, but less so for economies like Japan, Korea, Germany, and France. The relative contributions of FDI and domestic production capacity hinge on the significance of foreign producers for the exporting country and the extent of FDI diversion. For example, in Mexico, foreign producers constitute a substantial portion of the manufacturing sector's production capacity, and Mexico also has seen large increases in inward FDI stocks.

Finally, I highlight the critical role of heterogeneous FDI diversion elasticities in shaping the patterns of FDI diversion and their subsequent implications. China experiences a large decrease in its inward FDI stock as it becomes a less favorable location for exports, while its outward FDI investment increases. These FDI changes are highly heterogeneous. Japan and Korea experience a much more pronounced percentage drop in their FDI stocks in China, whereas the decrease is less significant for Germany and France, owing to the difference in bilateral FDI elasticities. Similarly, 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. In comparison, a model assuming homogeneous FDI elasticities would predict much more uniform changes in bilateral FDI in and out of China.

Neglecting this heterogeneity would result in markedly different welfare outcomes for countries like Vietnam. Comparing the results from models with homogeneous and heterogeneous FDI elasticities, the larger increase in FDI stocks in Vietnam in the model accounting for heterogeneity leads to a more substantial rise in wage rates but a reduction in producer profits from domestic operations.

**Related Literature**

My paper contributes to the vast literature on the impact of trade policies. The recent China-US trade tension has 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, which are frequently featured in media headlines and are of considerable policy concern, e.g., IMF (2023). My paper offers a general equilibrium model that directly links FDI to trade and production fundamentals, and shows 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 the source and receiver countries (e.g., Helpman 1984; Helpman, Melitz and Yeaple 2004; Ramondo and Rodriguez-Clare 2013; Irarrazabal, Moxnes and Opromolla 2013; Arkolakis et al. 2018). In this paper, I emphasize the producer's choice of FDI location across all potential receiver countries, where the optimal location for a producer is used as an export platform (e.g., Ramondo and Rodriguez-Clare 2013; Tintelnot 2017).

Compared to these papers, I clarify the channels through which tariff changes affect a country's welfare. My decomposition, based on Ossa (2014), takes FDI production and producer profits into account, altering the traditional terms-of-trade effect and introducing two other important channels: the profit-shifting effect and the relocation effect. As a result, FDI diversion can have varying implications for household in a country as consumers and as producers, leading to large distributional effects.

My paper also contributes to the theory of optimal tariffs, which traditionally centers on the terms-of-trade manipulation incentives for imposing tariffs (e.g., Dixit 1985). Ossa (2014) discusses the profit-shifting effect, which is related to the relocation effect as in Venables (1987). In comparison, my model features both the profit-shifting and relocation effects, demonstrating their distinct impacts in a setting with FDI production. I show that FDI diversion greatly heightens the incentives for countries to impose tariffs on their trading partners. Relatedly, Ju et al. (2024) sheds 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 is to recognize the large heterogeneous responsiveness of FDI across source countries to a common shock to the receiver country, 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; Lind and Ramondo 2023). I apply the generalized extreme value distribution method from Lind and Ramondo (2023) for my FDI analysis, offering a tractable yet flexible enough method to generate heterogeneous FDI elasticities governed by data. I show through quantitative exercises that such heterogeneity carries large implications for both FDI diversion patterns and welfare implications.

My paper also relates to the large international macroeconomics literature on global capital allocations and country imbalances, 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); Li, Nie and Wang (2020); Davis, Valente and van Wincoop (2021); Kleinman et al. (2022); Hu (2023). As FDI generates income that is repatriated to the domestic owners, my model generates endogenous trade imbalances. By incorporating imperfect substitutability and frictions in goods and FDI, my model matches perfectly with data for both trade and FDI, rationalizing larger gross capital holdings than net holdings and capital flows from poorer to richer countries.

# 2 Empirical Evidence

This section offers two empirical analyses of global FDI movements. The first analysis provides evidence that trade policy shocks, such as the Trump tariffs, generate FDI responses in countries that are neither the instigator nor the target. This results in what I refer to as FDI diversion.

This concept of FDI diversion with respect 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). There have also been numerous concerns that China's integration into the world economy has diverted investment away from other developing economies.

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, namely Vietnam, it is hard to quantify the magnitude of FDI responses with respect to tariff 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 hard to compare across different investment agreements. By contrast, the shock of the Trump tariffs complements these empirical studies by offering a large enough shock that has the potential to affect many countries to varying degrees, which can be measured quantitatively.

After introducing the data, I construct a trade diversion index that gauges 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 then show that countries with higher trade diversion indices tend to have relatively larger increases in inward FDI stocks following the Trump tariffs. I show in Appendix A.3 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 a change of 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 considerable variations in bilateral FDI stock changes for the same FDI receiving country and systematic deviations from a standard FDI gravity model. Importantly, these deviations are not solely due to idiosyncratic bilateral shocks. Instead, part of these deviations is correlated with bilateral country observables, suggesting a systematic connection between country characteristics and FDI responsiveness. This empirical exercise highlights the need to depart from existing benchmarks to understand the FDI and welfare implications of the Trump tariffs.

## 2.1 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.[1]

The OECD database is limited in terms of available countries. 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). 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.[2] For certain economies that I will need for quantitative exercises but are not fully covered by the international 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.[3][4] In sum, this combined dataset from multiple official FDI datasets offers

[1]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 problem 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 how much actual production capacity is deployed in a receiver country and ultimately owned by a source country. In the OECD database, each reporting country would report 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 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 will 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.

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

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

[4]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

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-level database called fDi Markets offered by *Financial Times*, which tracks cross-border greenfield investments globally.[5] 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, and 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 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.

## 2.2 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. The Trump tariffs have been used to study 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. Given that I do not have FDI data

such complications.

[5]The dataset is at the project level and details are available since 2003.

at the product level, I construct a trade diversion index at both the country and sector levels, by 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.[6] Using this trade diversion index, I test whether the Trump tariffs diverted FDI.

I take the HS 6-digit level tariff increases imposed by the US on China from Fajgelbaum et al. (2020).[7] I then use BACI trade flow data to construct weights for the tariff increases.[8] Intuitively, countries that specialize in goods hit by a larger tariff increase 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 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 $\nu$, I calculate country $i$'s export revenue share, $r_i(\nu)$, country $i$'s export revenue share from the US, $r_{\mathrm{US},i}(\nu)$, and the US import share from China, $\pi_{\mathrm{US,CN}}(\nu)$.[9]

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

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

[6] 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).

[7] The authors extend the data through the end of 2019. The tariff changes are rescaled in proportion to their duration within a 24-month interval. For example, if a 10 p.p. tariff was implemented for some variety in September 2018, the scaled tariff for 2018 would be 3.33 p.p ($= 10 \times \frac{4}{12}$). If a further 15 p.p. tariff increase was implemented for this variety in June 2019, the scaled tariff for 2019 would be 18.75 p.p ($= 25 \times \frac{7}{12} + 10 \times (1 - \frac{7}{12})$).

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. Thus, 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 change my results below qualitatively.

[8] BACI provides data on bilateral trade flow data 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`.

[9] Let $\mathrm{EX}_{hit}(\nu)$ be the export value from country $i$ to $h$ for a good $\nu$ in year $t$, then the three

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

## 2.3 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

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

where $\mathrm{FDK}_{it}$ is the inward FDI stock for country $i$ at time $t$, and $\mathbb{1}_{t'}$ is the time dummy for year $t'$.

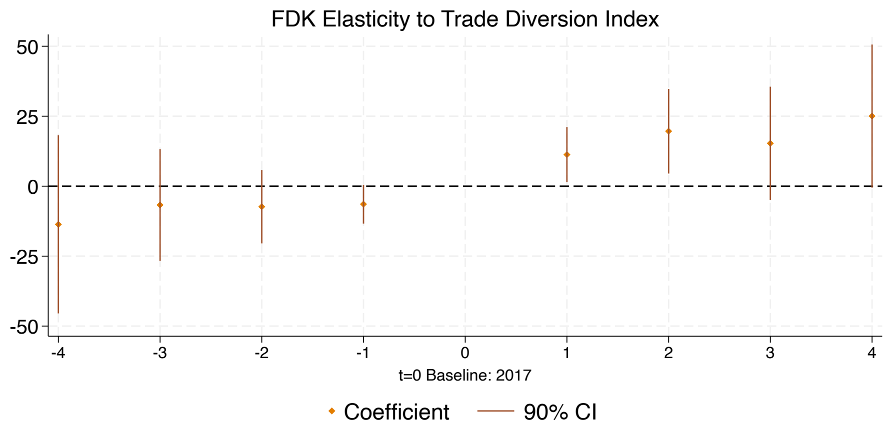
Figure 1 plots the coefficients $\vartheta_{t'}$, providing the baseline evidence for how FDI responds to the constructed trade diversion index. Given that the coefficients for post-event years are approximately 20, and the 95th percentile trade diversion index is around 0.004 (which is Vietnam), it can be estimated 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. Appendix A.1 presents four different specifications of a similar regression, employing exchange-rate-adjusted FDI values, constructing the trade diversion index at the ISIC 2-digit level tariff changes[10], using bilateral FDI stocks, and directly using the observed export

weights are calculated as

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

[10]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 better location solely based on its export of dining tables. If it specializes in furniture production, it could adjust its production capacity accordingly, making it a likely destination for increased FDI.

growth as the explanatory variable instead of the trade diversion index. Across these alternative specifications used as robustness checks, I find a consistent positive effect of the trade diversion index on the inward FDI.



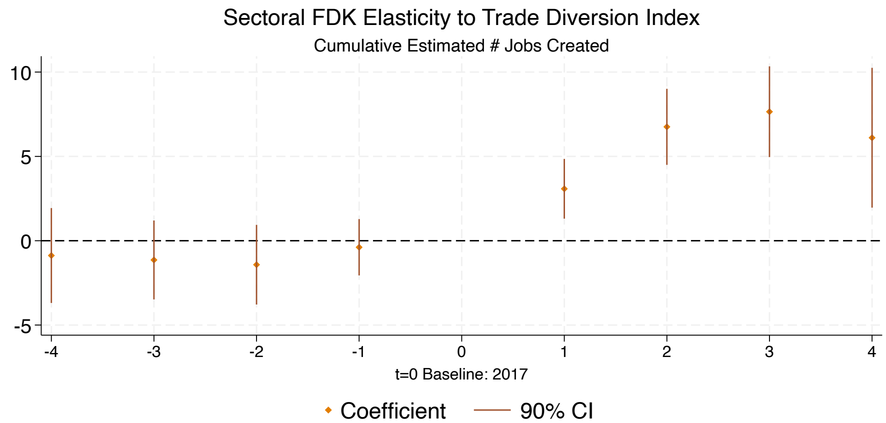

*Notes*: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax havens. This results in 117 countries included in the regression (2). The trade diversion index is constructed using equation (1), with $\nu$ 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. I control for the receiver-country-year, source-country-year, and sector-year fixed effects. The dependent variable is the cumulative estimated number of jobs created.[11] Appendix A.2 shows 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 discriminatory tariffs divert FDI.

[11] More specifically, the regression is

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




*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 $\nu$ 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

## 2.4 Heterogeneous Bilateral FDK Responsiveness

In addressing the question of how FDI diverts, or the patterns of FDI diversion, I extend my analysis beyond the scope of the Trump tariffs as the sole drivers of FDI movement across economies. Instead, I aim to demonstrate that the patterns of bilateral FDK changes exhibit a clear deviation from the predictions of most existing models of bilateral FDI with a gravity structure. These models typically suggest that the changes of bilateral FDK have the following structure[12]

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

$\mathrm{d}\ln \mathrm{FE}_i$ captures the receiver country factor, while $\mathrm{d}\ln \mathrm{FE}_j$ captures the source country factor. 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.

[12]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.

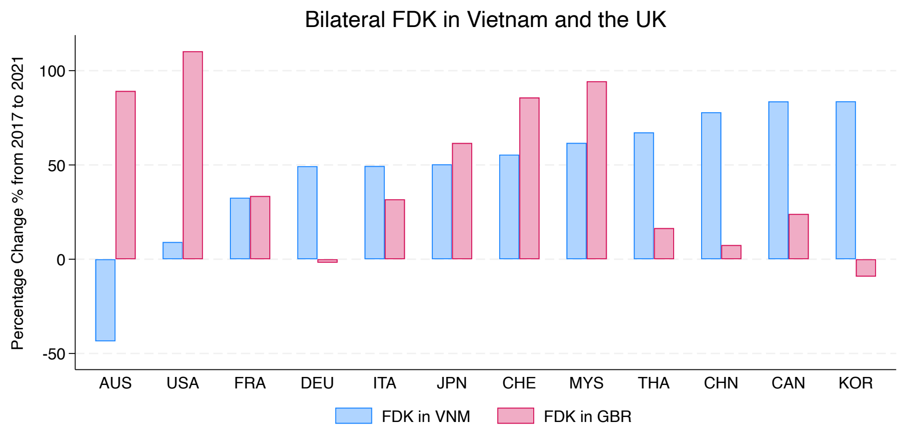



Figure 3: Deviation to Most Existing FDK Models

Vietnam and the UK experienced a 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 FDK in Vietnam and the UK are notably different. Consider two source countries, e.g., China and France, with different incentives to increase their outward FDI stocks, the above benchmark model would predict that they increase their bilateral FDK investments more in Vietnam or both more in the UK.

Any deviation from this prediction must be accounted for by the third term, $\mathrm{d}\ln u_{ij}$, which usually represents deviations due to bilateral operation frictions or trade costs. For instance, the two economies might enter a new treaty affecting FDI investments or could be influenced by unforeseen political tensions.

However, 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, which indicates a systematic variation in FDI responses that align with certain country characteristics. To explore this systematically, Regression (3) looks for factors that can explain the observed heterogeneity in FDI responses across country-pairs:

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

where $\boldsymbol{Z}_{ij}$ represents a vector of observable bilateral country characteristics. The fixed effect $\mathrm{FE}_i$ captures all common factors that affect the bilateral inward FDI stocks in country $i$, and $\mathrm{FE}_j$ 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 FDK 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) |
| $\mathrm{d}\ln \mathrm{FDK}_i \times \ln(\mathrm{GDPpc}_j)$ | 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, $\ln(\mathrm{Dist}_{ij})$,[13] is a standard gravity variable commonly used in predicting bilateral trade values. The estimates suggest that distance is negatively correlated with bilateral FDI *responses* given the receiver's and source economy's unilateral FDI change. For example, 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 of the source country. The positive coefficient suggests that a more developed source country tends to have systematically larger FDI response to

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

a receiver country that attracts more FDI. Finally, the variable $\text{ComparaAdv}_{ij}$ 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.

I will show later that standard stochastic assumptions about FDI location choices fail to generate heterogeneous FDI elasticities across source countries in response to a common shock to a receiver country. One of the main 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 elasticities in the model.

# 3 Model

I study a world economy that consists 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 $\omega$. Each producer has a technology to produce a differentiated variety. Each $\omega$ is constrained to operate in one production country $i$, and sells its variety to all potential importing countries $h$.[14]

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 elasticities across country-pairs.

I discuss three model simplifying assumptions and their implications at the end

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

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 the extension of the model to incorporate heterogeneity in both trade and FDI elasticities.

## 3.1 Demand & Household

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 $\tau_{hi}^s$. More specifically,

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

where $q_{hij}^s(\omega)$ is the quantity of variety $\omega$ in sector $s$ imported by $h$, produced in $i$, and owned by a producer from $j$ (including domestically produced varieties when $h = i$). $\epsilon^s$ is the sector-specific elasticity of substitution across varieties. The demand for a variety owned by a producer $\omega$ from $j$, operating in $i$ and $s$ is given by

$$q_{hij}^s(\omega) = \left( \frac{p_{hij}^s(\omega)}{P_h^s} \right)^{-\epsilon^s} Q_h^s,$$

following the CES demand system, where $P_h^s$ is the associated price index of the sectoral composite good

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

The sectoral composites are then purchased 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 $\phi_h^s$ 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

$$w_h L_h + D_h + T_h - \Gamma_h.$$

The right-hand-side represents the household's total income, which includes labor income (with wage rate $w_h$) 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 domestic household, (ii) government-collected tariff revenue $T_h$, and (iii) an exogenous country-level transfer $\Gamma_h$. The transfer could represent reserves or other mechanisms that affect the country's balance of payments but are not endogenously captured within the model.

## 3.2 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 $\omega$ from $j$ in sector $s$ receives across all potential production locations $i$. I will suppress the superscript $s$ and the argument $\omega$ that indicates individual producer 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 $\theta$, a scale parameter $z_j$ and a correlation function $G^j$,[15]

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

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 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 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 different source countries $j$, 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 elasticities across country pairs.

Consider a producer from $j$ in sector $s$, operating in $i$ with an individual 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 $\kappa_{ij}^s$ 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 $h$, denoted as $p_{hij}^s(a)$, and the quantity of labor to hire $l_{ij}^s(a)$, 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, and fixed costs of operation by assuming a fixed mass of producers for each source country and

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

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 Melitz (2003) for export and Tintelnot (2017) for FDI. However, I will argue in more detail at the end of this section that abstracting from them gains tractability for the model, and my calibration method matches the country-level aggregate FDI diversion elasticity as shown in the data.

## 3.3 Market Clearing and Equilibrium

Let $\pi^s_{hi}$ be the import share of goods that are 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 $D_j \equiv \sum_i \sum_s D^s_{ij}, \mathcal{D}_j \equiv \sum_i \sum_s D^s_{ji}$ to be country $j$'s total inward and outward profits. In this static framework, where actual 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.

## 3.4 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 mark-up over marginal cost. The mark-up is given by the sector-specific elasticity of substitution, $\frac{\epsilon^s}{\epsilon^s-1}$. 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

$$v^s_{ij}(a) \equiv \frac{1}{\epsilon^s - 1} A^s_i w_i^{1-\epsilon^s} \frac{a}{\kappa^s_{ij}{}^{\epsilon^s-1}},$$

where $A^s_i = \sum_h \left(d^s_{hi}\right)^{-\epsilon^s} \left(\tau^s_{hi}\right)^{1-\epsilon^s} \left(\frac{\epsilon^s}{\epsilon^s-1}\right)^{-\epsilon^s} \left(P^s_h\right)^{\epsilon^s} Q^s_h$ captures the market access of country $i$ as a production location for sector $s$.

Suppressing the superscript $s$, I derive in Appendix C the probability that a location $i$ is the best choice for a producer from $j$

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

where $G^j_i \equiv \frac{\partial G^j(x_1,x_2,\ldots,x_N)}{\partial x_i}$, and $\tilde{v}_{ij} = v_{ij}(1)$ is the profits 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, taking the correlation structure of productivity draws across locations into account. The denominator is the sum of this measure across all locations, i.e., $G^j(\tilde{v}^\theta_{1j}, \tilde{v}^\theta_{2j}, \ldots, \tilde{v}^\theta_{Nj}) = \sum_i \tilde{v}^\theta_{ij} G^j_i(\tilde{v}^\theta_{1j}, \tilde{v}^\theta_{2j}, \ldots, \tilde{v}^\theta_{Nj})$.

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 $\theta$.

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 depends on the correlation structure, which is important for the patterns of FDI diversion in response to trade policies such as the trade war.

The conditional distribution of productivity of producers from $j$ in $i$ is

$$\tilde{\mathbb{F}}_{ij}(a)\equiv\mathbb{P}\left(a_{ij}<a|v_{ij}\left(a_{ij}\right)=\max_{i'} v_{i'j}\left(a_{i'j}\right)\right)=e^{-z_j\frac{G^j\left(\tilde{v}_{1j}^{\theta},\tilde{v}_{2j}^{\theta},\ldots,\tilde{v}_{Nj}^{\theta}\right)}{\tilde{v}_{ij}^{\theta}}a^{-\theta}}.$$

Given these endogenous producer distributions, I can derive the aggregate variables, including sectoral price indices $P_h^j$, country price indices $P_h$, and bilateral sectoral profits $D_{ij}^s$. See Appendix C for details.

A key property of the model is that the producers' location choices will respond to changes in model parameters. For example, suppose that the US imposes a tariff increase on Chinese exports in sector $s$: $\mathrm{d}\ln\tau_{US,CN}^s$. 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 trade fundamentals. To see this more clearly, China's market access in sector $s$, $A_{CN}^s$, is directly affected by $\mathrm{d}\ln\tau_{US,CN}^s$, which in turn affects the values of operation $\tilde{v}_{ij}^s$, and the equilibrium producer allocations $\tilde{\mathbb{F}}_{ij}^s(a)$.

## 3.5 Decomposition: Welfare Change Induced by Tariff Changes

To better understand how FDI diversion affects a country's aggregate welfare, namely its real consumption, I now derive a decomposition formula. Using the country budget constraint and the aggregate price index, one can show that up to a first-order approximation

$$
\begin{aligned}
\mathrm{d}\ln C_j \approx\ & \frac{w_j L_j}{X_j}\,\mathrm{d}\ln w_j + \sum_i \sum_s \frac{D_{ij}^s}{X_j}\,\mathrm{d}\ln w_i - \sum_i \sum_s \frac{\mathcal{T}_{ji}^s}{X_j}\,\mathrm{d}\ln w_i \\
& + \sum_i \sum_s \frac{D_{ij}^s}{X_j}\left(\mathrm{d}\ln D_{ij}^s - \mathrm{d}\ln w_i\right) \\
& + \sum_i \sum_s \frac{1}{\epsilon^s - 1}\frac{\tau_{ji}^s \mathcal{T}_{ji}^s}{X_j} \sum_{j'} \omega_{ij'}^s\,\mathrm{d}\ln \tilde{M}_{ij'}^s \\
& + \sum_i \sum_s \frac{\left(\tau_{ji}^s - 1\right)\mathcal{T}_{ji}^s}{X_j}\left(\mathrm{d}\ln \mathcal{T}_{ji}^s - \mathrm{d}\ln w_i\right) \\
& - \frac{\Gamma_j}{X_j}\,\mathrm{d}\ln \Gamma_j\,,
\end{aligned}
\tag{4}
$$

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 is the traditional terms-of-trade effect of tariff changes. This effect captures the differential changes in world prices of the production and consumption bundles of country $j$. Note that since labor is the only production factor and that producers charge a constant markup, wage changes are proportional to changes in world prices. 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 $i$ and sector $s$, which are represented by $w_j L_j$ and $D_{ij}^s$. The price change of the consumption bundle is the weighted average of all wage changes with the weights being the factual import value shares by country $j$.

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. The third line is the production relocation effect. Household in $j$ consumes varieties that are exported from all countries $i$, while the varieties produced in $i$ are again from all potential 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.[16]

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

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 and FDI diversion, the scenario alters significantly. I will illustrate that US consumers may actually experience gains from a substantially lower price index due to the relocation effect. Conversely, US producers might face losses due to increased domestic production costs and diminished foreign profits.

## 3.6 FDI Diversion & Elasticity

I derive in Appendix C the aggregate profits that producers from $j$ in sector $s$ get from operating in $i$

$$D_{ij}^{s} = \frac{\left(\tilde{v}_{ij}^{s}\right)^{\theta} G_{i}^{j}}{G^{j}} \left(G^{j}\right)^{\frac{1}{\theta}} \tilde{z}_{j}.$$

The first term is the probability that location $i$ is chosen (remember $G^{j} = \sum_{i} \left(\tilde{v}_{ij}^{\theta}\right)^{\theta} G_{i}^{j}$). The second term $(G^{j})^{\frac{1}{\theta}} \tilde{z}_{j}$ represents the aggregate profits that producers from $j$ obtain across all locations, which depends on the correlation function $G^{j}$, values of operation $\left\{\tilde{v}_{ij}^{s}\right\}_{i=1}^{N}$, the normalized productivity $\tilde{z}_{j} \equiv \Gamma\left(1-\frac{1}{\theta}\right) z_{j}^{\frac{1}{\theta}}$, and the parame-

[16] 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 be of different direction.

ter $\theta$. Denoting the aggregate sectoral profits for producers from $j$ as $D_j^s = \left(G^j\right)^{\frac{1}{\theta}} \tilde{z}_j$, the above bilateral profits can be expressed in a gravity equation form,

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

I now examine the determinants of the magnitude and heterogeneity of the elasticity of the FDI diversion with respect to the values of operation $\tilde{v}_{ij}^s$ due to shocks such as tariffs, which hinges 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)[17]). An important feature of these assumptions is that they could not generate heterogeneous FDI elasticities.

**Example 1: No correlation**

Consider a correlation function that implies independence of draws across locations, $G^j\left(x_1, x_2, \ldots, x_N\right) \equiv \sum_{i=1}^N x_i$. In this case, the joint distribution of $\mathbf{a}_j$ (suppressing superscript $s$) follows a standard Fréchet distribution that is i.i.d. across locations, i.e.,

$$\mathbb{P}\left(a_{1j} \leq a_1, a_{2j} \leq a_2, \ldots, a_{Nj} \leq a_N\right) = e^{-z_j \sum_{i=1}^N a_i^{-\theta}}.$$

In this case, the FDI gravity simplifies to

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

where $G^j = \sum_{i'} \left(\tilde{v}_{i'j}\right)^\theta$. The first-order deviation of $D_{ij}$ across two equilibria in response to any shocks, using $\tilde{v}_{ij} = A_i w_i^{1-\epsilon^s} / \kappa_{ij}^{\epsilon^s - 1}$, and defining $\tilde{A}_i \equiv A_i w_i^{1-\epsilon^s}$,

$$\mathrm{d} \ln D_{ij} = \theta \left[ \mathrm{d} \ln \tilde{A}_i - \left(\epsilon^s - 1\right) \mathrm{d} \ln \kappa_{ij} \right] + \mathrm{d} \ln \frac{D_j}{G^j}. \tag{5}$$

$\mathrm{d} \ln \tilde{A}_i$ captures the changes of attractiveness of $i$ as an FDI receiver country (either due to changes in market access, or cost of production). There are two observations

[17] Arkolakis et al. (2018) uses a similar assumption that is based on a multivariate Pareto distribution.

from this equation on the FDI diversion elasticity. First, the magnitude of the FDI diversion elasticity is governed by the dispersion parameter $\theta$. When $\theta$ is larger, the dispersion of productivity draws is smaller, and thus the changes of the values of operation have larger impacts on the producers' location choices, and thus the FDI diversion.

Second, the FDI elasticity is 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 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 $G^j\left(x_1, x_2, \ldots, x_N\right) = \left(\sum_{i=1}^N x_i^{\frac{1}{1-\rho}}\right)^{1-\rho}$ with $0 < \rho < 1$, which introduces correlation to productivity draws across locations. A higher value of $\rho$ 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

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

The FDI elasticity is now characterized by $\theta/(1-\rho)$ – amplified by $\rho$. However, the elasticity is 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, which basically combines the above two extreme cases together.

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

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 still idiosyncratic, but there is 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, as parametrized by the correlation coefficient $0 < \rho < 1$. In this case, the quality of $a^s_{ij}$ gives some indication of the quality of $\left\{a^s_{i'j}\right\}_{i' \neq i}$ in other locations.

These latent technology types with different correlations are a way of building 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 $\eta_{ij}$ indicates that such goods account for a larger fraction of all investments from $j$ to $i$.[18] This weight can be derived from the relative aggregate productivity levels for these two technology types between each country-pair $i - j$. For example, when $\eta_{ij}$ is larger, it is as if that second technology type on average gives higher productivity for producers from $j$ to operate in $i$.[19] Thus, the second technology type is used more often, both conditional and unconditional on the location $i$ being chosen by the producers. To see this more clearly, the profit share $\lambda_{ij} \equiv \frac{D_{ij}}{D_j}$ can be decomposed as

$$\lambda_{ij} = \lambda_j^{\mathrm{B}} \lambda_{ij}^{\mathrm{W}} + \lambda_j^{\mathrm{B}*} \lambda_{ij}^{\mathrm{W}*},$$

where $\lambda_j^{\mathrm{B}}, \lambda_j^{\mathrm{B}*}$ denote the between technology type profit shares for the source country

[18]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 $\eta_{ij}$ would be high when $j$ is China and $i$ is an Asian country.

[19]In principle, the correlation function $G^j$ can have more nests, each representing a distinct technology that is correlated across a different set of production locations with varying correlation levels and due to different reasons.

$j$, and $\lambda_{ij}^{\mathrm{W}}, \lambda_{ij}^{\mathrm{W}*}$ denote the within productivity type profit shares from each receiver country $i$ for source country $j$. Here, the superscript $^*$ refers to the shares related to the second technology type with correlation $\rho$.[20]

The weights $\eta_{ij}$ and the correlation parameter $\rho$ are crucial in determining the shares of investments across different latent technology types, and thus the cross-substitution elasticities across country-pairs. A source country with larger $\lambda_j^{\mathrm{B}*}$ is likely to have a larger FDI elasticity. A country pair with larger $\lambda_{ij}^{\mathrm{W}*}$ and $\eta_{ij}$ is likely to have a higher bilateral FDI elasticity. To see this more clearly, the first-order deviation of $D_{ij}$ across equilibria is

$$\begin{aligned}\mathrm{d}\ln D_{ij} = \theta\left(1+\frac{\rho}{1-\rho}\frac{\eta_{ij}\left(\lambda_{ij}^{W*}\right)^{\rho}}{(1-\eta_{ij})+\eta_{ij}\left(\lambda_{ij}^{W*}\right)^{\rho}}\right)\left[\mathrm{d}\ln\tilde{A}_i-(\epsilon^s-1)\,\mathrm{d}\ln\kappa_{ij}\right] \\ -\frac{\rho}{1-\rho}\frac{\eta_{ij}\left(\lambda_{ij}^{W*}\right)^{\rho}}{(1-\eta_{ij})+\eta_{ij}\left(\lambda_{ij}^{W*}\right)^{\rho}}\,\mathrm{d}\ln\lambda_j^{\mathrm{B}*}+\mathrm{d}\ln\frac{D_j}{G^j}\,. \qquad (6)\end{aligned}$$

The FDI elasticity now becomes heterogeneous in the sense that a change in the receiver country's $\tilde{A}_i$ leads to different responsiveness of bilateral FDK for different source countries $j$. This bilateral heterogeneity is crucial for aligning the model with the empirical findings presented in the empirical section.

## 3.7 Discussion of Simplifying Assumptions

**Simplifying Assumption 1: Static Model**

The model is formulated as a static framework. However, transition dynamics

[20]More specifically,

$$\lambda_j^{\mathrm{B}*}=\frac{\left(\sum_{i'}\left(\eta_{i'j}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}{\sum_{i'}(1-\eta_{i'j})\tilde{v}_{i'j}^{\theta}+\left(\sum_{i'}\left(\eta_{i'j}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}},\quad \lambda_j^{\mathrm{B}}=1-\lambda_j^{\mathrm{B}*},$$

$$\lambda_{ij}^{\mathrm{W}*}=\frac{\left(\eta_{ij}\tilde{v}_{ij}^{\theta}\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}},\quad \lambda_{ij}^{\mathrm{W}}=\frac{(1-\eta_{ij})\tilde{v}_{ij}^{\theta}}{\sum_{i'}(1-\eta_{i'j})\tilde{v}_{i'j}^{\theta}}.$$

Thus, $\lambda_j^{\mathrm{B}*}$ is the share of profits from all producers that use the technology type with correlation for the source country $j$, and $\lambda_{ij}^{\mathrm{W}*}$ is the share of profits from country $i$ conditional on using this type of technology.

are interesting and potentially important, as the elasticities of producers' relocation decisions might be different from a static framework and the welfare implications need to take the transition 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 goes to foreign owners.

In Appendix C, I extend the static baseline model to a dynamic version with explicit capital investments. The representative household in each country makes a consumption and saving decision, and the saving equals lending to domestic producers for investments. The producers use both capital and labor for production, and the investment for capital is borrowed from the domestic household, subject to an endogenous interest rate.

The producers make similar production and location choices as in the static model. Moreover, they could also make relocation decisions 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 the dynamic model retains the properties in the static baseline model, with the exploration of dynamic transitions currently ongoing.

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

This assumption, however, has implications for the FDI diversion elasticity. 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.

As a result, 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.

**Simplifying Assumption 3: Homogeneous Trade Elasticity**

Finally, I focus on the heterogeneity of the FDI diversion elasticity, 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 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, namely the heterogeneity of FDI elasticities.

# 4 Calibration

I now take the model to data by calibrating it to the world economy in 2017 as the original equilibrium. In the next section, I will conduct counterfactuals to analyze the effects of the Trump tariffs. The calibrated model has thirteen economies[21] 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 $\epsilon^s$ are calibrated using a standard gravity regression with fixed effects. The FDI elasticities are calibrated using indirect inference, including $\theta, \rho$, and $\eta_{ij}$ that govern the country-pair magnitude and heterogeneity of FDI elasticities.

## 4.1 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 $\phi_h^s$ 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.

[21] 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.

## 4.2 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.[22] The trade shares $\pi_{hi}^s$ 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 $\lambda_{ij}^s$ in my model equals $\frac{\text{FDK}_{ij}^s}{\sum_{i'}\text{FDK}_{i'j}^s}$ 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 level measures of price indexes, I normalize the productivities to be the same across sectors for each country.

## 4.3 Trade Elasticities $\epsilon^s$

The partial trade elasticities in the model are governed by the preference parameters $\epsilon^s$ alone, despite the presence of FDI. The ratio of imports from country $i$ to the domestic import value (excluding tariff payments) for a sector can be represented as

[22] 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 $\frac{N_{ij}^s}{\sum_{s'}N_{ij}^{s'}}\text{FDK}_{ij}$.

follows

$$\frac{X_{hi}^s}{X_{hh}^s} = \frac{\Phi_i^s \left(d_{hi}^s\right)^{1-\epsilon^s} \left(\tau_{hi}^s\right)^{-\epsilon^s}}{\Phi_h^s}.$$

Thus, I can use the standard regression method with fixed effects to estimate the trade elasticities using tariff changes as cost shifters.

More specifically, I run the following regression separately for sectors $s = 1, 2$,

$$\ln \mathrm{EX}_{hit}^s = \mathrm{FE}_{ht}^s + \mathrm{FE}_{it}^s - \epsilon^s \ln \tau_{hit}^s + u_{hit}^s,$$

where the regression coefficient $\hat{\epsilon}^s$ is used for calibration. 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, I substitute $\ln \tau_{hit}^s$ in the above regression with $\ln \mathrm{RER}_{hit}$. Since the real exchange rate is defined such that $\mathrm{RER}_{hit} = \mathrm{RER}_{hjt}\mathrm{RER}_{jit}$, the fixed effects $FE_{ht}^s, FE_{it}^s$ would absorb all variations. Thus, I use $FE_h^s, FE_i^s, FE_t^s$ as fixed effects instead:

$$\ln \mathrm{EX}_{hit}^3 = \mathrm{FE}_h^3 + \mathrm{FE}_i^3 + \mathrm{FE}_t - \epsilon_{\mathrm{RER}}^3 \ln \mathrm{RER}_{hit} + u_{hit}^3.$$

The bilateral trade values data from 2008 to 2021 are sourced from BACI. I constrain the sample to the largest 100 economies in terms of their total export values in 2017. I aggregate the HS 6-digit product-level export values to the model's three sectors and calculate the tariffs for each sector weighted by the product-level export values, where the tariffs are the AVEMFN from WITS TRAINS. For the service sector, I get the total service trade values from ICIO for the available countries from 2008 to 2018 (the 2021 version ICIO is only available up to 2018). The real exchange rates are calculated using official exchange rates and PPP from WDI.

It is well-known that the trade elasticities inferred from RER shifters are often significantly lower than those inferred from tariff shifters.[23] To ensure that the elasticity for the service sector is comparable to those of the other two sectors, I

[23] See a survey paper related to this by Burstein and Gopinath (2014).

assume that the underlying factors causing the discrepancy between RER and tariff pass-throughs affect all sectors similarly. Consequently, I adjust the service sector's estimated elasticity from RER shifters by multiplying it with the ratio of the manufacturing sector's estimated elasticities from both tariff and RER shifters. This approach yields the following calibrated parameter values: $\hat{\epsilon}^1 = 5.34, \hat{\epsilon}^2 = 3.29$, and $\hat{\epsilon}^3 = 2.84$.[24]

## 4.4 FDI Elasticities $\theta, \rho, \eta_{ij}$

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 $\kappa_{ij}^s$), akin to tariffs for trade. Based on the empirical estimations in Section 2, I use the following indirect inference method for calibration.

Intuitively, both $\theta$, $\rho$ and $\eta_{ij}$ play a crucial role in determining the average level of the FDI diversion elasticity. The first two dictate the FDI elasticities corresponding to the two latent nests, while $\eta_{ij}$ defines the weights between the two nests. Moreover, $\rho$ and $\eta_{ij}$ 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 $\eta_{ij}$ and the data, I parameterize $\eta_{ij}$ 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

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

[24] Let $\hat{\epsilon}^2_{\text{tariff}}$ and $\hat{\epsilon}^2_{\text{RER}}$ be the coefficients estimated using tariff and RER shifters, respectively, for the manufacturing sector, and let $\hat{\epsilon}^3_{\text{RER}}$ be the coefficients estimated using RER shifters for the service sector. I infer the elasticity that would have been estimated if there were tariff shifters to the service sector to be $\hat{\epsilon}^3_{\text{RER}} \times \frac{\hat{\epsilon}^2_{\text{tariff}}}{\hat{\epsilon}^2_{\text{RER}}}$. The regressions have $\hat{\epsilon}^3_{\text{RER}} = 0.066, \hat{\epsilon}^2_{\text{RER}} = 0.077$, and thus $\hat{\epsilon}^3_{\text{RER}} \times \frac{\hat{\epsilon}^2_{\text{tariff}}}{\hat{\epsilon}^2_{\text{RER}}} = 2.84$.

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

$$\mathrm{d}\ln K_i = \vartheta \mathrm{DI}_i + u_i, \tag{8}$$

$$\mathrm{d}\ln K_{ij} = \mathrm{FE}_i + \mathrm{FE}_j + \boldsymbol{Z}_{ij}\tilde{\boldsymbol{\psi}} + (\mathrm{d}\ln K_i \cdot \boldsymbol{Z}_{ij})\,\boldsymbol{\psi} + u_{ij},. \tag{9}$$

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. This can be seen more clearly by examining the decomposition in equation (6), which suggests that the error terms are correlated with the regressors in equation (9).

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

The parameters $\theta$ and $\rho$ are intrinsically linked to the estimate of $\vartheta$. The simulated shocks using the backed-out distribution of $\mathrm{d}\ln\tilde{\kappa}_{ij}^s$ give us a set of regression coefficients $\theta$. It turns out that $\rho$ exerts a considerable influence on the median of the $\vartheta$ estimates, while $\theta$ has large impacts on the standard error of the $\vartheta$ estimates in the model. Hence, I adjust $\theta, \rho$ to target for the point estimate and standard error of $\vartheta$ in regression (8) in the data.[25]

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 $\zeta_0$, the empirical estimates have only three moments $\hat{\psi}_1, \hat{\psi}_2, \hat{\psi}_3$. However, the parameters $\boldsymbol{\zeta}$ only affect the $\eta_{ij}$ in the model. Given a set of $\boldsymbol{\zeta}$, and a different value for $\zeta_0$, I can always find another set of $\zeta_1, \zeta_2, \zeta_3$ that yield very similar $\eta_{ij}$.

**Fitting of the Indirect Inference**

Table 2 displays the calibration results for $\theta$ and $\rho$ using regression (8), and Table 3 shows the calibration results for $\boldsymbol{\zeta}$ using regression (9).

| | Outcome: $\mathrm{d}\ln K_i$ | | Calibration | |
|---|---|---|---|---|
| | Data | Model | Parameter | Value |
| $\mathrm{DI}_i$ | 18.67 ** | 18.29 | $\rho$ | 0.82 |
| | (7.83) | (7.60) | $\theta$ | 5.79 |
| $R^2$ | 0.471 | | | |
| # of Obs. | 117 | | | |

*Notes*: The first column reports empirical regression coefficient for $\vartheta$. 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: $\theta, \rho$

[25] I alco conduct sensitivity check by showing calibration and counterfactual results using alternative calibration parameters in Appendix D.4. I fix $\theta = 14$, which is higher than the baseline value $\theta = 0.58$. Given this, I calibrate all other parameters, without targeting the standard error of the $\vartheta$ estimates. The resulting calibration and counterfactual results are qualitatively similar to the baseline calibration results. The magnitude of FDI diversion in counterfactuals is in general a little bit larger than the baseline case.

| | Outcome: $\mathrm{d}\ln K_{ij}$ | | Calibration | |
|---|---|---|---|---|
| | Data | Model | Parameter | Value |
| $\mathrm{d}\ln K_i \times \ln(\mathrm{Dist}_{ij})$ | -0.169* | -0.176 | $\zeta_1$ | -7 |
| | (0.090) | | | |
| $\mathrm{d}\ln K_i \times \ln\left(\mathrm{GDPpc}_j\right)$ | 0.117** | 0.116 | $\zeta_2$ | 5 |
| | (0.059) | | | |
| $\mathrm{d}\ln K_i \times \mathrm{ComparaAdv}_{ij}$ | 0.576*** | 0.521 | $\zeta_3$ | 19 |
| | (0.219) | | | |
| | | | $\zeta_0$ | -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: $\boldsymbol{\zeta}$

Figure 4 shows the resulting bilateral $\eta_{ij}$ values, where each column represents a producer economy, and each row represents a receiver economy. Rich economies in general have high $\eta_{ij}$ to most of the receiver economies. Economy pairs that are close to each other also have high $\eta_{ij}$. The VNM row highlights the comparison between Taiwan and French FDI investment in it. The smaller geographic distance and larger comparative advantage similarity between Vietnam and Taiwan, compared to Vietnam and France, contribute to a much larger $\eta_{\mathrm{VNM,TWN}}$ than $\eta_{\mathrm{VNM,DeFr}}$.

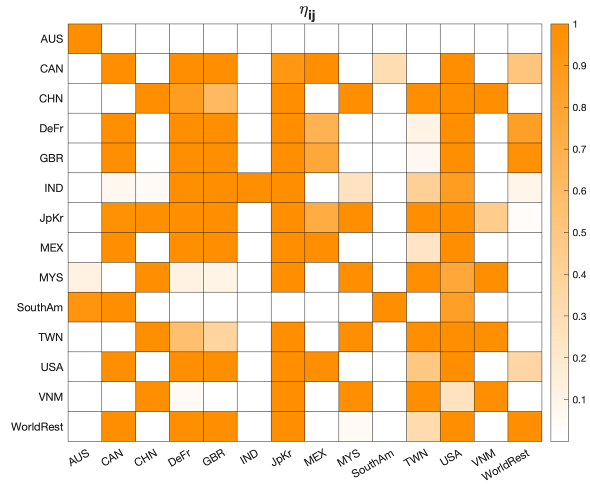



Figure 4: Calibrated $\eta_{ij}$

# 5 Quantitative Implications of the Trump Tariffs

I now use the calibrated model to evaluate the quantitative implications of the Trump tariffs. I highlight the importance of FDI diversion and, furthermore, the role of heterogeneous FDI diversion elasticities in influencing the effects of the Trump tariffs on trade, FDI allocation, and country welfare.

I implement tariff increases at the sector level on Chinese exports to the US.[26] 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. I conduct two decompositions of the aggregate welfare changes to clarify the mechanisms and the distributional implications of the Trump tariffs.

[26]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 and indirect effects of a tariff shock.

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 how FDI diversion substantially raises countries' incentives to impose tariffs on their trading partners.

I next study the role of FDI diversion in a country's export responses to the Trump tariffs. I elucidate why FDI is a more significant factor in influencing export responses in certain economies compared to others.

Finally, I present the model's predictions regarding the unilateral and bilateral FDI stock responses, which underscores 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.

## 5.1 The Importance of FDI Diversion

Figure 5 shows the responses of the aggregate real consumption for each economy in the baseline model.

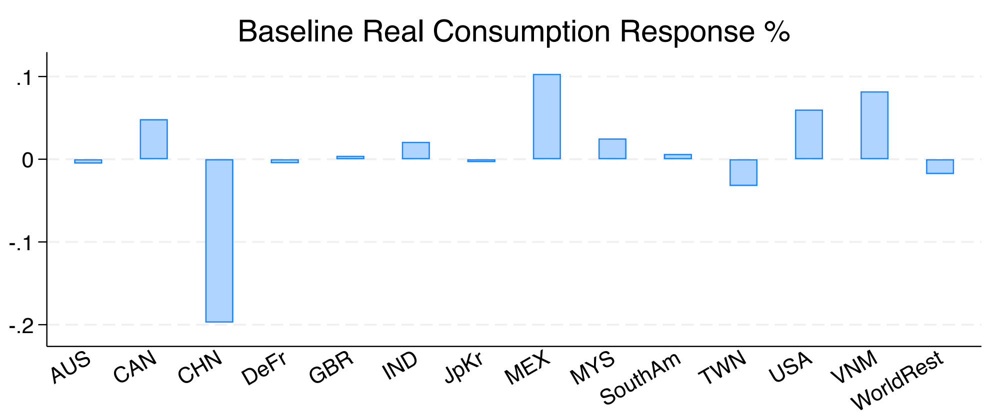



Figure 5: Real Consumption Responses: Baseline

China experiences a real consumption loss of around 0.2% while the US experiences a gain of about 0.05%. By contrast, the analysis in Fajgelbaum et al. (2020)

indicates that the US experienced a net loss of roughly 0.04%.[27] Economies that are major exporters to the US, 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. Figure 6 contrasts the implications from the baseline model with those from an alternative model termed "Fixed FDI," where producers are free to adjust their pricing and production decisions, while the producers are held fixed at their original locations.

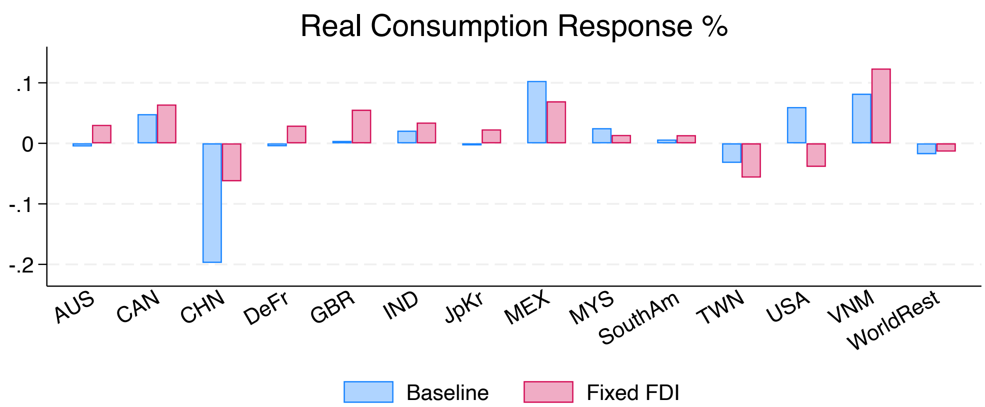



Figure 6: Real Consumption Responses: Baseline vs. Fixed FDI

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.

[27]In their calculation, the losses due to higher prices outweigh gains from tariff revenues and increased profits for domestic producers.

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. These effects 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.

### 5.1.1 Distributional Implications on Real Consumption

Turning to the distributional implications of real consumptions in response to the Trump tariffs, I break down the aggregate welfare changes into various incomes sources: wages, profits from producers operating domestically, profits from producers operating abroad, and the sum of tariff revenues and transfers. Since these income sources are typically distributed among various population groups in reality (Helpman, Melitz and Yeaple (2004)), this decomposition offers a basic illustration of the distributional implications of the Trump tariffs. In fact, one of the motivations behind the Trump tariffs, as argued by policymakers, is to encourage the return of manufacturing, thereby benefiting labor.

Figure 7 presents the real consumption responses of China and the US, along with their decompositions.

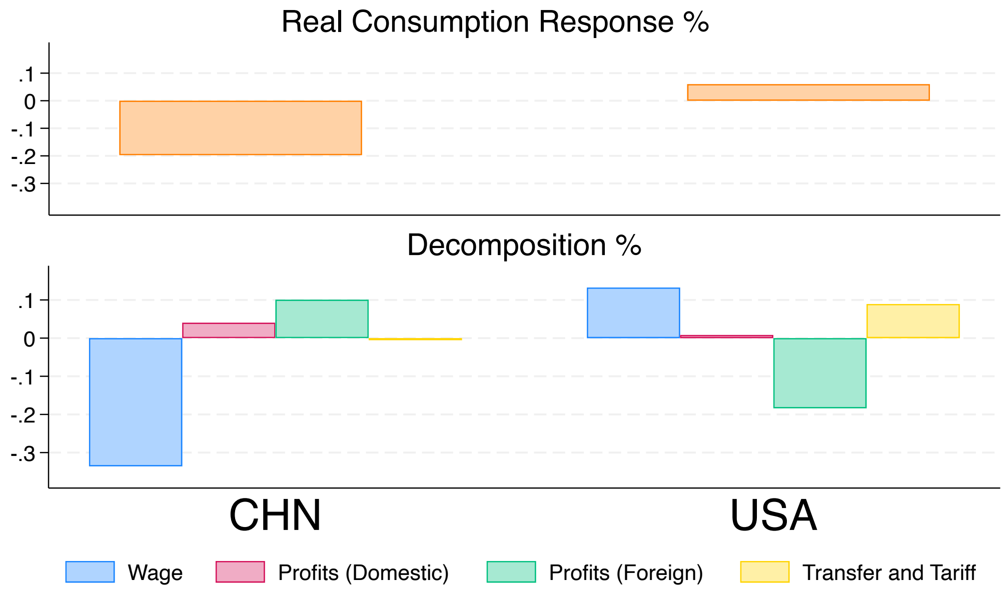



Figure 7: Real Consumption Implications for China and US

As previously discussed, FDI diversion leads to significant losses for China 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. 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 with high productivities 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 8 presents the corresponding aggregate and distributional welfare implications for the two other economies that are significantly affected by the Trump tariffs, Mexico and Vietnam.

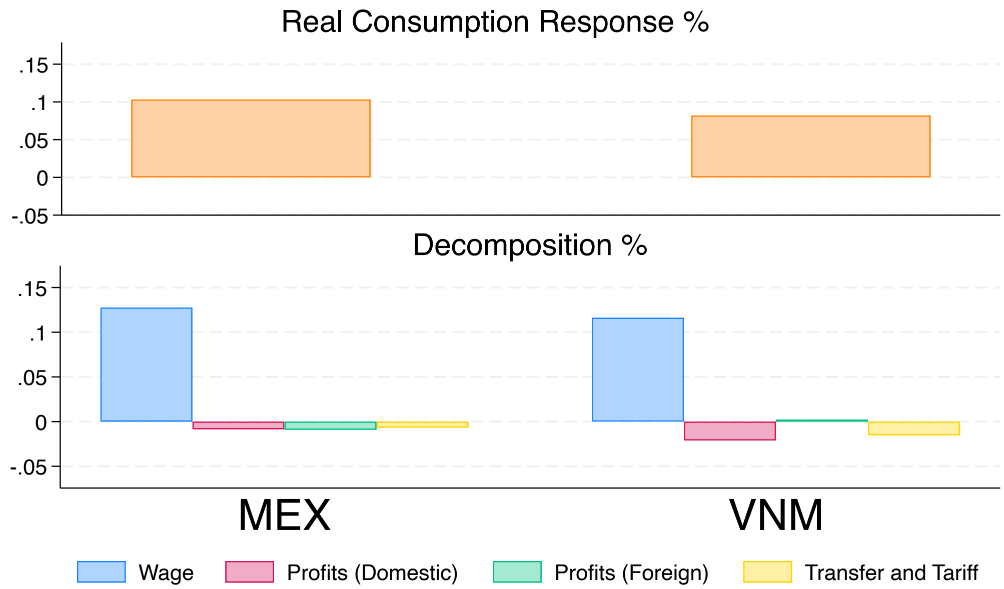



Figure 8: Real Consumption Implications for Mexico and Vietnam

Both economies experience an approximate 0.1% increase in aggregate consumption, primarily driven by increases in domestic wage rates. However, domestic profits for both countries decrease slightly, which is again related to the fact that the influx of more productive foreign producers raises the production costs in Mexico and Vietnam's domestic markets.

Figure 9 presents the welfare implications for the remaining calibrated economies.

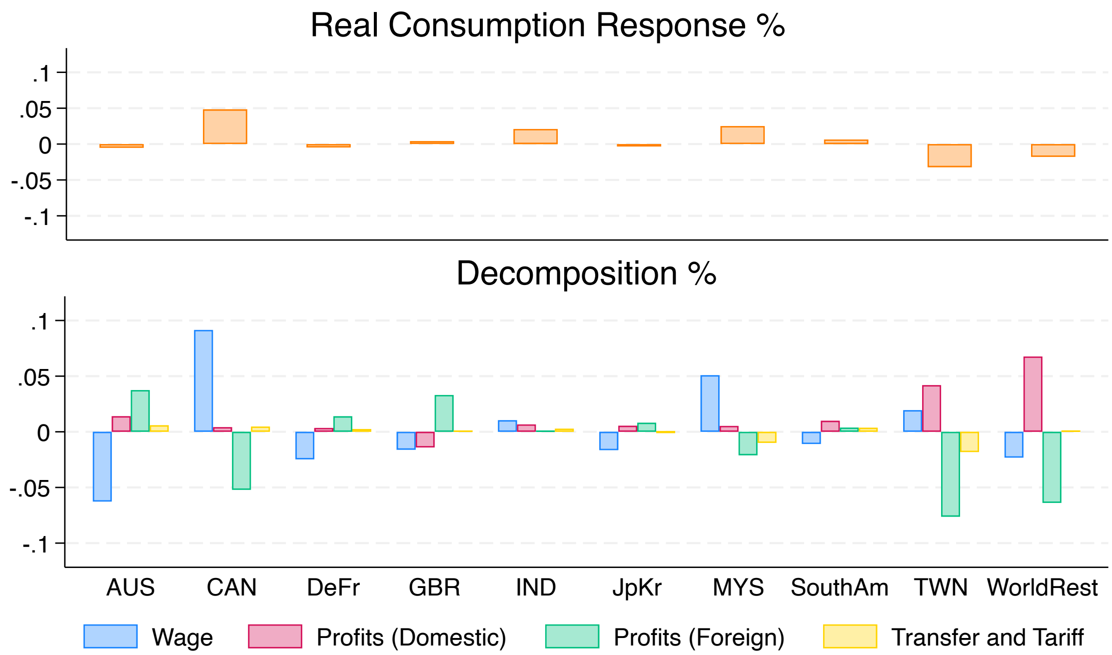



Figure 9: Real Consumption Implications for Other Economies

Canada and Malaysia's gains are primarily due to wage rate increases, similar to the US and Vietnam. Taiwan's losses are mostly attributable to decreasing profits, as Taiwan heavily invests in China. Some Taiwanese producers move back to Taiwan, leading to increases in labor and domestic profits.

Finally, in Appendix D.3, I compare the welfare implications from the baseline model with those from two alternative models: the trade-only model and the homogeneous FDI elasticity model.[28] The trade-only model gives similar implications to the Fixed FDI model. Most economies experience gains from higher wages and domestic profits due to diverted import demand from the US, while FDI diversion changes both the aggregate and distributional implications for each country in different ways.

The differences in welfare implications between the homogeneous FDI elasticity model and the baseline model are unsurprisingly larger for economies that have larger differences in FDI diversion predictions between the two models, such as Vietnam, Japan/Korea, and the Rest of the World. These disparities highlight the potential

[28] In the trade-only model, producers can only operate domestically. This model is calibrated using the same values for $\epsilon^s, L_i, \phi^s_h, \tau^s_{hi}$, while $z_j, d^s_{hi}$ are recalibrated to match the 2017 equilibrium observables $X_h$ and $\pi^s_{hi}$.

for misjudgments of the implications of the Trump tariffs when using standard models in the literature that either overlook FDI or fail to incorporate the substantial heterogeneity inherent in FDI diversion elasticities.

### 5.1.2 Decomposition of Real Consumption Responses

The second decomposition, based on equation (4), offers a theoretical perspective on the distributional implications of the Trump tariffs. It considers the representative household in a country as both a consumer and a producer, impacted by the tariffs through different channels.

The decomposition presented in Figure 10 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. The relocation effect, which reflects the welfare implications for households as consumers, is particularly impactful. It represents the changes in consumer prices due to shifts in producer production locations. On the other hand, the profit-shifting effect, representing the welfare implications for households as producers, indicates how tariffs influence producer profits. These outweigh the traditional terms-of-trade effect typically associated with tariff changes.

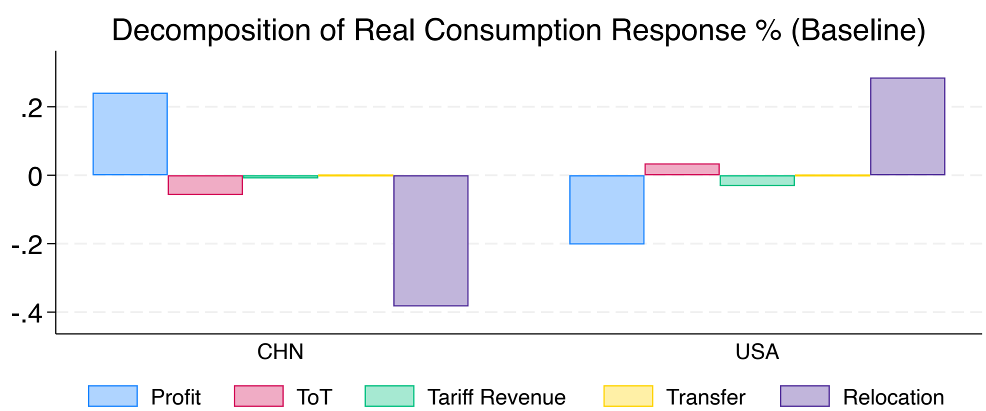



Figure 10: Decomposition of Real Consumption Responses: Baseline

China's losses from the Trump tariffs are mainly driven by the relocation effect. This is because some varieties become more costly when they need to be imported or produced in foreign countries. However, the profit-shifting effect somewhat 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.

Notably, this decomposition suggests that the Trump tariffs have very different implications for the consumer and producer sides in the US compared to existing literature, such as Fajgelbaum et al. (2020). Figure 27 in Appendix D.1 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.

## 5.2 "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, I analyze the implications for US welfare following a uniform increase in tariffs on all sectors for exports from China, starting from the original equilibrium. This analysis assumes that China and all other countries do not respond to the US's tariff changes. I show that 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. Second, I turn to an analysis of Nash tariffs, where both China and the US increase tariffs on each other's imports, maintaining the assumption that other countries remain passive. I show that the equilibrium Nash tariff increases between China and the US are much higher in a scenario that includes FDI diversion compared to a scenario without it. This heightened tariff war leads to decreased welfare outcomes for both countries.

Figure 11 plots the welfare changes for the US (left plot) and China (right plot) 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 constant.

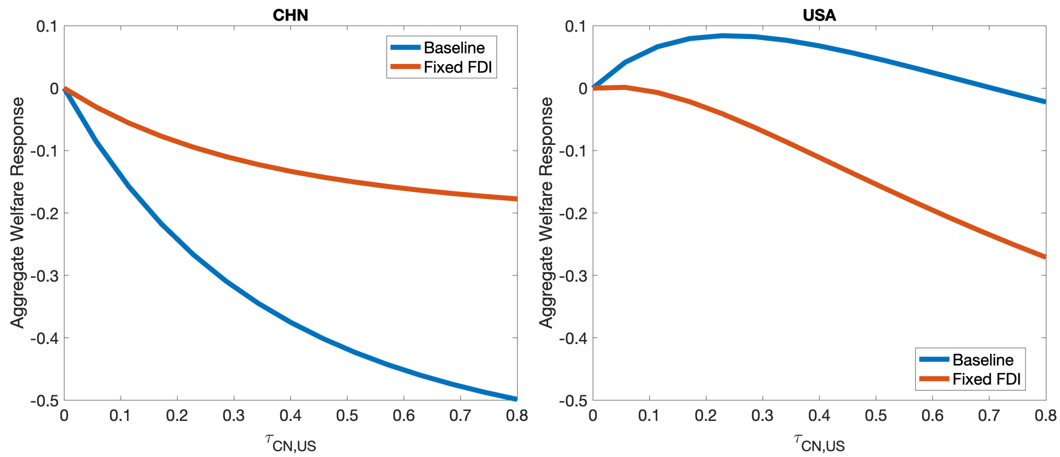



Figure 11: Optimal Tariffs by the US on Chinese Exports

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. The US welfare in the Baseline suggests that tariffs on Chinese exports could be beneficial for the US up to approximately a 25% increase, marking an "optimal" tariff level. This optimal level is significantly higher than in the Fixed FDI scenario, where even minor tariff increases start to have negative welfare implications.

Figure 12 extends this analysis to a Nash equilibrium setting, considering simultaneous tariff increases by both the US and China.

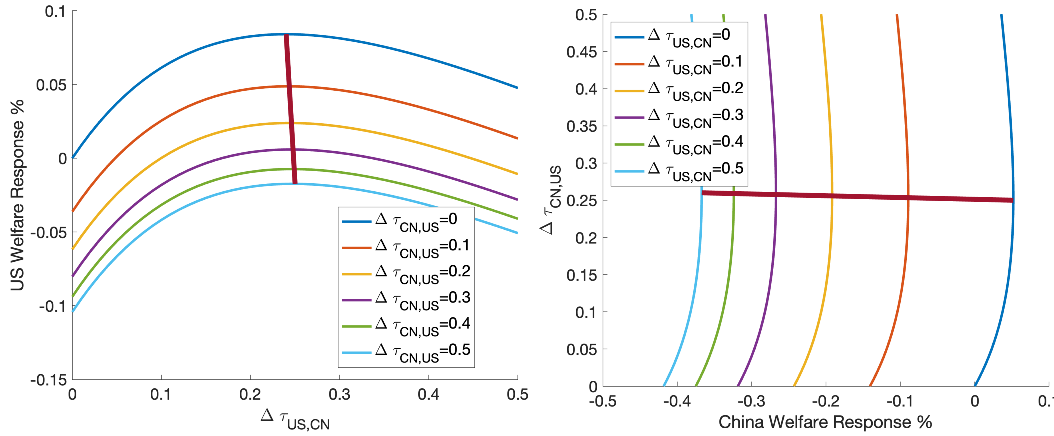



Figure 12: Nash Optimal Tariffs (Baseline)

When the Chinese tariff increase on US exports is higher (for example, comparing the dark and light blue curves in the left plot), the US welfare implication is always lower for the same tariff increase by the US on Chinese exports. The bold red curve traces out the optimal tariff increases, or the best responses for the US to various levels of Chinese tariff increases. The right plot shows the corresponding welfare implications from China's perspective. Figure 28 in Appendix D.2 shows the corresponding results under the Fixed FDI assumption.

The combined best responses of China and the US are numerically illustrated in Figure 13. This figure compares the Nash equilibrium tariff increases by the US and China under both the Baseline (left plot) and Fixed FDI (right plot).

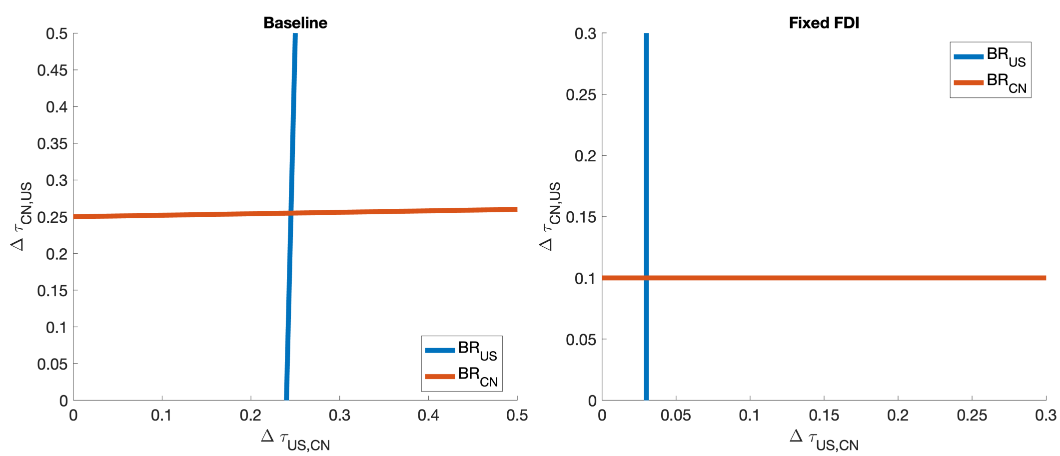



Figure 13: Nash Optimal Tariffs

The key takeaway from these exercises is the significant increase in incentives 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.

## 5.3 Export Response Decomposition

I will now study the implications of the Trump tariffs on a country's export responses, within the context of the baseline model that incorporates FDI diversion. The export value net of tariff payments from country $i$ to country $h$ in sector $s$ can be expressed as (see Appendix C):

$$\frac{X_{hi}^s}{\tau_{hi}^s} = \frac{X_h^s}{\tau_{hi}^s}\pi_{hi}^s = \frac{X_h^s}{\tau_{hi}^s}\frac{\sum_j \tilde{M}_{ij}^s \left(P_{hij}^s\right)^{1-\epsilon^s}}{\left(P_h^s\right)^{1-\epsilon^s}},$$

where $\tilde{M}_{ij}^s \equiv \left(\left(\tilde{v}_{ij}^s\right)^{\theta} G_i^j/G^j\right)^{\frac{\theta-1}{\theta}} \left(G_i^j\right)^{\frac{1}{\theta}}$, and $P_{hij}^s = \frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s \kappa_{ij}^s w_i / \left(\left(\Gamma(1-\frac{1}{\theta})\right) z_j^{\frac{1}{\theta}}\right)^{\frac{1}{\epsilon^s-1}}$. $\tilde{M}_{ij}^s \left(P_{hij}^s\right)^{1-\epsilon^s}$ captures the aggregate price index for varieties that are imported to $h$ by producers from $j$ operating in $i$ in sector $s$. $\tilde{M}_{ij}^s$ captures the mass of producers, adjusted for the productivity distribution of producers from $j$ that are located in $i$, while $P_{hij}^s$ takes into account the producer fundamentals $z_j$, production location cost $w_i$, and bilateral frictions $d_{hi}^s, \tau_{hi}^s, \kappa_{ij}^s$. The numerator captures the contributions to exports from $i$ to $h$ by all producers from different source countries $j$, and the denominator captures the exports from different $i$, including those domestically from $h$. The first-order deviation decomposes the change of export values $\frac{X_{hi}^s}{\tau_{hi}^s}$ into three parts:

$$\mathrm{d}\ln\frac{X_{hi}^s}{\tau_{hi}^s} = \mathrm{d}\ln\frac{X_h^s}{\tau_{hi}^s}\frac{1}{\left(P_h^s\right)^{1-\epsilon^s}} + \left(1-\omega_h^s\right)\mathrm{d}\ln\tilde{M}_{ii}^s\left(P_{hii}^s\right)^{1-\epsilon^s} + \omega_h^s\,\mathrm{d}\ln\sum_{j\neq i}\tilde{M}_{ij}^s\left(P_{hij}^s\right)^{1-\epsilon^s}, \tag{10}$$

where $\omega_h^s \equiv \frac{\sum_{j\neq i}\tilde{M}_{ij}^s\left(P_{hij}^s\right)^{1-\epsilon^s}}{\sum_j \tilde{M}_{ij}^s\left(P_{hij}^s\right)^{1-\epsilon^s}}$ captures the share of foreign production capacity in country $i$ for sector $s$. The first term on the right-hand-side captures the change of the importer's sectoral expenditure, which includes general equilibrium effects on its sectoral price index, and the effect of direct tariff change. The second and third terms capture the export value changes that are associated with adjustments in domestic and foreign production capacity.

Figure 14 shows the aggregate changes in export values to the US for all economies (other than China) at the country level (aggregated over sectors), as well as the decomposition into the three terms specified in equation (10).

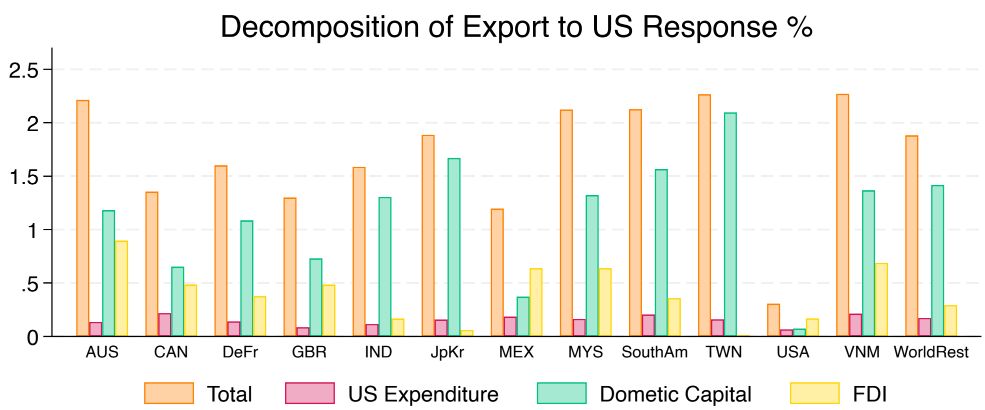



Figure 14: Export Response Decomposition

All economies substitute for Chinese exports to the US in terms of total export responses (shown in orange). Moreover, there are large heterogeneities in the relative contributions from FDI (shown in yellow) and domestic production capacity (shown in green) across economies. FDI is particularly important for Mexico, and is also significant for economies such as Vietnam, Australia, Canada, the UK, and Malaysia. In contrast, FDI is less impactful for economies like Japan/Korea, Germany/France, and Taiwan. The relative importance of FDI versus domestic production capacity hinges on the significance of foreign producers for the exporting economy $i$, as well as the extent of FDI diversion. For example, FDI accounts for a large part of the production capacity in the manufacturing sector for economies such as Mexico, Australia, Canada, and the UK, while its role is small for Japan/Korea. In the case of Mexico, it also experiences a large increase in inward FDI stocks (see next section). What's more, Mexico's domestic producers are relatively less productive compared to the incoming foreign producers, further amplifying the importance of FDI diversion in the country's export growth.

In the empirical section, I show that country more exposed to the Trump tariffs have higher relative FDK following the Trump tariffs. In Appendix B, I show that countries more exposed, counterintuitively, have lower domestic capital after the Trump tariffs. This observation should not be misconstrued as implying that more exposed countries necessarily have reduced domestic capital following the tariffs. For example, the large increase of FDK in Mexico can itself be a reason for smaller increase of domestic capital in a general equilibrium environment. The empirical analysis in Appendix B and model decomposition in this section suggest a narrative where countries more exposed receive more FDK, and the impact of these FDI responses is significant enough that these countries increase their domestic capital investment by a lesser amount.

## 5.4 FDI Diversion

I now present the model's predictions about FDI diversion. Figure 15 shows the bilateral FDI stock responses, where each column represents a source economy and each row represents a receiver economy.

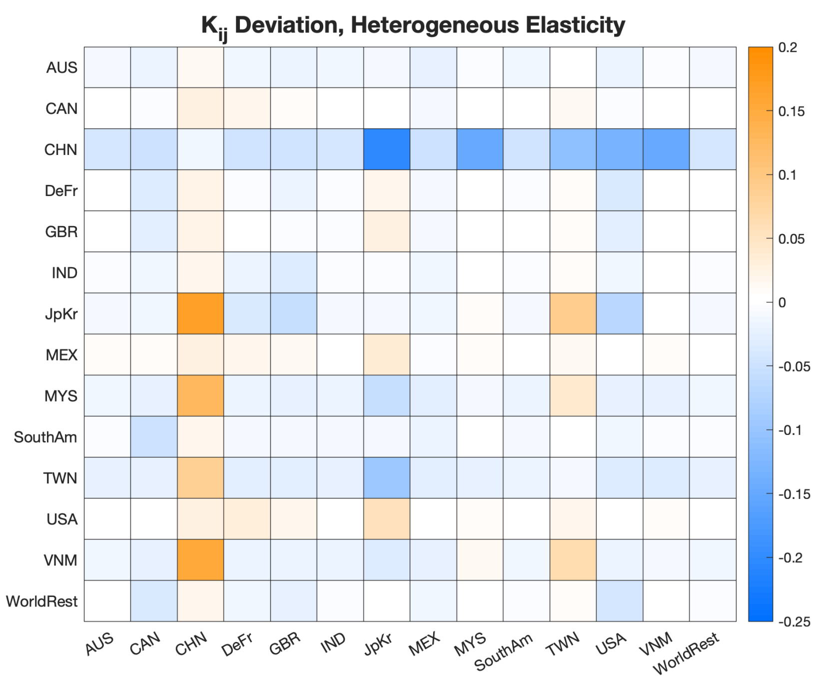



Figure 15: Bilateral FDK Diversion

The US tariffs on Chinese exports make China a less favorable place from which to serve the US market, leading to a decline in FDI investments in China from nearly all economies. The large relocation of FDI is also salient for two other economies that have large FDI stocks in China, namely Japan/Korea and Taiwan. On the other hand, China significantly increases its outward FDI investments as other economies become relatively more attractive locations for production.

Crucially, the responsiveness of FDI diversion exhibits significant heterogeneity, both from a range of source economies to China and from China to various receiver economies. For instance, 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.

The patterns of FDI diversion are the direct results of the calibration procedure to account for the heterogeneous FDI responsiveness. Unsurprisingly, the receiver economies with large increases are those with large $\eta_{ij}$ values in the calibration. However, these quantitative results highlight the magnitude of such heterogeneity in response to the Trump tariffs. In Figure 29 in Appendix D, I provide a comparison between the FDI diversion predictions from the baseline model and those from a model with homogeneous FDI elasticities. 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 (5), 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 Trump's tariffs are impacting economies, exemplified by the situation in Vietnam.

Figure 16 shows the unilateral inward FDI stock responses under the homogeneous and heterogeneous FDI elasticity model.

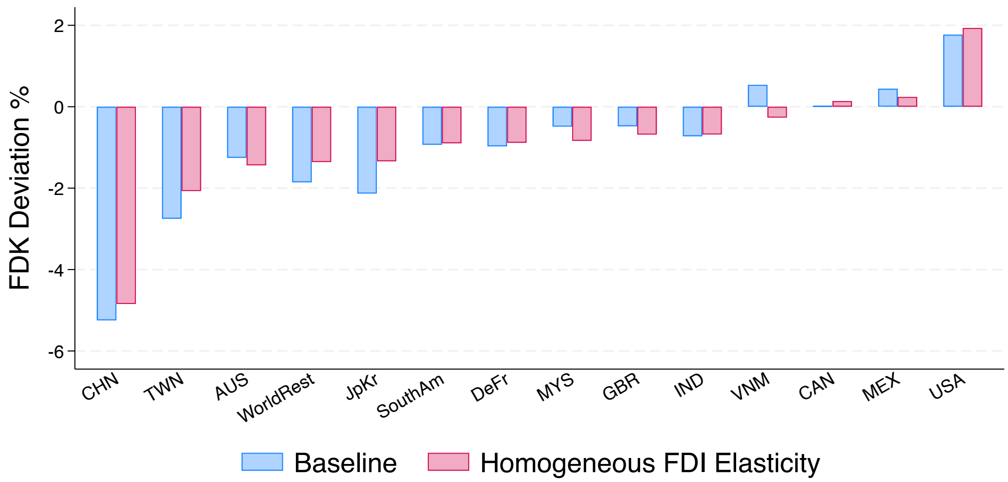



Figure 16: FDK Response: Baseline vs. Homogeneous FDI Elasticity

Let's first concentrate on the predictions of the baseline model, represented by the blue bars. As the world, overall, becomes less efficient, world output and expenditure decrease. FDI, as part of production capacities, also decreases for most economies. Economies that are closer to China tend to experience larger FDI decreases, while the opposite is true for those that are closer to the US.

The Trump tariffs make economies that were significant exporters to the United States more attractive production locations for serving the US market. The US itself is the main source country to serve its domestic markets, and thus receives large increase in FDI. While both Mexico and Canada are large exporters to the US, the increase in their domestic prices makes them less attractive for FDI. Additionally, the fact that they are close substitutes for FDI as production locations to the US further diminishes their appeal as destinations for FDI diversion in this particular scenario.

Finally, the predictions for inward FDI stock responses exhibit considerable variance between the two models, particularly for economies such as Vietnam, Taiwan, Japan/Korea, and the Rest of the World. Figure 17 shows the welfare responses and the decomposition for Vietnam under three different cases: the Fixed FDI, the baseline model with heterogeneous FDI diversion elasticities, and the model with homogeneous FDI diversion elasticities.

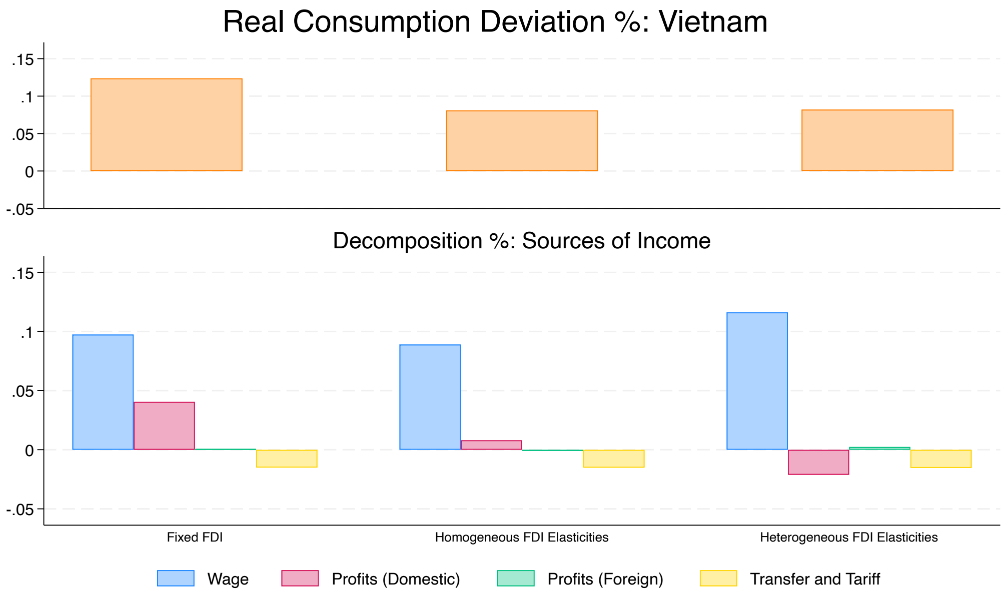



Figure 17: Vietnam Welfare Response: The Role of Heterogeneous FDI Elasticities

By comparing models with homogeneous and heterogeneous FDI elasticities, the much larger increase in FDK 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.

# 6 Conclusion

This paper underscores the significance of taking FDI diversion, along with the associated frictions and country-specific characteristics related to FDI, into account 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 and leads to significant distributional implications. While China can mitigate some of the losses through outward FDI investments, FDI diversion makes the well-being of domestic labor and consumers a larger concern. In the case of the US, the counterfactual scenarios suggest the potential to attract capital for reshoring, but they also emphasize that the scale and composition of reshored investments could have important implications for welfare. Future research could delve into empirical evidence and examine potential policy measures aimed at addressing these dimensions of the issue.

I demonstrate the critical role of considering heterogeneous FDI elasticities in understanding the patterns of FDI diversion. While this paper focuses on certain economic outcomes like wage rates and domestic 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 leads to such heterogeneity is an area for future research and can inform policy designs.

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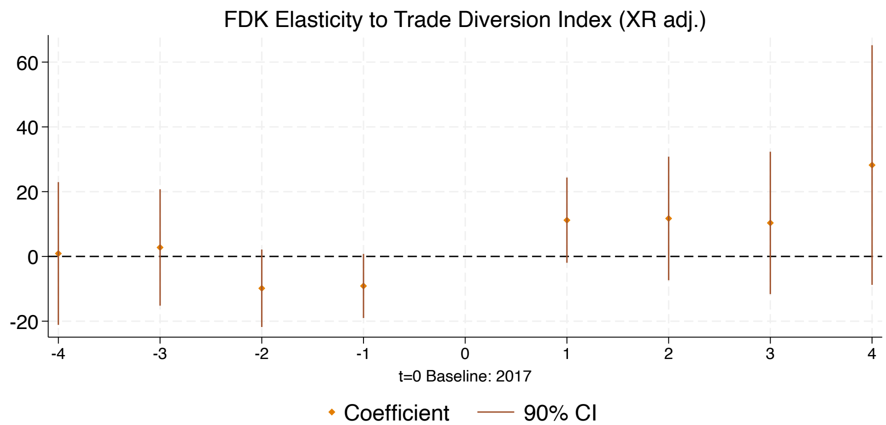
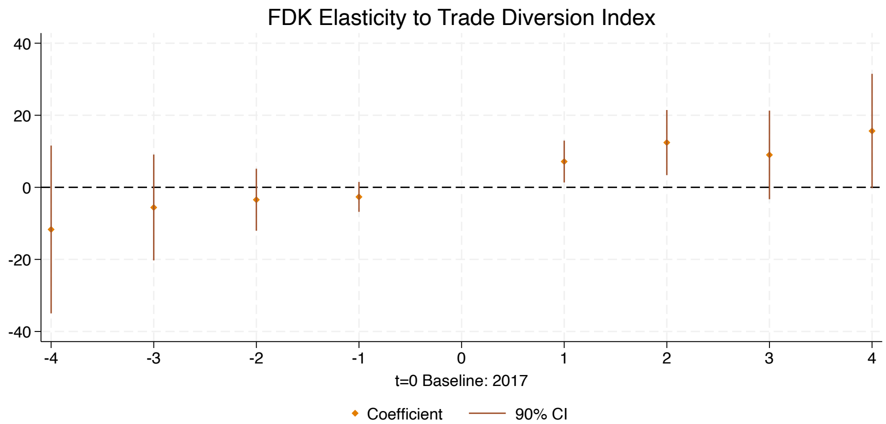
# A Extra Empirical Analysis

## A.1 Robustness Check for Country-Level Result



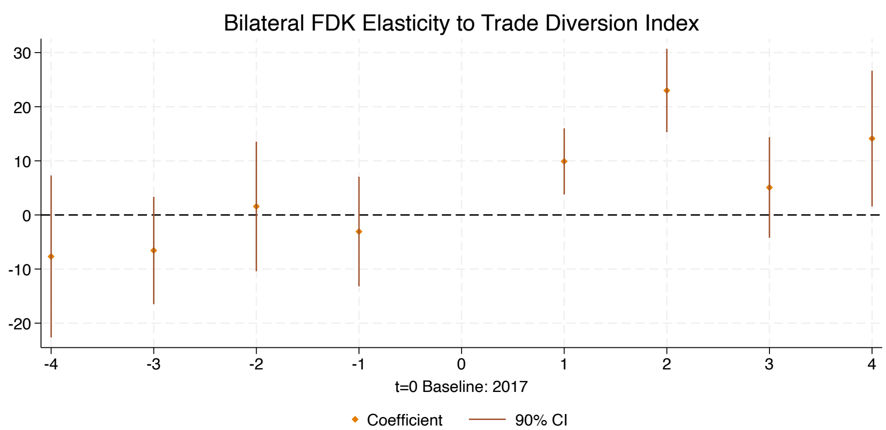

*Notes*: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax havens. This results in 91 countries. The FDI stocks are exchange rate adjusted, i.e., $\text{FDI}_i^{\text{XR}} = \text{FDI}_i \frac{\text{XR}_i^{\text{official}}}{\text{PPP}_i}$, where $\text{XR}_i^{\text{official}}$ is the official exchange rate of country $i$'s currency to USD, and $\text{PPP}_i$ is country $i$'s purchasing power parity to the US, both from World Development Index by World Bank. The trade diversion index is constructed using equation (1), with $\nu$ at HS 6-digit level, trade value from BACI for year 2017, and the Trump tariff increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 18: Robustness: Event Study at Country Level, Exchange Rate Adjusted FDI Stocks



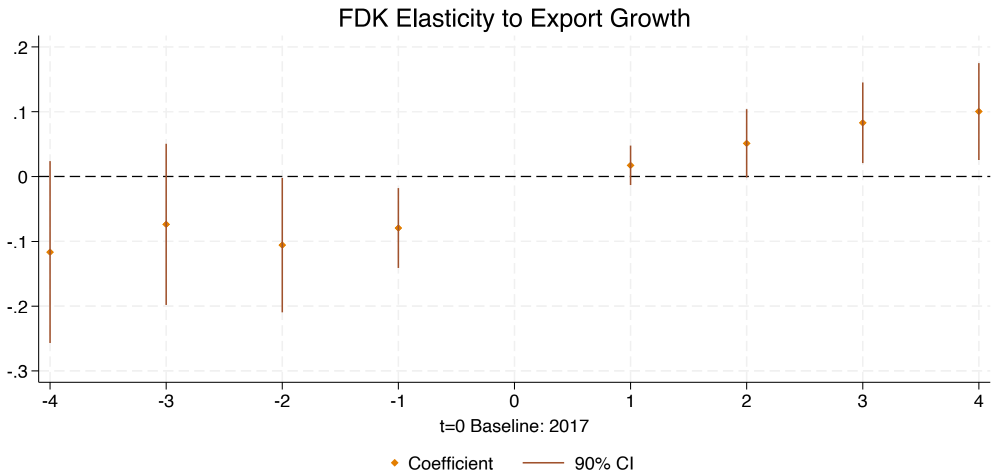

*Notes*: The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. I constrain the sample to include those countries with the largest inward FDI stocks in 2017, while excluding those typically considered tax havens. This results in 97 countries. The trade diversion index is constructed using equation (1), with $\nu$ at ISIC 2-digit level, trade values from BACI for the year 2017, and the Trump tariff increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 19: Robustness: Event Study at Country Level, ISIC 2-digit Level Tariffs




*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. I further constrain the sample to include receivers who have FDI investments from more than four source countries. This results in 74 source countries and receiver countries, and 1650 country pairs. The trade diversion index is constructed using equation (1), with $\nu$ at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariff increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

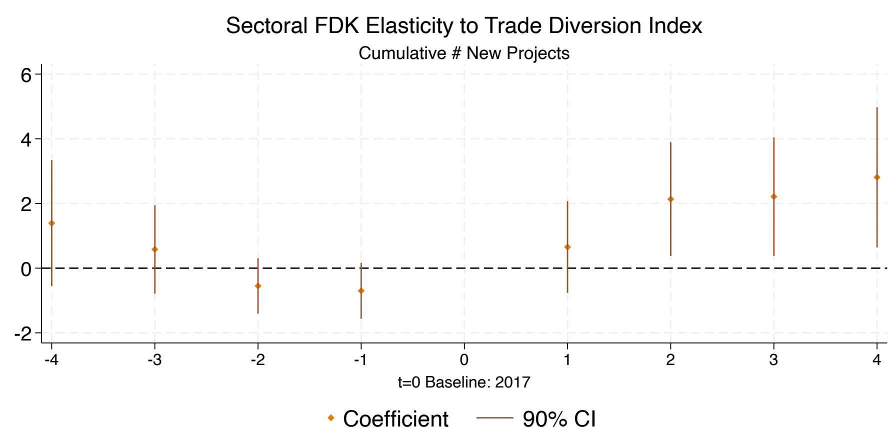
Figure 20: Robustness: Event Study at Country Level, Bilateral FDI Stocks




*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 145 countries. The export growth is constructed using BACI data collapsed to get each country's export value growth to the US from 2017 to 2021. Standard errors are clustered at the receiver country level.

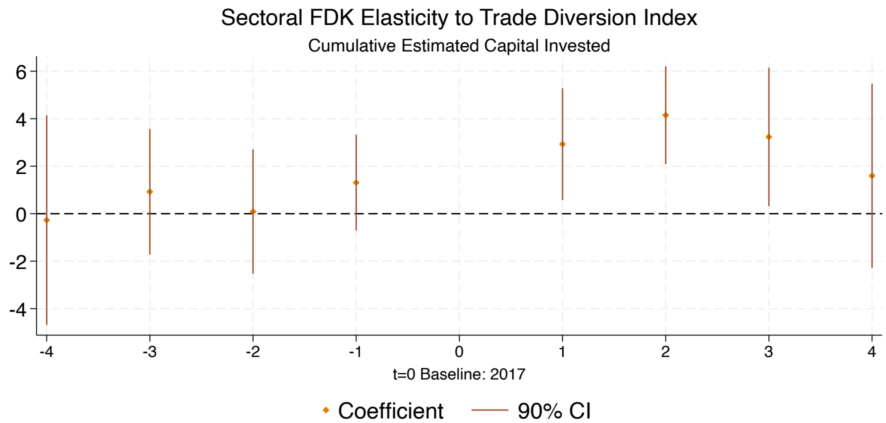
Figure 21: Robustness: Observed Export Growth as Explanatory Variable

## A.2 Robustness Check for Sector-Level Result




*Notes*: The FDI data used are the fDi Markets database measure of greenfield FDI investments. The dependent variable is the cumulative number of projects invested, aggregated at the source-receiver-sector level. The sectors are broadly categorized according to the NAICS 2012 3-digit level. I constrain the sample 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 $\nu$ at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariff increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 22: Robustness: Event Study at Sector Level, Number of Projects




*Notes*: The FDI data used are the fDi Markets database measure of greenfield FDI investments. The dependent variable is the cumulative estimated amount of capital invested 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 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 $\nu$ at the HS 6-digit level, trade values from BACI for the year 2017, and the Trump tariff increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 23: Robustness: Event Study at Sector Level, Estimated Capital Invested

## A.3 Additional Empirical Analysis on Export and FDI

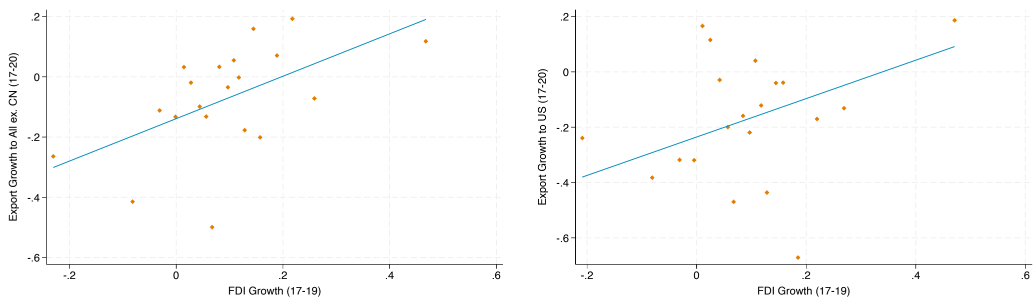
| | To All (ex. CN) | | To US | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Diversion Index | 26.692 | 14.536 | 88.429** | 74.273* |
| | (19.479) | (19.445) | (41.371) | (39.604) |
| FDK Growth | | 0.591*** | | 0.791** |
| | | (0.185) | | (0.383) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| R2 adj. | .02 | .06 | .07 | .09 |
| # of Obs. | 140 | 140 | 141 | 141 |

*Notes*: Data uses official inward FDI stocks from OECD, IMF CDIS, and UNCTAD, export value from BACI. The export growth is from 2017 to 2020, while FDI growth is from 2017 to 2019. The trade diversion index is constructed using equation (1), with $\nu$ at HS 6-digit level, and trade value from BACI for year 2017, the Trump tariff increases from Fajgelbaum et al. (2020), all at at HS 6-digit level. I constraint the country to be those with the largest inward FDI stocks in 2017 and exclude those that are usually regarded as tax havens, which results in about 140 countries. All regressions control for the log export, inward FDI stock, and GDP per capita levels in 2017. Standard errors in parentheses, $^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table 4: Export Growth on Trade Diversion Index and FDI Growth

# B Contribution of FDI Diversion to Export Growth

The FDI diversion caused by the Trump tariffs is interesting and could have many impacts on a country beyond the scope of this paper (e.g., technology diffusion), but I focus on the implications for trade. Figure 24 shows a positive correlation between export and FDI growth, which features bin-scatter plots illustrating this relationship.

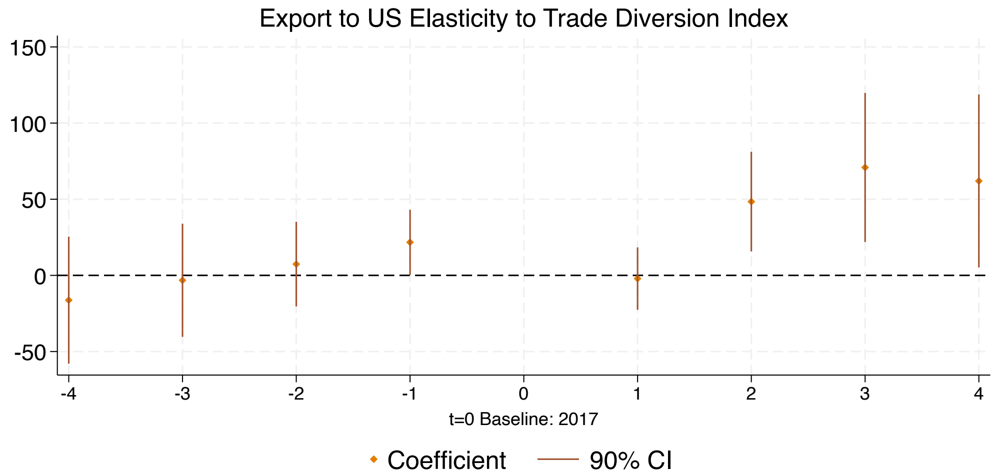



*Notes*: Data uses official inward FDI stocks from OECD, IMF CDIS, and UNCTAD, export value from BACI. I constraint the country to be those with the largest inward FDI stocks in 2017 and exclude those that are usually regarded as tax havens, which results in 140 countries.

Figure 24: Bin-scatter for Export and FDI growth

Complementary to existing findings in the literature (e.g., Fajgelbaum et al. 2021), I show that the trade diversion index constructed above predicts relative export growth. Figure 25 presents the results of regression (11), which is analogous to (2) with the log of export to the US for each country $\ln \mathrm{EX}_{\mathrm{US},i,t}$ as the dependent variable.

$$\ln \mathrm{EX}_{\mathrm{US},i,t} = \mathrm{FE}_i + \mathrm{FE}_t + \sum_{t'=2013,t'\neq 2017}^{2021} \vartheta_{t'}^{\mathrm{EX,DI}} \mathbb{1}_{t'} \times \mathrm{DI}_i + u_{it}. \tag{11}$$

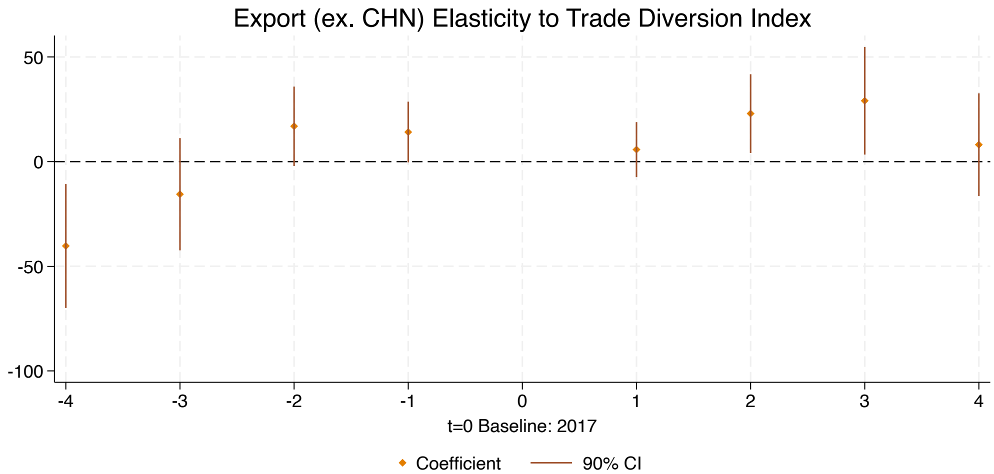



*Notes*: The dependent variable is the log of export value to the US for each country using data from BACI data from 2013 to 2021. I constrain the sample to include those countries with the largest export values in 2017, while excluding those typically considered tax havens, which results in a sample of 164 countries. The trade diversion index is constructed using equation (1), with $\nu$ at the HS 6-digit level, trade values from BACI for year 2017, and the Trump tariffs increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 25: Trade Diversion: Export (to US) Elasticity to Trade Diversion Index

Figure 26 shows a similar result to Figure 25 with the dependent variable being the log of a country's total export excluding China.[29]

[29]I exclude a country's export to China, given that China is the directly impacted country in the China-US trade war. Thus, its import demand is likely to be lower, exerting a downward pressure on the exports of other countries.




*Notes*: The dependent variable is the log of total export value (excluding China) for each country using BACI data from 2013 to 2021. I constrain the sample to include those countries with the largest export values in 2017, while excluding those typically considered tax havens, which results in a sample of 170 countries. The trade diversion index is constructed using equation (1), with $\nu$ at the HS 6-digit level, trade values from BACI for year 2017, and the Trump tariff increases from Fajgelbaum et al. (2020). Standard errors are clustered at the receiver country level.

Figure 26: Trade Diversion: Export (ex. CN) Elasticity to Trade Diversion Index

The impacts of the trade diversion index on relative export growth to the US may result from a combination of expanded domestic production capacity and increased production capacity through FDI. The next logical inquiry is to assess whether the FDI responses are important to a country's export growth. I assume that the contributions of per unit increase in domestic and FDI production capacities to export growth are identical.[30] In this case, I employ two key estimates, the responses of both FDK and domestic capital to the trade diversion index, to offer suggestive evidence on the importance of change in the quantities of FDK for a country's export to the US in response to the Trump tariffs.

The columns (1) and (3) in Table 5 displays the results of two regressions: one with the change in FDK and the other with the change in domestic capital, over the period 2017 to 2019, as dependent variables, examining their responsiveness to the trade diversion index. Columns (2) and (4) are the model regression counterparts used later in the calibration section.

[30]For example, in a world where domestic and foreign producers share identical export portfolios from a common exporting location, and constant returns to scale in production.

| | FDK | | Domestic Capital | |
|---|---|---|---|---|
| | Data | Model | Data | Model |
| | (1) | (2) | (3) | (4) |
| DI | 18.281** | 18.291** | -5.621 | -4.279 |
| | (8.180) | (7.600) | (3.766) | (4.469) |
| R2 adj. | .04 | | .01 | |
| # of Obs. | 100 | | 96 | |

*Notes*: Columns (1) and (3) reports empirical regression estimates of the coefficients on the Trade Diverion Index. I constrain the sample to include investors with sufficient large number of receivers, while excluding those typically considered tax havens. The dependent variables are FDK growth and domestic capital stocks growth from 2017 to 2019 at the country level. The FDI data used are the official inward FDI stocks from the OECD, IMF CDIS, and UNCTAD. The data for domestic capital use IMF domestic capital from 2017, and GDP growth to infer the 2019 value. Columns (2) and (4) report the median of regression coefficients from 10 model simulation runs explained in calibration. Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: FDK and Domestic Capital Responses to the Trade Diversion Index

It suggests that, for those countries that are more exposed to the trade diversion from the Trump tariffs, FDK is likely to be a major contributor of a country's relative export growth to the US in response to the Trump tariffs. In fact, those who are more exposed to the trade diversion from the Trump tariffs might actually have relatively less growth of domestic capital.

To be clear, this is only a statement about the relative contribution of FDK and doestic capital responses across countries that are exposed to the Trump tariffs of different magnitudes. The following examples offer an illustration of the difference between relative and absolute contribution across countries that are exposed differently. Consider two countries, 1 and 2, where $\mathrm{DI}_1 = 1, \mathrm{DI}_2 = 0$. Suppose the FDK, domestic captail, and exports to the US before and after the Trump tariffs are the following.

Before the Trump Tariffs:

| | FDK | Domestic Capital | Export |
|---|---|---|---|
| Country 1 | 10 | 20 | 30 |
| Country 2 | 50 | 100 | 150 |

After the Trump Tariffs:

| | FDK | Domestic Capital | Export |
|---|---|---|---|
| Country 1 | 15 | 21 | 36 |
| Country 2 | 55 | 110 | 165 |

The elasticities of FDK and domestic capital with respect to the diversion index would thus be 40% and -5%. Country 1 would have exported even more to the US if its domestic capital responded of the same magnitude as that of Country 2. However, the absolute contribution of FDK and domestic capital to the two countries' export growth to the US are 5/(5+1), and 5/(5+10), and the total contribution of domestic capital is actually larger than FDK: $1 + 10 > 5 + 5$.

# C Model Derivation

I derive the model solution in an environment with capital. The production function is

$$q_{ij}^s(a) = \frac{a^{\frac{1}{\sigma^s - 1}}}{\kappa_{ij}^s} \left(k_{ij}^s(a)\right)^{\alpha_i} \left(l_{ij}^s(a)\right)^{1-\alpha_i}.$$

The model without capital in the main text simply takes $\alpha_i = 0$.

## C.1 Pricing

Let $\lambda_{ij}^s$ be the Lagrange multiplier on the output constraint; The FOC w.r.t. $p_{hij}$:

$$\begin{aligned} q_{hij}^s + p_{hij}^s \frac{\partial q_{hij}^s}{\partial p_{hij}^s} &= d_{hi}^s \tau_{hi}^s \lambda_{ij}^s \frac{\partial q_{hij}^s}{\partial p_{hij}^s}, \\ \Rightarrow \quad p_{hij}^s &= \frac{\epsilon^s}{\epsilon^s - 1} d_{hi}^s \tau_{hi}^s \lambda_{ij}^s; \end{aligned}$$

and FOC w.r.t. $l_{ij}(s)$:

$$w_i = \lambda_{ij}^s \frac{a^{\frac{1}{\epsilon^s - 1}}}{\kappa_{ij,t}^s} k^{\alpha_i^s} \left(1 - \alpha_i^s\right) \left(l_{ij}^s\right)^{-\alpha_i^s}.$$

Using the resource constraint

$$l_{ij}^s = \left[ A_i^s \left( \frac{w_i}{1-\alpha_i^s} \right)^{-\epsilon} \frac{a}{\left(\kappa_{ij}^s\right)^{\epsilon^s - 1}} k^{(\epsilon^s - 1)\alpha_i^s} \right]^{\frac{1}{1+(\epsilon-1)\alpha_i^s}},$$

$$\text{where } A_i^s = \sum_h \left(\tau_{hi,t}^s\right)^{-\epsilon^s} \left(d_{hi,t}^s\right)^{1-\epsilon^s} \left( \frac{\epsilon^s}{\epsilon^s - 1} \right)^{-\epsilon^s} \left(P_h^s\right)^{\epsilon^s} Q_h^s.$$

Plug this into the price,

$$p_{hij}^s = d_{hi}^s \tau_{hi}^s \frac{\epsilon^s}{\epsilon^s - 1} \left[ \left(A_i^s\right)^{\alpha_i^s} \left( \frac{w_i}{1-\alpha_i^s} \right)^{1-\alpha_i^s} \left( \frac{a^{\frac{1}{\epsilon^s - 1}}}{\kappa_{ij}^s} \right)^{-1} k^{-\alpha_i^s} \right]^{\frac{1}{1+(\epsilon^s-1)\alpha_i^s}}.$$

## C.2 Investment

The FOC w.r.t. $k'$ is

$$P_i R_j = \frac{\partial V_{ij}^s(k';a)}{\partial k'}$$

while the Benveniste-Scheinkman envelope condition is

$$\frac{\partial V_{ij}^s(k;a)}{\partial k} = \frac{\partial v_{ij}^s(k;a)}{\partial k} + \Theta_j R_j P_i (1-\delta).$$

In steady state, $\Theta_j = \beta, R_j = 1/\beta$, and thus the steady state capital and profit are

$$k_{ij}^s(a) = \Lambda_i^s P_i^{-\left(1+(\epsilon^s-1)\alpha_i^s\right)} \frac{a}{\left(\kappa_{ij}^s\right)^{\epsilon^s-1}} \left( \frac{w_i}{1-\alpha_i^s} \right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s,$$

$$\text{where } \Lambda_i^s \equiv \left( \left( \frac{\epsilon^s}{\epsilon^s-1} - (1-\alpha_i^s) \right) \frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s} \frac{1}{\frac{1}{\beta} - (1-\delta)} \right)^{1+(\epsilon^s-1)\alpha_i^s};$$

$$v_{ij}^s(a) = \left( \frac{\epsilon^s}{\epsilon^s-1} - (1-\alpha_i^s) \right) \left(\Lambda_i^s\right)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{-(\epsilon^s-1)\alpha_i^s} \left( \frac{w_i}{1-\alpha_i^s} \right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \frac{a}{\left(\kappa_{ij}^s\right)^{\epsilon^s-1}}.$$

Plug this back into the price,

$$p_{hij}^{s}=\frac{\epsilon^{s}}{\epsilon^{s}-1}d_{hi}^{s}\tau_{hi}^{s}\left(\Lambda_{i}^{s}\right)^{\frac{-\alpha_{i}^{s}}{1+(\epsilon^{s}-1)\alpha_{i}^{s}}}P_{i}^{\alpha_{i}^{s}}\left(\frac{w_{i}}{1-\alpha_{i}^{s}}\right)^{1-\alpha_{i}^{s}}\left(\frac{a^{\frac{1}{\epsilon^{s}-1}}}{\kappa_{ij}^{s}}\right)^{-1}.$$

## C.3 Location Choice

The entrants' investment decisions conditional on $i$ being the optimal location is

$$\max_{\iota} V_{ij}^{s}(\iota;a)-R_{j}P_{i}\iota,$$

which gives $\iota=k_{ij}^{s}(a)$. Thus, the entry value net of entry cost is $\frac{1}{1-\beta}$ times the following

$$\begin{aligned}\tilde{v}_{ij}^{s}(a)&\equiv V_{ij}^{s}(a)+\left(1-\delta-\frac{1}{\beta}\right)P_{i}k_{ij}^{s}(a)\\&=\tilde{\Lambda}_{i}^{s}\left(P_{i}^{-(\epsilon^{s}-1)\alpha_{i}^{s}}\left(\frac{w_{i}}{1-\alpha_{i}^{s}}\right)^{-(\epsilon^{s}-1)\left(1-\alpha_{i}^{s}\right)}A_{i}^{s}\frac{a}{\left(\kappa_{ij}^{s}\right)^{\epsilon^{s}-1}}\right),\\ \text{where } \tilde{\Lambda}_{i}^{s}&=\left(\frac{\epsilon^{s}}{\epsilon^{s}-1}-(1-\alpha_{i}^{s})\right)\left(\Lambda_{i}^{s}\right)^{\frac{(\epsilon^{s}-1)\alpha_{i}^{s}}{1+(\epsilon^{s}-1)\alpha_{i}^{s}}}+\left(1-\delta-\frac{1}{\beta}\right)\Lambda_{i}^{s}.\end{aligned}$$

Note that $\tilde{v}_{ij}^{s}(a)$ is a linear function in $a$. Denote $\tilde{v}_{ij}^{s}=\tilde{v}_{ij}^{s}(1)$ when suppressing the argument. I first derive the case under CES correlation function. Let the productivity draw be $a_{ij}^{s}, i=1,\ldots,N$, the probability of choosing location $i$ is

$$\begin{aligned}\Pr_{ij}^{s}&=\text{Prob}\left(\tilde{v}_{ij}^{s}(a_{ij}^{s})>\tilde{v}_{i'j}^{s}(a_{i'j}^{s}),\ \forall i'\neq i\right)=\text{Prob}\left(\tilde{v}_{ij}^{s}a_{ij}^{s}>\tilde{v}_{i'j}^{s}a_{i'j}^{s},\ \forall i'\neq i\right)\\&=\text{Prob}\left(a_{i'j}^{s}<\frac{\tilde{v}_{ij}^{s}}{\tilde{v}_{i'j}^{s}}a_{ij}^{s},\ \forall i'\neq i\right)=\int_{0}^{\infty}\prod_{i'\neq i}e^{-z_{j}\left(\frac{\tilde{v}_{ij}^{s}}{\tilde{v}_{i'j}^{s}}a_{i'j}^{s}\right)^{-\theta}}\mathrm{d}e^{-z_{j}\left(a_{ij}^{s}\right)^{-\theta}}\\&=\frac{\left(\tilde{v}_{ij}^{s}\right)^{\theta}}{\sum_{i'}\left(\tilde{v}_{i'j}^{s}\right)^{\theta}}.\end{aligned}$$

Thus, the productivity draw cdf conditional location $i$ being chosen is

$$G_{ij}^{s}(a) \equiv \frac{1}{\mathrm{Pr}_{ij}^{s}} \int_{0}^{a} \prod_{i' \neq i} e^{-z_j \left( \frac{\tilde{v}_{ij}^{s}}{\tilde{v}_{i'j}^{s}} a \right)^{-\theta}} \mathrm{d}e^{-z_j a^{-\theta}} = e^{-z_j \frac{\sum_{i'} \left( \tilde{v}_{i'j}^{s} \right)^{\theta}}{\left( \tilde{v}_{ij}^{s} \right)^{\theta}} a^{-\theta}},$$

which is a Fréchet distribution with parameter $z_j^s \frac{\sum_{i'} \left( \tilde{v}_{i'j}^{s} \right)^{\theta}}{\left( \tilde{v}_{ij}^{s} \right)^{\theta}}$.

Now I derive the similar result using CNCES. I will suppress the superscript $s$. First, the probability of $a_{ij}$ being the highest productivity draw across locations is

$$\mathbb{P}\left( a_{ij} = \max_{i'} a_{i'j} \right) = \frac{z_j G_i^j (z_j, z_j, \ldots, z_j)}{G^j \left( z_j, z_j, \ldots, z_j \right)},$$
$$\text{where } G_i^j = \frac{\partial G^j \left( x_1, x_2, \ldots, x_N \right)}{\partial x_i} |_{x_1 = z_j, \ldots, x_N = z_j}.$$

Since $\tilde{v}_{ij} \left( a_{ij} \right) = \tilde{v}_{ij} \frac{a_{ij}}{z_j}$, the vector of value across locations $\{\tilde{v}_{ij}\}$ follows a max-stable multivariate Fréchet distribution with shape $\theta$, correlation function $G^j$, and scale parameters $\left\{ z_j^{1-\theta} \tilde{v}_{ij} \right\}$. Thus, the probability that a location is the best choice is

$$\begin{aligned} \mathbb{P}\left( \tilde{v}_{ij} \left( a_{ij} \right) = \max_{i'} \tilde{v}_{i'j} \left( a_{i'j} \right) \right) &= \frac{\tilde{v}_{ij}^{\theta} G_i^j (\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta})}{G^j (\tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta})} \\ &= \frac{\left( 1 - \eta_{ij} \right) \tilde{v}_{ij}^{\theta} + \eta_{ij} \left( \frac{\left( \eta_{ij} \tilde{v}_{ij}^{\theta} \right)^{\frac{1}{1-\rho}}}{\sum_{i'} \left( \eta_{i'j} \tilde{v}_{i'j}^{\theta} \right)^{\frac{1}{1-\rho}}} \right)^{\rho} \tilde{v}_{ij}^{\theta}}{\sum_{i'} \left( 1 - \eta_{i'j} \right) \tilde{v}_{i'j}^{\theta} + \left( \sum_{i'} \left( \eta_{i'j} \tilde{v}_{i'j}^{\theta} \right)^{\frac{1}{1-\rho}} \right)^{1-\rho}}. \end{aligned}$$

The conditional distribution of value is

$$\mathbb{P}\left( \tilde{v}_{ij} \left( a_{ij} \right) < v | \tilde{v}_{ij} \left( a_{ij} \right) = \max_{i'} \tilde{v}_{i'j} \left( a_{i'j} \right) \right) = \mathbb{P}\left( \max_{i'} \tilde{v}_{i'j} \left( a_{i'j} \right) < v \right) = e^{-z_j^{1-\theta} G^j \left( \tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta} \right) v^{-\theta}},$$

which is a max-stable multivariate Frechet with $\theta$ and scale $z_j G^j \left( \tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta} \right)$. Correspondingly, the conditional distribution of productivity draw is

$$\mathbb{P}\left( a_{ij} < a | \tilde{v}_{ij} \left( a_{ij} \right) = \max_{i'} \tilde{v}_{i'j} \left( a_{i'j} \right) \right) = e^{-z_j \frac{G^j \left( \tilde{v}_{1j}^{\theta}, \tilde{v}_{2j}^{\theta}, \ldots, \tilde{v}_{Nj}^{\theta} \right)}{\tilde{v}_{ij}^{\theta}} a^{-\theta}},$$

which is again a max-stable multivariate Frechet with $\theta$ and scale $z_j \frac{G^j\left(\tilde{v}_{1j}^{\theta},\tilde{v}_{2j}^{\theta},\ldots,\tilde{v}_{Nj}^{\theta}\right)}{\tilde{v}_{ij}^{\theta}}$.

## C.4 Aggregate Variables

I now calculate the aggregate variables in steady state. The source-importer-sector level price index is

$$\begin{aligned} P_h^s &= \left(\sum_{j=1}^N \sum_{i=1}^N \int_{M_{ij}^s} p_{hij}^s(\omega)^{1-\epsilon^s} \,\mathrm{d}\omega\right)^{\frac{1}{1-\epsilon^s}} = \left(\sum_j \sum_i \Pr_{ij}^s \int_0^\infty p_{hij}^s(a)^{1-\epsilon^s} \,\mathrm{d}G_{ij}^s(a)\right)^{\frac{1}{1-\epsilon^s}} \\ &= \left(\sum_j \sum_i \left(\frac{\left(\tilde{v}_{ij}^s\right)^\theta}{\sum_{i'} \left(\tilde{v}_{i'j}^s\right)^\theta}\right)^{\frac{\theta-1}{\theta}} \Gamma\left(1-\frac{1}{\theta}\right)(z_j)^{\frac{1}{\theta}} \left(\frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s \kappa_{ij}^s \left(\Lambda_i^s\right)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{1-\alpha_i^s}\right)^{1-\epsilon^s}\right) \end{aligned}$$

Denote

$$\begin{aligned} \tilde{M}_{ij}^s &\equiv \left(\frac{\left(\tilde{v}_{ij}^s\right)^\theta}{\sum_{i'} \left(\tilde{v}_{i'j}^s\right)^\theta}\right)^{\frac{\theta-1}{\theta}}, \quad z_j^s \equiv \left(\Gamma\left(1-\frac{1}{\theta}\right)(z_j)^{\frac{1}{\theta}}\right)^{\frac{1}{\epsilon^s-1}}, \\ \text{and } P_{hij}^s &\equiv \frac{\epsilon^s}{\epsilon^s-1} d_{hi}^s \tau_{hi}^s \kappa_{ij}^s \left(\Lambda_i^s\right)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{1-\alpha_i^s} \left(z_j^s\right)^{-1}, \end{aligned}$$

so that I can ease notation

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

The source-production-sector level capital value is

$$\begin{aligned} K_{ij}^s &= \int_{M_{ij}^s} P_i k_{ij}^s(\omega) \,\mathrm{d}\omega \\ &= \tilde{M}_{ij}^s \left(\Lambda_i^s P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \left(\frac{z_j^s}{\kappa_{ij}^s}\right)^{\epsilon^s-1}\right), \\ D_{ij}^s &= \int_{M_{ij}^s} v_{ij}^s(\omega) \,\mathrm{d}\omega \\ &= \tilde{M}_{ij}^s \left(\left(\frac{\epsilon^s}{\epsilon^s-1} - (1-\alpha_i^s)\right) \left(\Lambda_i^s\right)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \left(\frac{z_j^s}{\kappa_{ij}^s}\right)^{\epsilon^s-1}\right). \end{aligned}$$

The trade share is

$$
\begin{aligned}
\pi_{hi}^{s} = \frac{X_{hi}^{s}}{X_{h}^{s}} &= \frac{\sum_j \int_{M_{ij}^s} p_{hij}^{s}(\omega) q_{hij}^{s}(\omega)\,\mathrm{d}\omega}{P_{h\cdot j}^{s} Q_{h\cdot j}^{s}} \\
&= \frac{\sum_j \tilde{M}_{ij}^{s} \left( \frac{\epsilon^s}{\epsilon^s - 1} d_{hi}^{s} \tau_{hi}^{s} \kappa_{ij}^{s} \left(\Lambda_i^s\right)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{1-\alpha_i^s} \left(z_j^s\right)^{-1} \right)^{1-\epsilon^s}}{\left(P_h^s\right)^{1-\epsilon^s}} \\
&= \frac{\sum_j \tilde{M}_{ij}^{s} \left(P_{hij}^{s}\right)^{1-\epsilon^s}}{\left(P_h^s\right)^{1-\epsilon^s}}.
\end{aligned}
$$

Finally, the following result helps for calibration

$$
\left( \frac{\tilde{v}_{ij}^{s}}{\tilde{v}_{i'j}^{s}} \right)^{\theta} = \frac{K_{ij}^{s}}{K_{i'j}^{s}} \left( \frac{\tilde{\Lambda}_i^s}{\tilde{\Lambda}_{i'}^s} / \frac{\Lambda_i^s}{\Lambda_{i'}^s} \right).
$$

Thus, I can calibrate variety masses from the observed capital stocks.

## C.5 Gravity Equation

Using $P_{hij}^{s}$ and $\tilde{v}_{ij}^{s}$,

$$
\left(P_{hij}^{s}\right)^{1-\epsilon^s} = \left( \frac{\epsilon^s}{\epsilon^s - 1} d_{hi}^{s} \tau_{hi}^{s} \right)^{1-\epsilon^s} \frac{\left(\Lambda_i^s\right)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}}}{\tilde{\Lambda}_i^s} \frac{1}{A_i^s} \tilde{v}_{ij}^{s} \left( \left(z_j^s\right)^{\epsilon^s - 1} \right).
$$

Thus, the import value from $i$ relative to domestic import value is

$$
\frac{X_{hi}^{s}}{X_{hh}^{s}} = \frac{\left(\Lambda_i^s A_i^s\right)^{\theta-1} \left( P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} \right)^{\theta} \frac{\left(\Lambda_i^s\right)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}}}{\tilde{\Lambda}_i^s} \left( \sum_j \left( \frac{z_j^s}{\kappa_{ij}^s} \right)^{\epsilon^s-1} \right)^{\theta} \left(\tau_{hi}^{s}\right)^{-\epsilon^s} \left(d_{hi}^{s}\right)^{1-\epsilon^s}}{\left(\Lambda_h^s A_h^s\right)^{\theta-1} \left( P_h^{-(\epsilon^s-1)\alpha_h^s} \left(\frac{w_h}{1-\alpha_h^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_h^s\right)} \right)^{\theta} \frac{\left(\Lambda_h^s\right)^{\frac{(\epsilon^s-1)\alpha_h^s}{1+(\epsilon^s-1)\alpha_h^s}}}{\tilde{\Lambda}_h^s} \left( \sum_j \left( \frac{z_j^s}{\kappa_{hj}^s} \right)^{\epsilon^s-1} \right)^{\theta}}.
$$

All terms other than $\left(\tau_{hi}^{s}\right)^{-\epsilon^s} \left(d_{hi}^{s}\right)^{1-\epsilon^s}$ above only depend on the exporting country $i$ and importing country $h$, and thus can be absorbed by fixed effects. The partial trade elasticity w.r.t. both trade cost and tariff (for tariff-inclusive export value) is simply $1 - \epsilon^s$.

Similarly, the bilateral FDI stock value can also be written in terms of $\tilde{v}$

$$K_{ij}^{s}=\frac{\left(\tilde{v}_{ij}^{s}\left(\left(z_{j}^{s}\right)^{\epsilon^{s}-1}\right)\right)^{\theta}\frac{\Lambda_{i}^{s}}{\tilde{\Lambda}_{i}^{s}}}{\left(\sum_{i'}\left(\tilde{v}_{i'j}^{s}\left(\left(z_{j}^{s}\right)^{\epsilon^{s}-1}\right)\right)^{\theta}\right)^{\frac{\theta-1}{\theta}}}.$$

While the total capital stocks the source country $j$ holds is

$$K_{j}^{s}\equiv\sum_{i}K_{ij}^{s}=\frac{\sum_{i}\left(\tilde{v}_{ij}^{s}\left(\left(z_{j}^{s}\right)^{\epsilon^{s}-1}\right)\right)^{\theta}\frac{\Lambda_{i}^{s}}{\tilde{\Lambda}_{i}^{s}}}{\left(\sum_{i'}\left(\tilde{v}_{i'j}^{s}\left(\left(z_{j}^{s}\right)^{\epsilon^{s}-1}\right)\right)^{\theta}\right)^{\frac{\theta-1}{\theta}}}.$$

Thus, the FDI gravity equation can be written as

$$K_{ij}^{s}=\frac{\left(\tilde{v}_{ij}^{s}\right)^{\theta}\frac{\Lambda_{i}^{s}}{\tilde{\Lambda}_{i}^{s}}}{\sum_{i'}\left(\tilde{v}_{i'j}^{s}\right)^{\theta}\frac{\Lambda_{i'}^{s}}{\tilde{\Lambda}_{i'}^{s}}}K_{j}^{s}.$$

Note that since $v_{ij}^{s}(\cdot)$ is linear in its argument, and the above FDI equation is capturing the same source country $j$, the argument in the $v_{ij}^{s}(\cdot)$ function does not matter. Further plug in the $v_{ij}^{s}(\cdot)$ function,

$$K_{ij}^{s}=\frac{\left(\tilde{\Lambda}_{i}^{s}P_{i}^{-(\epsilon^{s}-1)\alpha_{i}^{s}}\left(\frac{w_{i}}{1-\alpha_{i}^{s}}\right)^{-(\epsilon^{s}-1)\left(1-\alpha_{i}^{s}\right)}A_{i}^{s}\left(\kappa_{ij}^{s}\right)^{1-\epsilon^{s}}\right)^{\theta}\frac{\Lambda_{i}^{s}}{\tilde{\Lambda}_{i}^{s}}}{\sum_{i'}\left(\tilde{\Lambda}_{i'}^{s}P_{i'}^{-(\epsilon^{s}-1)\alpha_{i'}^{s}}\left(\frac{w_{i'}}{1-\alpha_{i'}^{s}}\right)^{-(\epsilon^{s}-1)\left(1-\alpha_{i'}^{s}\right)}A_{i'}^{s}\left(\kappa_{i'j}^{s}\right)^{1-\epsilon^{s}}\right)^{\theta}\frac{\Lambda_{i'}^{s}}{\tilde{\Lambda}_{i'}^{s}}}K_{j}^{s}.$$

It's easy to see that the partial FDI elasticity (FDI stock value w.r.t. operation friction $\kappa$) is $\theta\left(1-\epsilon^{s}\right)$.

## C.6 Aggregate Variables & Gravity Equations with CNCES

Again, the above variables can be defined in similar ways.

$$\tilde{M}_{ij}^s \equiv \left( \frac{\left(\tilde{v}_{ij}^s\right)^\theta G_i^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)}{G^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)} \right)^{\frac{\theta-1}{\theta}} G_i^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)^{\frac{1}{\theta}},$$

while $z_j^s$, $P_{hij}^s$ are all defined the same as before. The trade shares also have the same form

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

I next derive the FDI gravity. First, the bilateral capital value is of the same form with differently defined $\tilde{M}_{ij}^s$

$$K_{ij}^s = \tilde{M}_{ij}^s \left( \Lambda_i^s P_i^{-(\epsilon^s-1)\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s \left(\frac{z_j^s}{\kappa_{ij}^s}\right)^{\epsilon^s-1} \right).$$

The FDI gravity becomes

$$K_{ij}^s = \frac{\left(\tilde{v}_{ij}^s\right)^\theta G_i^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right) \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}}{\sum_{i'} \left(\tilde{v}_{i'j}^s\right)^\theta G_{i'}^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right) \frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}} K_j,$$

which is basically the entry probability adjusted for capital intensity for each production location. Note that $\sum_{i'} \left(\tilde{v}_{i'j}^s\right)^\theta G_{i'}^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right) = G^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)$, and $G^j \left(\tilde{v}_{1j}^s, \tilde{v}_{2j}^s, \ldots, \tilde{v}_{Nj}^s\right)^{\frac{1}{\theta}} \equiv \tilde{v}_j$ can be understood as an aggregate value index for $j$, analogous to the usual ideal aggregate price index. I can redefine the correlation function to adjust for the capital intensity

$$G^j \left(x_1, x_2, \ldots, x_N\right) = \sum_{i=1}^N \left(1-\eta_{ij}\right) \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s} x_i + \left( \sum_{i=1}^N \left(\eta_{ij} \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s} x_i\right)^{\frac{1}{1-\rho}} \right)^{1-\rho}.$$

The investment portfolio for producers from $j$ can be denoted in a simpler way

$$\lambda_{ij}^{s}=\frac{\left(\tilde{v}_{ij}^{s}\right)^{\theta}\tilde{G}_{i}^{j}\left(\tilde{v}_{1j}^{s},\tilde{v}_{2j}^{s},\ldots,\tilde{v}_{Nj}^{s}\right)}{\sum_{i'}\left(\tilde{v}_{i'j}^{s}\right)^{\theta}\tilde{G}_{i'}^{j}\left(\tilde{v}_{1j}^{s},\tilde{v}_{2j}^{s},\ldots,\tilde{v}_{Nj}^{s}\right)}.$$

With our specific correlation function, this portfolio share can be decomposed as

$$\begin{aligned}
\lambda_{ij}^{s} &= \frac{\left(1-\eta_{ij}\right)\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\tilde{v}_{ij}^{\theta}+\eta_{ij}\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\left(\frac{\left(\eta_{ij}\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\tilde{v}_{ij}^{\theta}\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}}\right)^{\rho}\tilde{v}_{ij}^{\theta}}{\sum_{i'}\left(1-\eta_{i'j}\right)\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}+\left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}} \\
&= \underbrace{\frac{\left(1-\eta_{ij}\right)\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\tilde{v}_{ij}^{\theta}}{\sum_{i'}\left(1-\eta_{i'j}\right)\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}}}_{\equiv\lambda_{ij}^{W}}\underbrace{\frac{\sum_{i'}\left(1-\eta_{i'j}\right)\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}}{\sum_{i'}\left(1-\eta_{i'j}\right)\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}+\left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv\lambda_{j}^{B}} \\
&+ \underbrace{\frac{\eta_{ij}\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\left(\frac{\left(\eta_{ij}\frac{\Lambda_i^s}{\tilde{\Lambda}_i^s}\tilde{v}_{ij}^{\theta}\right)^{\frac{1}{1-\rho}}}{\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}}\right)^{\rho}\tilde{v}_{ij}^{\theta}}{\left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv\lambda_{ij}^{W*}}\underbrace{\frac{\left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}{\sum_{i'}\left(1-\eta_{i'j}\right)\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}+\left(\sum_{i'}\left(\eta_{i'j}\frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s}\tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}\right)^{1-\rho}}}_{\equiv\lambda_{j}^{B*}}.
\end{aligned}$$

$\lambda_{ij}^{W}$ and $\lambda_{ij}^{W*}$ are the within-factor share for the technology type without correlation (no $*$) and with correlation $\rho$ (with $*$), and $\lambda_{j}^{B}$ and $\lambda_{j}^{B*}$ are the between-factor share. $\lambda_{ij}^{W}\lambda_{j}^{B}$ measures the overall share of producer capitals from $j$ that use the first technology type to operate in country $i$, while $\lambda_{ij}^{W*}\lambda_{j}^{B*}$ measures the share the other technology type.

The cross-elasticity can be shown to be

$$\frac{\partial\ln\lambda_{ij}}{\partial\ln\frac{\tilde{v}_{i'j}}{\tilde{v}_{j}}}=\theta\frac{\tilde{v}_{i'j}^{\theta}\tilde{G}_{ii'}^{j}\left(\tilde{v}_{1j}^{s},\tilde{v}_{2j}^{s},\ldots,\tilde{v}_{Nj}^{s}\right)}{\tilde{G}_{i}^{j}\left(\tilde{v}_{1j}^{s},\tilde{v}_{2j}^{s},\ldots,\tilde{v}_{Nj}^{s}\right)}.$$

Plug in again the specific form of the correlation function,

$$\frac{\partial \ln \lambda_{ij}}{\partial \ln \frac{\tilde{v}_{i'j}}{\tilde{v}_j}} = -\theta \frac{\rho}{1-\rho} \lambda_{ij}^{W*} \lambda_{i'j}^{W*} \frac{\lambda_j^{B*}}{\lambda_{ij}}.$$

When two production locations have similar within-factor shares for the producer, they are strong head-to-head choices and this elasticity is high. Similarly, when two production locations have operation technology concentrated on the type with high correlation across countries (high $\rho$), they are more substitutable. Since the first technology type has zero correlation across $i$, it does not appear in the formula. As I will assume in later quantitative analysis $\eta_{jj} = 1, \forall j$, this cross-elasticity of portfolio share in $i$ with respect to relative domestic value change can be further simplified to

$$\frac{\partial \ln \lambda_{ij}}{\partial \ln \frac{\tilde{v}_{jj}}{\tilde{v}_j}} = -\theta \frac{\rho}{1-\rho} \lambda_{ij}^{W*} = -\theta \frac{\rho}{1-\rho} \frac{\left(\eta_{ij} \frac{\Lambda_i^s}{\tilde{\Lambda}_i^s} \tilde{v}_{ij}^{\theta}\right)^{\frac{1}{1-\rho}}}{\sum_{i'} \left(\eta_{i'j} \frac{\Lambda_{i'}^s}{\tilde{\Lambda}_{i'}^s} \tilde{v}_{i'j}^{\theta}\right)^{\frac{1}{1-\rho}}}.$$

For example, when China is hit by tariff from the US and thus domestic production value $\tilde{v}_{jj}$ is relatively lower, countries $i$ with relative higher $\eta_{ij}$ will see larger increase of FDI investment from China.

## C.7 Trade-only Model

I compare the baseline model to the one without the FDI possibility. In other words, the producers only produce domestically, with the same productivity draws, but no reallocation and entry decisions. There is only one layer of demand system (besides across sectors). I specify the different parts from the baseline model.

The price index for goods that country $h$ imports from country $i$ in sector $s$ is

$$\begin{aligned} P_{hi}^s &\equiv \left( \int_0^\infty p_{hi}^s(a)^{1-\epsilon^s} \, \mathrm{d}G_i^s(a) \right)^{\frac{1}{\theta(1-\epsilon^s)}} \\ &= \frac{\epsilon^s}{\epsilon^s - 1} \gamma_{hi}^s \tau_{hi}^s \left(\Lambda_i^s\right)^{\frac{-\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{\alpha_i^s} \left(\frac{w_i}{1-\alpha_i^s}\right)^{1-\alpha_i^s} \left(\Gamma\left(1-\frac{1}{\theta}\right) (z_i^s)^{\frac{1}{\theta}}\right)^{\frac{1}{1-\epsilon^s}}. \end{aligned}$$

The aggregate capital stocks and profits for country $i$ in sector $s$ is

$$
\begin{aligned}
K_i^s &= \int_0^\infty k_i^s(a)\,\mathrm{d}G_i^s(a) \\
&= \Gamma\left(1-\frac{1}{\theta}\right)(z_i^s)^{\frac{1}{\theta}}\left(\Lambda_i^s P_i^{-\left(1+(\epsilon^s-1)\alpha_i^s\right)}\left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s\right), \\
D_{ij}^s &= \int_0^\infty d_i^s(a)\,\mathrm{d}G_i^s(a) \\
&= \Gamma\left(1-\frac{1}{\theta}\right)(z_i^s)^{\frac{1}{\theta}}\left(\left(\frac{\epsilon^s}{\epsilon^s-1}-(1-\alpha_i^s)\right)(\Lambda_i^s)^{\frac{(\epsilon^s-1)\alpha_i^s}{1+(\epsilon^s-1)\alpha_i^s}} P_i^{-(\epsilon^s-1)\alpha_i^s}\left(\frac{w_i}{1-\alpha_i^s}\right)^{-(\epsilon^s-1)\left(1-\alpha_i^s\right)} A_i^s\right).
\end{aligned}
$$

# D Counterfactuals: Extra Results

## D.1 Decomposition of Real Consumption Responses

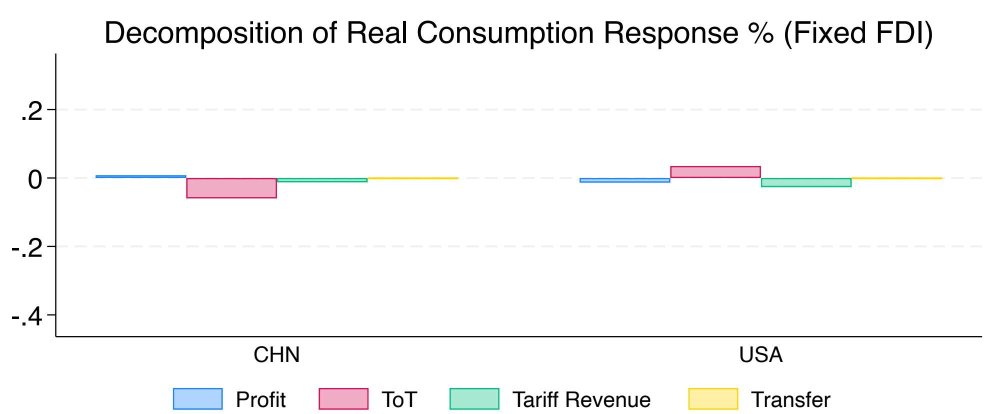



Figure 27: Decomposition of Real Consumption Responses: Fixed FDI

## D.2 Optimal Tariffs under Fixed FDI

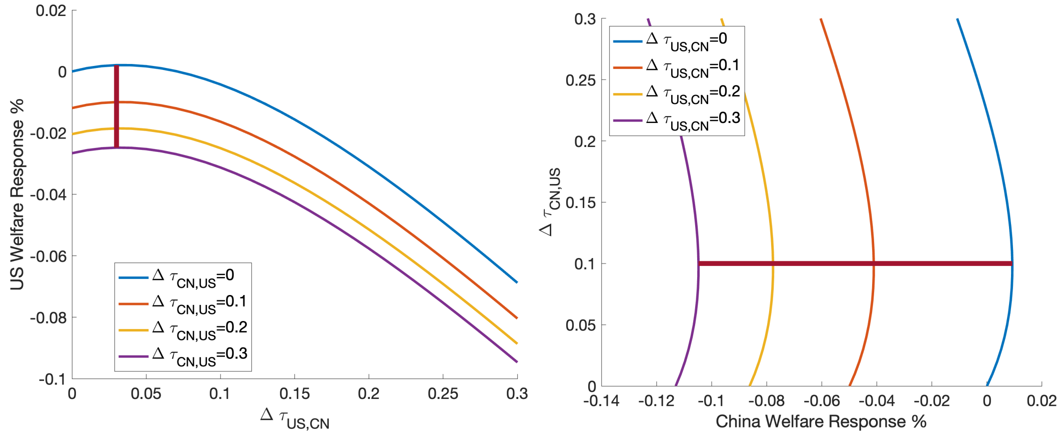



Figure 28: Nash Optimal Tariffs (Fixed FDI)

## D.3 Counterfactuals Comparison: Homogeneous vs. Heterogeneous FDI Elasticities

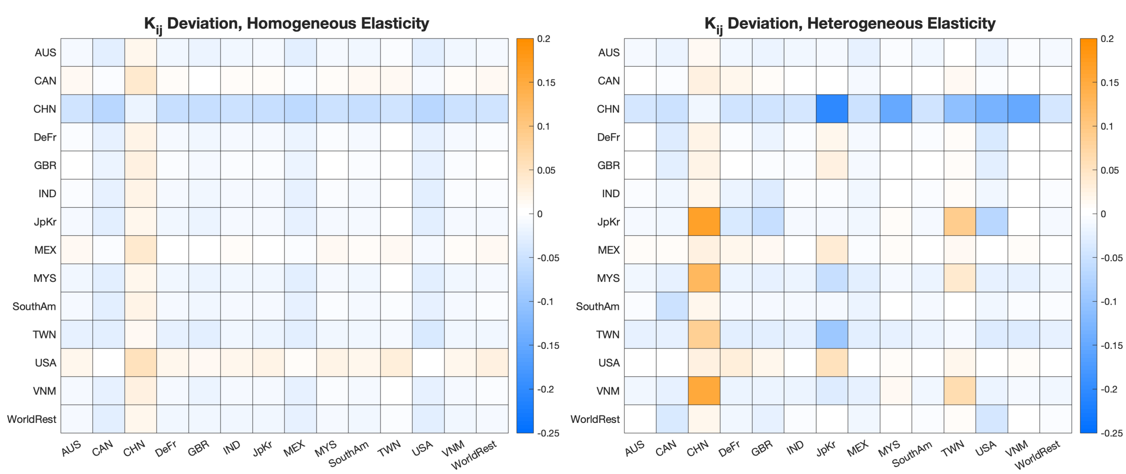



Figure 29: Bilateral FDK Deviation: Homo. vs. Hetero. Elasticity Model

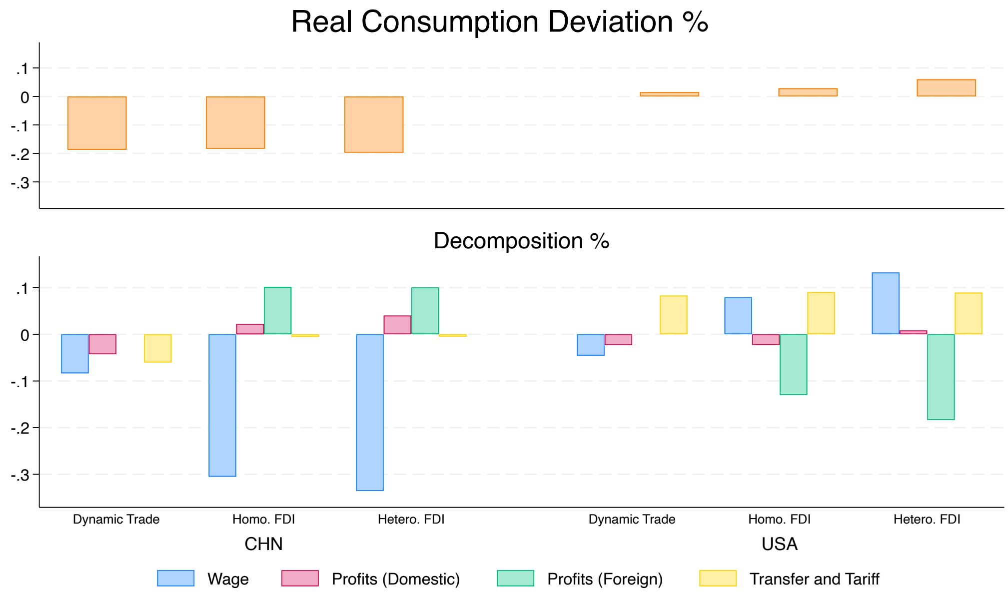



Figure 30: Real Consumption Deviation for China and US

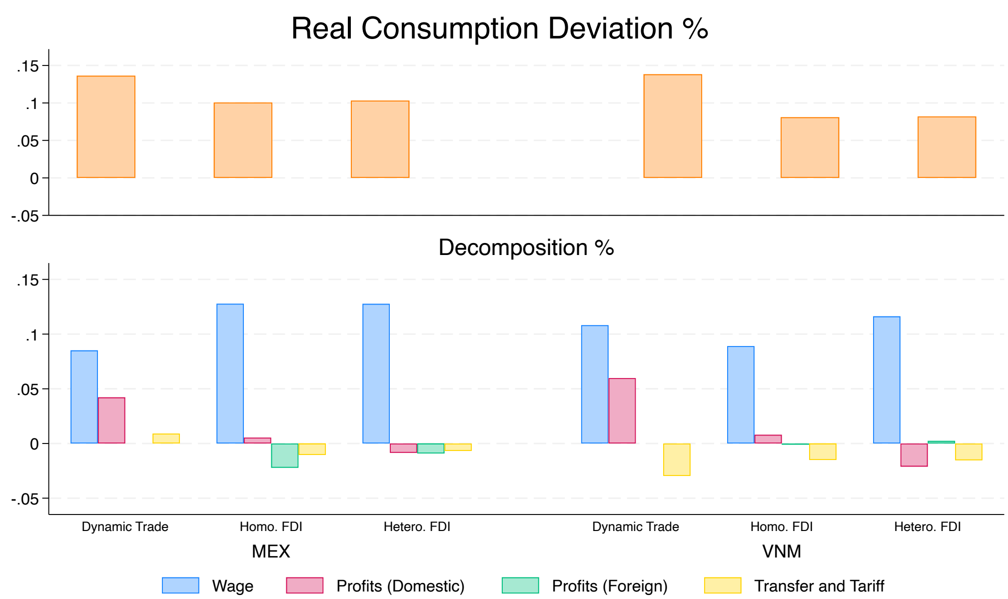



Figure 31: Real Consumption Deviation for Mexico and Vietnam

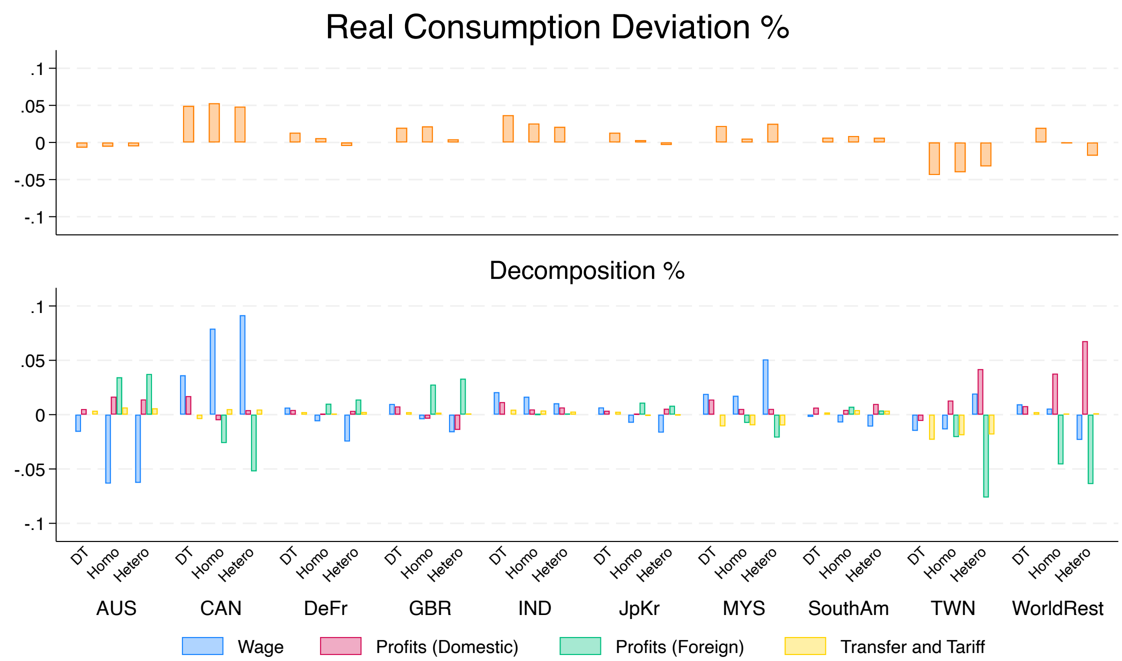



Figure 32: Real Consumption Deviation for Other Economies

## D.4 Sensitivity Check: Alternative Calibration for Parameters Related to FDI Elasticities

I conduct sensitivity checks by showing calibration and counterfactual results using alternative calibration parameters. I fix $\theta = 14$, which is higher than the baseline value $\theta = 0.58$. Given this, I calibrate all other parameters, without targeting the standard error of the $\vartheta$ estimates. The resulting calibration and counterfactual results are qualitatively similar to the baseline calibration results. The magnitude of FDI diversion in counterfactuals is in general a little bit larger than the baseline case.

| | Outcome: $\mathrm{d}\ln K_i$ | | Calibration | |
|---|---|---|---|---|
| | Data | Model | Parameter | Value |
| $\mathrm{DI}_i$ | 18.67 ** | 18.90 | $\rho$ | 0.84 |
| | (7.83) | (7.02) | $\theta$ | 14 |
| $R^2$ | 0.471 | | | |
| # of Obs. | 117 | | | |

*Notes*: The first column reports empirical regression coefficient for $\vartheta$. 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 6: Sensitivity Check with Given $\theta = 14$: Calibration for FDI Elasticities: $\rho$

| | Outcome: $\mathrm{d}\ln K_{ij}$ | | Calibration | |
|---|---|---|---|---|
| | Data | Model | Parameter | Value |
| $\mathrm{d}\ln K_i \times \ln(\mathrm{Dist}_{ij})$ | -0.169* | -0.181 | $\zeta_1$ | -7 |
| | (0.090) | | | |
| $\mathrm{d}\ln K_i \times \ln\left(\mathrm{GDPpc}_j\right)$ | 0.117** | 0.122 | $\zeta_2$ | 4.5 |
| | (0.059) | | | |
| $\mathrm{d}\ln K_i \times \mathrm{ComparaAdv}_{ij}$ | 0.576*** | 0.634 | $\zeta_3$ | 16.5 |
| | (0.219) | | | |
| | | | $\zeta_0$ | -7 |
| $R^2$ | 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 7: Sensitivity Check with Given $\theta = 14$: Calibration for FDI Elasticities: $\boldsymbol{\zeta}$

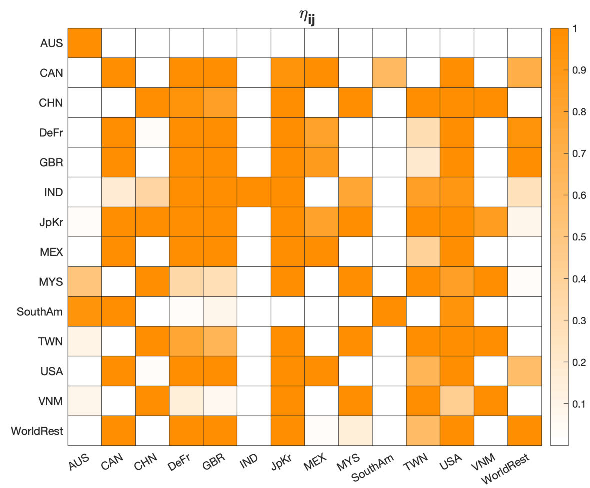



Figure 33: Sensitivity Check with Given $\theta = 14$: Calibrated $\eta_{ij}$

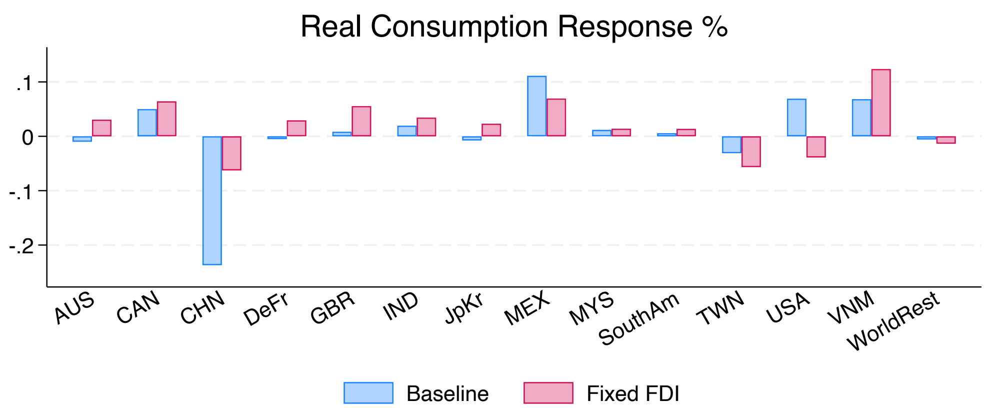



Figure 34: Sensitivity Check with Given $\theta = 14$: Real Consumption Responses: Fixed FDI vs. FDI Diversion

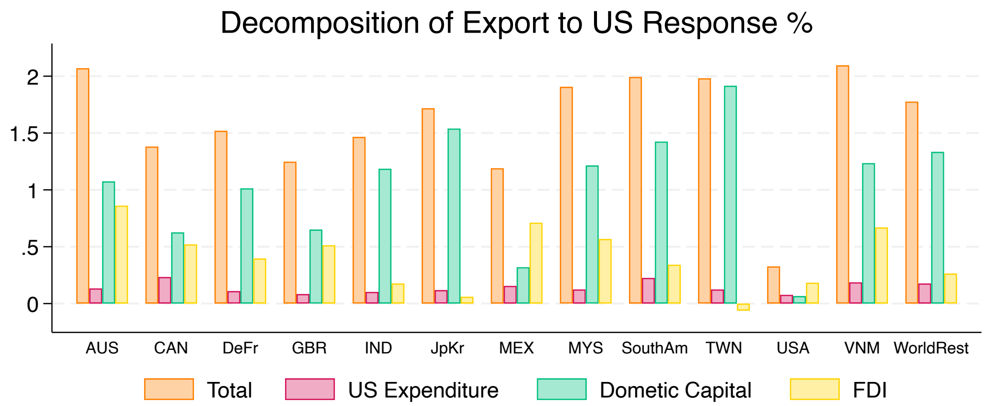



Figure 35: Sensitivity Check with Given $\theta = 14$: Export Deviation Decomposition

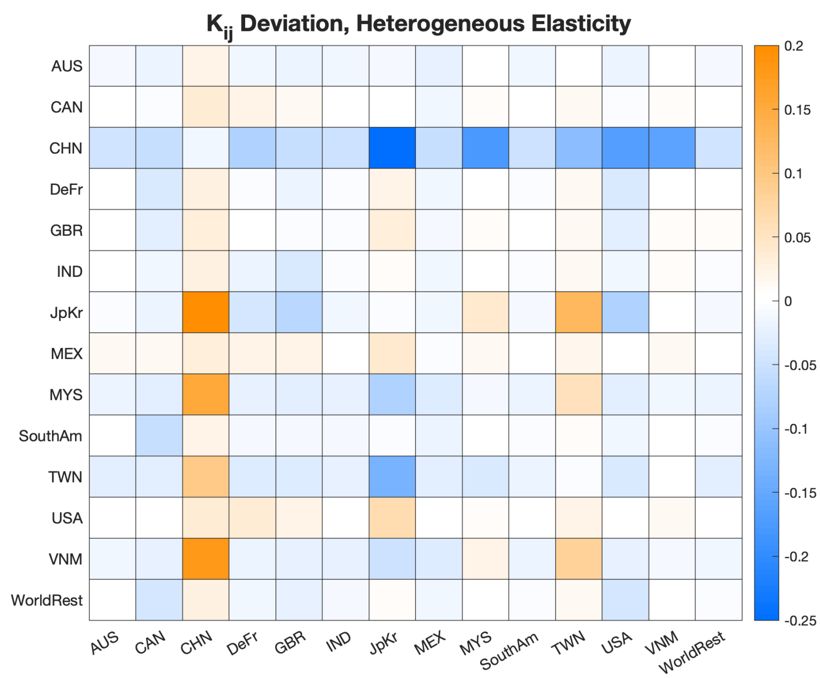



Figure 36: Sensitivity Check with Given $\theta = 14$: Bilateral FDK Diversion

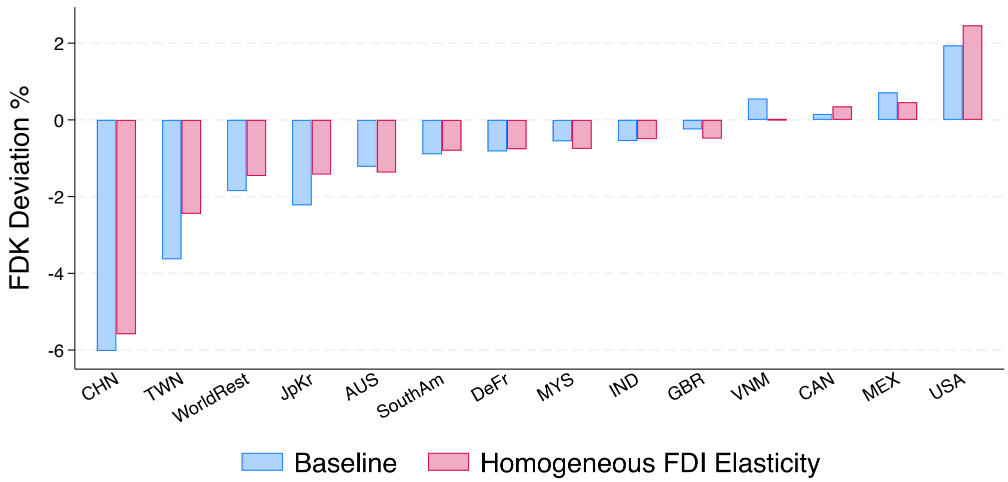



Figure 37: Sensitivity Check with Given $\theta = 14$: FDK Response: Baseline vs. Homogeneous FDI Elasticity

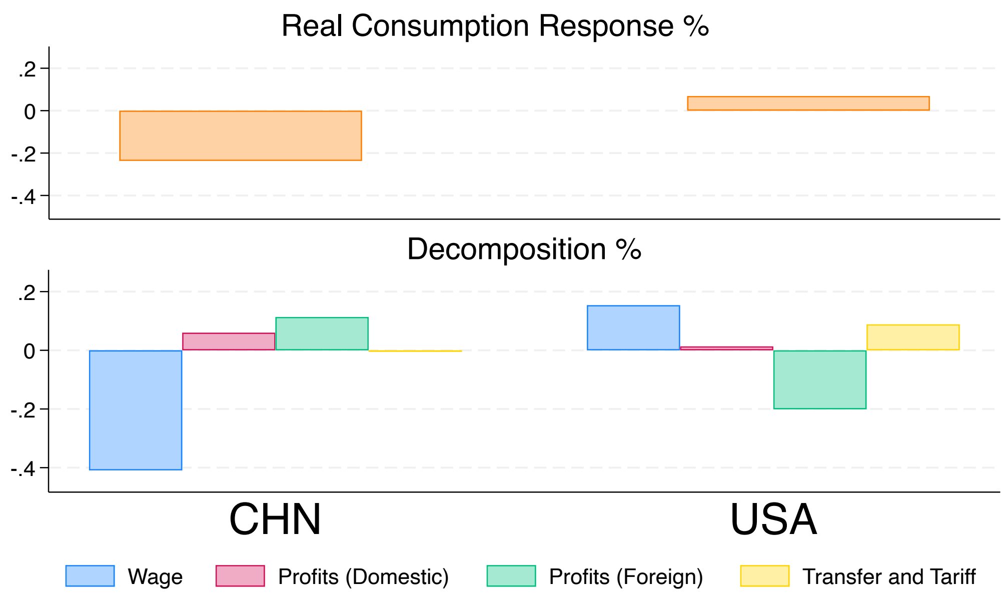



Figure 38: Sensitivity Check with Given $\theta = 14$: Real Consumption Implications for China and US

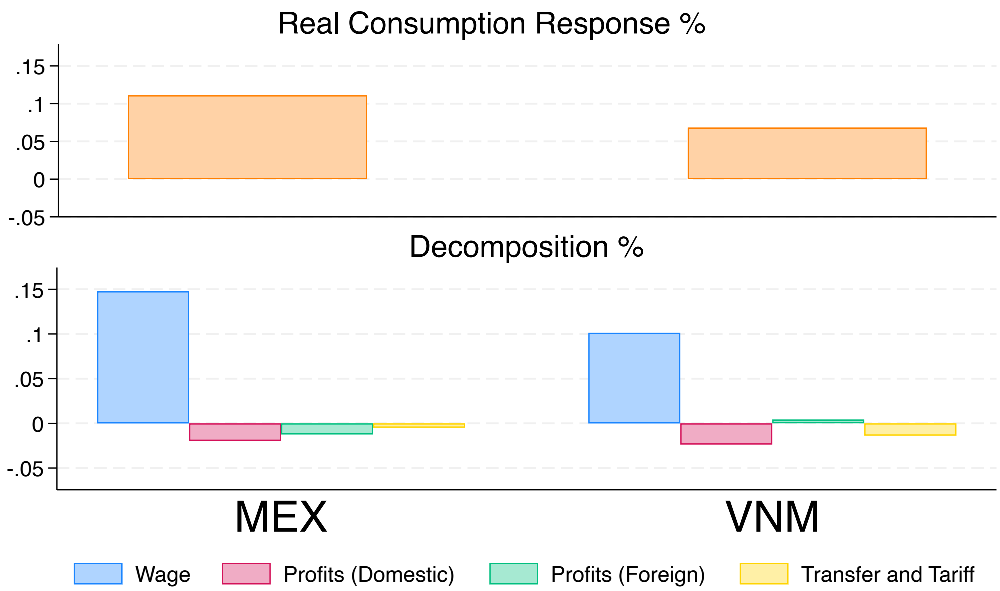



Figure 39: Sensitivity Check with Given $\theta = 14$: Real Consumption Implications for Mexico and Vietnam

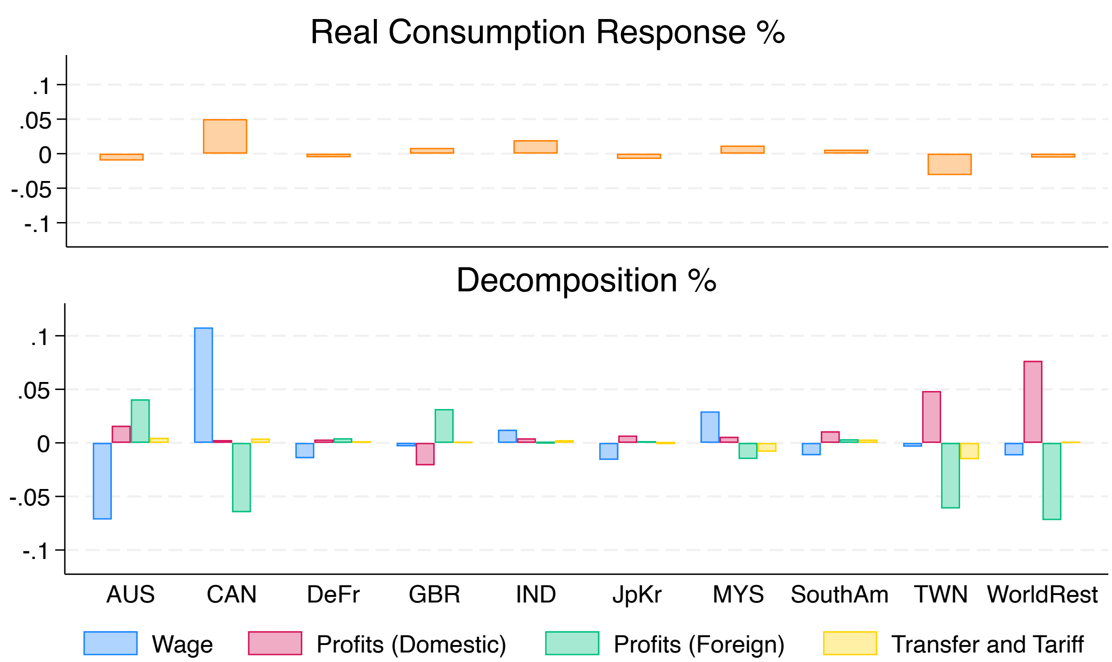



Figure 40: Sensitivity Check with Given $\theta = 14$: Real Consumption Implications for Other Economies